NON-INVASIVE END-OF-LINE QUALITY INSPECTION OF ELECTRIC MOTORS SUPPORTED BY ARTIFICIAL INTELLIGENCE

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Doctoral Dissertation
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Doctoral Dissertation

NEINVANZIVNA KONČNA KONTROLA KAKOVOSTI ELEKTRIČNIH MOTORJEV, PODPRTA Z UMETNO INTELIGENCO

Doktorska disertacija

Supervisor: Asst. Prof. Gregor Dolanc

Ljubljana, Slovenia, June 2026

To my wife, my parents, my family and everyone who has walked this journey with me

Acknowledgments

Life is a journey. At times, it is demanding and challenging, while at others, it is light and fulfilling. Either way, life never leaves us without experience. Some experiences are challenging and painful, while others are rewarded with various achievements. In academia, earning a Ph.D. and becoming a doctor represents one of the greatest achievements. However, the path toward this achievement cannot be traveled alone, and there are many individuals whose support has been invaluable.

First and foremost, I would like to express my deepest gratitude to my supervisor, Asst. prof. Dr. Gregor Dolanc, for his guidance, insight, and unwavering support throughout this journey. His mentorship has been invaluable in shaping this dissertation and my development as a researcher.

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In conclusion, a Ph.D. is never a solo adventure. I am deeply grateful to have walked this path alongside such remarkable people. Yet the journey does not end here. As a future doctor of science, I am committed to continuing the path I have begun—growing, contributing, and using the knowledge and talents entrusted to me responsibly and with integrity: “From everyone who has been given much, much will be demanded; and from the one who has been entrusted with much, much more will be asked” (Luke 12:48).

Abstract

Electric motors are produced in very high volumes and are critical parts of modern industrial and consumer systems, devices and appliances. Ensuring their reliability requires robust and automated End-of-Line (EoL) quality inspections that can detect mechanical and electromechanical defects. The EoL quality inspection is usually performed at the end of the manufacturing line and must follow the production rate of the manufacturing line. Cost constraints are also present. During quality inspection, various electrical, vibrational, acoustic, and other signals are captured. These signals are processed using predefined signal processing methods (e.g., multiple digital filtering, down-sampling and Hamming window) to extract discrete scalar values, known as features, that describe the characteristics of each inspected instance. This process is commonly known as feature engineering. However, traditional EoL inspection systems rely heavily on expert-defined features, threshold-based rules, and manual commissioning procedures. These systems are limited in their adaptability and robustness in modern, high-variability industrial environments.

This dissertation investigates applying machine learning, transfer learning, and deep learning approaches to intelligent EoL quality inspection of brushless DC motors using real industrial data from automated manufacturing lines. Three complementary approaches are developed and evaluated.

First, supervised machine learning combined with automated feature selection reduces diagnostic complexity while improving classification performance and interpretability. Second, transfer learning accelerates the commissioning of inspection systems for new motor types with limited preproduction data by reusing knowledge from mass-production models. Third, a deep learning approach based on Mel-frequency spectrograms and a hybrid convolutional neural network (CNN) and bidirectional gated recurrent unit (BiGRU) architecture is proposed to detect faults directly from raw vibration and acoustic signals, eliminating the need for manual (human expert based) feature engineering.

All methods are validated using large-scale industrial datasets obtained from fully automated EoL inspection system. The results demonstrate that automated feature selection improves efficiency and robustness; transfer learning significantly reduces data requirements and commissioning time; and deep learning improves the detection of complex fault signals. These findings confirm that AI-based inspection systems can reduce dependence on human experts and provide scalable, adaptive, and reliable quality inspection systems for modern electric motor manufacturing.

Povzetek

Električni motorji se proizvajajo v izjemno velikih količinah in so ključni deli sodobnih industrijskih in potrošniških sistemov ter naprav. Za zagotovitev njihove zanesljivosti so potrebni robustni avtomatski sistemi končnega nadzora kakovosti (EoL), ki lahko odkrijejo mehanske in elektromehanske napake. Končna kontrola kakovosti se izvaja na koncu proizvodnih linij, mora slediti tempu proizvodnje in je predmet stroškovnih omejitev. Med postopkom kontrole kakovosti se zajemajo različni električni, vibracijski, akustični in drugi signali. Ti signali se obdelajo po vnaprej določenih metodah obdelave signalov (npr. digitalno filtriranje, zmanjševanje vzorčne frekvence, Hammingovo okno) z namenom določanja diskretnih skalarnih vrednosti, imenovanih značilke, ki opisujejo lastnosti posameznega preiskovanega primerka. Ta postopek se pogosto imenuje inženiring značilk (ang. feature engineering). Vendar se tradicionalni sistemi močno opirajo na značilke, ki jih opredelijo strokovnjaki, pravila, ki temeljijo na mejnih pragovih, in vnaprej definiranih testnih postopkih. Ti sistemi so omejeni v prilagodljivosti in robustnosti v sodobnih, zelo spremenljivih industrijskih okoljih.

Ta disertacija preučuje uporabo pristopov strojnega učenja, prenosa znanja in globokega učenja za inteligentni končni nadzor kakovosti brezkrtačnih enosmernih motorjev med proizvodnjo z uporabo dejanskih industrijskih podatkov iz avtomatiziranih proizvodnih linij. Razviti in ovrednoteni so trije dopolnjujoči se pristopi.

Prvič, nadzorovano strojno učenje v kombinaciji z avtomatizirano izbiro značilk zmanjšuje kompleksnost diagnostike ter hkrati izboljšuje učinkovitost klasifikacije in obrazložljivost. Drugič, prenos znanja pospeši zagon sistemov za nove tipe motorjev z omejenimi podatki iz predproizvodnje, saj ponovno uporabi znanje iz modelov za masovno proizvodnjo. Tretjič, predlagan je pristop globokega učenja, ki temelji na Mel-frekvenčnih spektrogramih ter hibridni konvolucijski nevronski mreži (CNN) in arhitekturi dvosmerne ponavljajoče se nevronske mreže (BiGRU), za odkrivanje napak neposredno iz surovih vibracijskih in akustičnih signalov, kar odpravlja potrebo po ročni obdelavi značilk, ki jo sicer opravijo eksperti.

Vse metode so preverjene z uporabo obsežnih industrijskih podatkov, pridobljenih iz popolnoma avtomatiziranega sistema za končni nadzor kakovosti. Rezultati kažejo, da avtomatizirana izbira značilk izboljša učinkovitost in robustnost, prenos znanja znatno zmanjša zahteve glede podatkov in čas zagona proizvodnje, globoko učenje pa izboljša odkrivanje kompleksnih signalov napak. Ti izsledki potrjujejo, da lahko sistemi za končni nadzor kakovosti, ki temeljijo na umetni inteligenci, zmanjšajo odvisnost od strokovnjakov ter zagotovijo prilagodljive in zanesljive rešitve za sodobno proizvodnjo elektromotorjev.

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Abbreviations

AI	...	Artificial Intelligence
BiGRU	...	Bidirectional Gated Recurrent Unit
BLDC	...	Brushless Direct Current
CNN	...	Convolutional Neural Network
DL	...	Deep Learning
EoL	...	End-of-Line
E2E	...	End-to-End
MFSs	...	Mel-frequency spectrogram
ML	...	Machine Learning
NDA	...	Non-Disclosure Agreement
NN	...	Neural Network
RMS	...	Root mean square
TL	...	Transfer Learning

Chapter 1

Introduction

1.1 Background and Motivation

Electric motors represent one of the most widely produced and used electromechanical devices [1], [2]. Their purpose is the conversion of electrical energy into mechanical work, most commonly rotational motion.

In a competitive market, producers strive to optimize the trade-off between manufacturing cost and product quality [1], [2]. To achieve the lowest feasible production costs, motor production lines are typically highly automated, employing sophisticated machining, winding, assembly, and testing equipment. However, even in well controlled production environments, unpredictable variations such as material inconsistencies, component tolerances, equipment wear, process drifts or assembly anomalies, can reduce product quality [3], [4]. As a result, faulty or substandard units may be produced.

To ensure that such units do not reach customers or cause failures in the systems and devices into which they are built, manufacturers usually apply 100% End-of-Line (EoL) quality inspection as a crucial component of the production workflow [2]. Because complete disassembly or invasive inspection is infeasible at this stage, EoL testing must extract diagnostic information from externally measurable signals, such as vibration, sound, temperature, electrical characteristics or torque responses [2], [4], [5], [6]. These signals are acquired using a non-invasive diagnostic method based on captured vibration and acoustic signals. The acquired signals are digitally processed using predefined procedures (e.g. filtering, downsampling and application of a Hamming window) to obtain stable representations in the time and frequency domains. From these representations, discrete scalar quantities—such as signal power in selected frequency bands—are extracted to describe the state of each inspected motor. These quantities are called features, and their systematic extraction and transformation constitutes the process of feature engineering. Unfortunately, the increasing structural complexity of motor assemblies makes the diagnosis procedures more challenging. Sensitive mechanical or electromechanical faults may only manifest through weak, nonlinear or noise-sensitive features that are difficult to detect with traditional rule-based approaches [6], [7].

Consequently, the design, commissioning and maintenance of reliable EoL inspection systems require extensive domain knowledge, expert-crafted features, carefully tuned thresholds and test procedures that must be adapted for every new motor type and its variants [2]. This dependence on human expertise leads to long commissioning times, complex inspection procedures and significant challenges in scaling inspection capabilities across diverse product variants.

These limitations motivate the integration of machine learning (ML), deep learning (DL) and transfer learning (TL) methods to improve the intelligence, robustness and

adaptability of EoL quality inspection. By utilizing the information content embedded in vibration, acoustic and electrical signals, Artificial Intelligence (AI) based inspection systems have the potential to autonomously detect complex fault signatures, eliminate manual feature engineering, reduce dependence on human experts, accelerate commissioning and improve both production efficiency and product reliability [7], [8], [9], [10].

1.2 Problem Description and Challenges

Although electric motors are produced on highly automated manufacturing lines, the increasing mechanical and functional complexity of modern motor assemblies introduces significant challenges for EoL quality inspection [1], [2], [9]. Motors are no longer simple combinations of rotors and stators; in many applications they have integrated additional mechanical units such as actuators, gears, linear drives, mixers, cutters, or other load-specific components [1], [3]. These attachments expand product functionality but also represent new sources of variability, dynamic behavior and potential faults. As a result, fault patterns in vibration, acoustic or current-based measurements become more diverse and less predictable [4], [6], [7].

Even in highly stable automated production systems, unpredictable anomalies (tool wear, material inconsistencies, environmental changes or transient process instabilities) can influence product quality [1], [4], [9]. These anomalies are difficult to model and can cause faulty motor production.

Despite the availability of large amounts of sensor data, traditional EoL inspection still relies heavily on manually engineered features, expert-defined thresholds and deterministic rules [11], [12], [13]. Designing these elements requires expert knowledge of motor physics, signal interpretation and fault specifications [2], [7]. Commissioning an inspection system for each new motor type therefore becomes time-consuming [8]. This dependence limits scalability, especially in manufacturing environments with frequent introductions of new product variants [9], [14].

Furthermore, the complexity of the produced units leads to complex signal structures, making it difficult for classical feature-based approaches to capture all relevant fault information [6], [7]. Many defect signatures are nonlinear, time-varying or hidden in noise and may only appear under specific operating conditions [4], [11], [15]. As a result, traditional systems are often less sensitive to subtle faults while generating false alarms due to normal production variability [7], [16].

A related challenge arises during the commissioning of new products: only small volumes of labelled data are available in the pre-production stage [8], [17]. Conventional machine learning methods typically require large datasets to achieve stable performance [7], [18]. Without this, models overfit, generalise poorly, and become unsuitable for real production environments [17]. Transfer learning offers a solution to these issues by leveraging knowledge from existing motor classes [19], [20], [21], [22], [23], but its application in EoL inspection of electric motors is still limited and requires careful methodological adaptation [10].

In addition, deep learning models can extract informative patterns directly from raw sensor data, eliminating the need for data preprocessing and manual feature design [10], [24], [25], [26]. However, these models require large amounts of training data [1], [8], [21] and must be computationally efficient to meet the requirements of automated lines [27], [28]. Their limited interpretability further complicates industrial acceptance, especially when traceability and decision explainability are crucial [29], [30], [31].

In summary, today's EoL inspection systems face fundamental challenges driven by increasing product complexity, unpredictable process influences, dependence on expert knowledge, insufficient data during commissioning, and the limitations of traditional diagnostic approaches [1], [2], [7], [9]. Addressing these issues is essential for the development of intelligent, scalable, and robust quality inspection systems capable of supporting modern high-throughput electric motor production.

1.3 The Purpose of the Dissertation

The purpose of this dissertation is to explore and demonstrate how modern AI and ML methods can improve industrial EoL quality inspection, with a particular focus on electric motor production. The purpose of the dissertation consists of four main aspects:

1. Automating the detection and classification of defects in electric motors. The first purpose is to design and validate AI-driven diagnostic models that automatically detect and classify motor defects using raw or minimally processed vibration and acoustic signals. This includes the development of machine learning approaches that identify the most informative features for classification, enabling more objective and consistent decision-making than traditional expert-defined thresholds.
2. Improving inspection accuracy and reliability while reducing manual effort and cost. The second purpose is to demonstrate how ML-based feature reduction and classifier optimization can increase diagnostic performance while minimising engineering effort. By eliminating unnecessary or less relevant features, the research aims to simplify the inspection procedure and develop a more robust, interpretable and cost-efficient quality inspection system.
3. Enabling faster and more automated deployment of inspection systems for new motor types with minimal data availability. The third purpose addresses the challenge of commissioning new or preproduction motor subtypes, where only limited labelled data are typically available. Applying transfer learning, the dissertation investigates how knowledge gained from mass-production models can be transferred to smaller preproduction datasets. This reduces the amount of required training data, shortens commissioning time and improves the scalability of EoL inspection.
4. Reducing dependence on highly skilled human experts. The fourth purpose is to reduce reliance on expert knowledge during development and commissioning. By utilizing ML-based feature selection, transfer learning strategies and deep learning models based on Mel-frequency spectrograms, the dissertation aims to automate and simplify tasks traditionally performed by experts, such as feature engineering, threshold tuning and pre-processing design. This supports more autonomous, adaptable and objective inspection systems.

1.4 Goals

Modern EoL quality inspection systems employ various analytical and signal – based methods. Each of them has specific advantages, limitations and requirements for optimal application conditions. Therefore, their effectiveness depends on appropriate configuration, the availability of representative learning data and the knowledge of experts involved during commissioning. Inappropriate method selection can lead to false diagnostics, inefficient inspection pipelines and extended commissioning times. With these considerations in mind, the goals of this dissertation are:

1. **Reducing system complexity and improving interpretability by employing machine learning-based methods for feature selection and classification:** The goal addresses the need to simplify industrial EoL inspection workflows while improving diagnostic interpretability. Existing inspection systems typically rely on large feature sets and expert-defined thresholds, which increase commissioning time and reduce robustness. This dissertation aims to design and evaluate machine learning-based methods for feature selection and classification that can autonomously identify the most informative features, reduce model and system complexity and preserve or improve the accuracy of conventional inspection procedures.

2. **Enhancing diagnostic performance in low-data conditions through transfer learning:** Introducing new motor types into production presents a significant challenge due to the limited training data available during preproduction. The goal is to implement and validate transfer learning methods that transfer knowledge from mass-produced motor variants to newly introduced subtypes. By leveraging pretrained hyperparameters and feature relevance patterns, the objective is to improve classification accuracy, reduce misclassification costs, and significantly shorten commissioning times under low-data conditions.

3. **Developing a deep learning-based inspection framework using Mel-frequency spectrograms of raw sensor signals**: Traditional approaches often require extensive manual feature engineering and automated signal preprocessing procedures, designed by human experts, considering the physical models of the motors. The goal is to create and evaluate a deep learning model capable of operating directly on Mel-frequency spectrograms generated from raw vibration and acoustic signals. This approach aims to eliminate the need for handcrafted features, improve fault detection performance and provide a scalable alternative for complex signal patterns that traditional models fail to capture.

4. **Benchmarking AI-based methods against conventional inspection techniques:** To ensure industrial applicability, suggested methods must demonstrate improvements in accuracy, scalability, operational reliability and computational efficiency. The goal is to systematically compare machine learning, deep learning and transfer learning approaches with existing threshold-based inspection methods using consistent evaluation metrics on realistic industrial data.

5. **Validating all proposed methods on large-scale real industrial data:** The final goal is to ensure that all developments are grounded in realistic industrial conditions. All analyses, model training and performance evaluations have been executed using real datasets obtained from existing EoL inspection systems on electric

motor manufacturing lines. This ensures that the results are not only scientifically relevant but also directly transferable to industrial environments.

1.5 Hypotheses

The dissertation is based on the following hypotheses:

Hypothesis 1: The manual task of feature selection can be substituted by automated feature selection using machine learning techniques, which also significantly improves classification accuracy and reduces computational complexity in EoL inspection.

Hypothesis 2: Commissioning of quality inspection systems for new product subtypes and variants can be significantly accelerated by using Transfer learning from large-scale production datasets to small preproduction datasets.

Hypothesis 3: Complex data preprocessing, developed by human experts, can be eliminated by introducing deep learning models using Mel-frequency spectrograms and a hybrid architecture that combines Convolutional Neural Networks and Bidirectional Gated Recurrent Units (CNN+BiGRU). This technique uses raw measurement data and outperforms traditional threshold-based and machine learning models in detecting early-stage faults.

1.6 Scientific Contribution

The contributions of this thesis are the following:

- A novel application of machine learning and artificial intelligence to non-invasive quality inspection of electric motors. This dissertation demonstrates that vibration- and acoustic-based diagnostics can be effectively automated using ML and AI methods. By replacing traditional signal preprocessing procedures with the transformation of raw vibration and acoustic signals into MEL spectrograms, and substituting threshold-based decision rules with data-driven models, this dissertation expands the methodological possibilities of industrial quality inspection. Furthermore, it provides new insights into how fault-related behavior in electric motors is reflected in acoustic and vibration signal domains.

- Elimination of human-dependent commissioning steps through automated feature selection, automated threshold determination, and the replacement of existing case-dependent data preprocessing with MEL spectrograms. Current EoL inspection systems depend heavily on expert knowledge to define features, determine acceptable thresholds and design preprocessing procedures. This dissertation shows that these steps can be replaced by ML methods, reducing subjective variability and substantially increasing scalability. Therefore, the contribution is primarily methodological adaptation and industrial validation: it defines when and how expert-defined logic can be substituted with reproducible data-driven alternatives.

- Significant improvement in inspection efficiency through advanced feature selection techniques. The dissertation demonstrates that appropriate feature selection strategies can reduce data dimensionality while preserving or improving classification accuracy. This leads to simpler, faster and more interpretable

diagnostic models, addressing well-known bottlenecks caused by the complexity of industrial inspection systems.

- Introduction of transfer learning into industrial EoL inspection, addressing the challenge of limited data in pre-production. A major contribution is showing that knowledge from mass-produced motor types can be transferred to new variants with limited datasets. This fills a gap in the existing literature, where transfer learning for industrial EoL inspection remains unexplored. The research shows that transferred hyperparameters and feature relevance patterns significantly improve accuracy and lower misclassification risk in the early production stages.

- Reduction of required training data and commissioning time for new motor types. By leveraging transfer learning and automated feature selection, the methods introduced in the dissertation reduce the amount of data and time needed to commission diagnostic models for new products. This contribution is especially relevant for industry, where early-phase data scarcity is a persistent limitation.

- Development of a deep learning framework based on Mel-frequency spectrograms, eliminating the need for manual feature engineering and the need for case-dependent pre-processing of the measured data. The dissertation introduces a deep neural architecture capable of learning discriminative representations directly from spectrograms of raw acoustic and vibration signals. This represents a shift from handcrafted features to fully automated representation learning, providing a scalable foundation for future intelligent inspection systems.

- High industrial applicability with measurable impact on production efficiency, cost reduction and quality control reliability. All developed methods were validated on real data from operating manufacturing lines, ensuring direct relevance for industrial environments. The results confirm that AI-based inspection can outperform traditional methods in accuracy, consistency and adaptability. Consequently, the work contributes not only to the academic domain of industrial AI but also to practical advancements that can enhance reliability and efficiency in electric motor manufacturing.

The dissertation examines the key challenges in the automated quality inspection of electric motors and related devices, alongside an analysis of the potential and capabilities of artificial intelligence and machine learning. Building on this foundation, it develops a roadmap demonstrating how AI and ML can contribute to automated quality inspection processes. Based on a thorough understanding of AI and ML methods, it proposes suitable techniques, adapts and configures them for quality inspection tasks, and compares their performance. The scientific novelty of this dissertation therefore lies not in the development of new AI or machine learning algorithms, but in their systematic adaptation, integration and validation in real industrial EoL quality inspection. More specifically, the work addresses a number of insufficiently explored industrial challenges. These include reducing dependence on expert knowledge during commissioning, operating under conditions of limited data availability, eliminating the need for case-specific signal preprocessing and validating using large-scale data acquired under actual production conditions. The added value of the dissertation is positioned at the intersection of three engineering and research areas (1. Automated quality inspection of electric motors, 2. Digital data processing and

analysis, and 3. Artificial intelligence and machine learning methods), as illustrated by Figure 1.1.

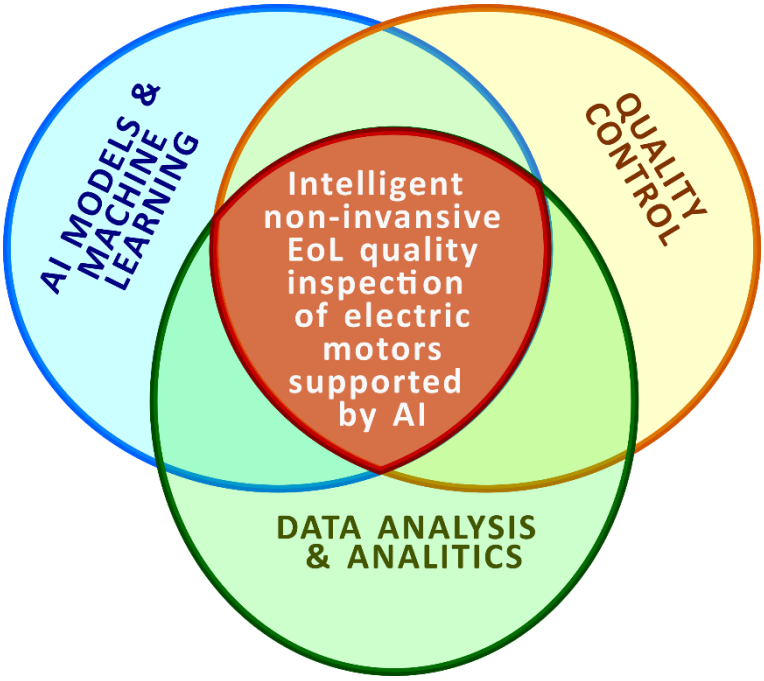


Figure 1.1: Interdisciplinary research framework showing the integration of AI models, data analytics, and manufacturing environments for intelligent End-of-Line quality inspection.

1.7 Structure of Dissertation

The dissertation is structured as follows. Chapter 2 provides an overview of the state of the art relevant to intelligent EoL quality control. It first summarizes industrial practice in electric motor quality control inspection, then contrasts traditional rule-based inspection with modern AI-driven approaches, and finally reviews machine learning, deep learning, and transfer learning methods applicable to industrial inspection tasks.

Chapter 3 presents the research methodology adopted throughout the dissertation. It describes the industrial data sources and acquisition procedures, outlines the architecture of the EoL testing environment and presents the evaluation metrics and validation principles used for benchmarking the proposed methods.

Following the methodological foundation, Chapters 4, 5, and 6 contain the original scientific contributions of the dissertation. Chapter 4 investigates the optimization of reliability and computational performance of industrial EoL inspection systems using a machine learning approach. It focuses on methods for automated feature selection, threshold estimation, and data pre-processing design, addressing key bottlenecks in commissioning new motor types.

Chapter 5 then introduces a transfer-learning framework for EoL inspection, designed to reduce the required quantity of learning data and accelerate commissioning during pre-series and early production stages of new motor types. It demonstrates how knowledge gained from existing motor types can be efficiently reused to ensure robust detection performance under limited data availability.

Chapter 6 presents a deep-learning approach based on Mel-frequency spectrogram representations of vibration and acoustic signals. A neural-network architecture tailored for industrial inspection is introduced, eliminating manually engineered features and related data pre-processing, resulting in fully data-driven fault detection.

Chapter 7 synthesizes the findings from the three research studies. It compares the performance and applicability of the proposed approaches, discusses their integration into industrial workflows, and reflects on practical constraints and implications observed in real manufacturing settings.

Finally, Chapters 8 and 9 conclude the dissertation by summarizing the scientific contributions, discussing their industrial relevance, and suggesting directions for future research, respectively.

Chapter 2

State of the Art of the Research and Technology

2.1 Introduction

The rapid evolution of electric motor manufacturing, driven by increasing product complexity, stricter quality requirements, and growing production volumes, has placed EoL quality inspection at the heart of modern industrial quality assurance [1], [2], [9]. As described in Chapter 1, traditional inspection systems based on handcrafted signal features, expert-defined thresholds, and deterministic decision logic are increasingly challenged by variability in production processes, the introduction of new motor variants, and demands for faster commissioning and greater inspection reliability [4], [6], [7], [11]. These developments have motivated a shift toward approaches based on AI that promise greater adaptability, scalability, and diagnostic performance [7], [8], [10].

In recent years, there has been an increase in the number of studies investigating the use of ML, DL, and related data-driven techniques in industrial quality control [18], [32], [33]. However, this research is highly fragmented across multiple disciplines, including mechanical engineering, electrical engineering, signal processing, and AI [1], [6], [7]. Studies often focus on individual aspects of the inspection process, such as feature extraction, classifier selection, or neural network (NN) architectures [11], [12], [13], [24], while differing significantly in assumptions, data sources, evaluation strategies, and industrial relevance [9], [16]. Therefore, it remains a challenge to systematically and consistently evaluate the current state of the art in intelligent EoL quality control, especially from the perspective of real-world electric motor production [2], [7].

The purpose of this chapter is to provide a comprehensive and structured overview of existing approaches to intelligent EoL quality inspection, with a particular focus on electric motor manufacturing. To this end, Chapter 2 is based on the peer-reviewed review article "AI-Enabled End-of-Line Quality Control in Electric Motor Manufacturing: Methods, Challenges and Future Directions" [34], which summarizes and critically analyses current research trends in this field. The article is included in this dissertation as a separate sub-chapter, providing a conceptual and methodological foundation for the original research presented in the following chapters. The review analyzes the evolution of EoL quality inspection from traditional signal-processing-based methods to AI-driven solutions. It discusses the role and objectives of EoL inspection, the use of non-invasive measurement techniques, and the advantages and limitations of ML, DL, and TL approaches in industrial environments. Special focus is given to challenges that are critical in industrial environments, such as limited availability of labelled data, class imbalance, real-time constraints, robustness to production variability, and dependence on expert knowledge.

2.2 AI-Enabled End-of-Line Quality Control in Electric Motor Production

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Review

AI-Enabled End-of-Line Quality Control in Electric Motor Manufacturing: Methods, Challenges, and Future Directions

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Abstract

End-of-Line (EoL) quality control plays a crucial role in ensuring the reliability, safety, and performance of electric motors in modern industrial production. Increasing product complexity, tighter manufacturing tolerances, and rising production quantities have exposed the limitations of conventional EoL inspection systems, which rely primarily on manually crafted features, expert-defined thresholds, and rule-based decision logic. In recent years, artificial intelligence (AI) techniques, including machine learning (ML), deep learning (DL), and transfer learning (TL), have emerged as promising solutions to overcome these limitations by enabling data-driven, adaptive, and scalable quality inspection. This paper presents a comprehensive and structured review of the latest advances in intelligent EoL quality inspection for electric motor production. It systematically surveys the non-invasive measurement techniques that are commonly employed in industrial environments and examines the evolution from traditional signal processing-based inspection to AI-based approaches. ML methods for feature selection and classification, DL models for raw signal-based fault detection, and TL strategies for data-efficient model adaptation are critically analyzed in terms of their effectiveness, robustness, interpretability, and industrial applicability. Furthermore, this work identifies key challenges that prevent the widespread adoption of AI-based EoL inspection systems, including dependence on expert knowledge, limited availability of labeled fault data, generalization between motor variants and production condition, and the lack of standardized evaluation methodologies. Based on the identified research gaps, this review outlines research directions and emerging concepts for developing robust, interpretable, and data-efficient intelligent inspection systems suitable for real-world manufacturing environments. By synthesizing recent advances and highlighting open challenges, this review aims to support researchers and experts in designing next-generation intelligent EoL quality control systems that enhance production efficiency, reduce operational costs, and improve product reliability.

Keywords: end of line quality inspection; fault detection; artificial intelligence; machine learning; deep learning; condition monitoring; electric motor manufacturing

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1. Introduction

Electric motors are indispensable key components that power a wide range of industrial, automotive, and consumer applications worldwide. They play a crucial role in manufacturing systems, transportation, robotics, household appliances, and energy infrastructure. As global demand for electrification continues to grow, electric motors are expected to provide higher energy efficiency, operational reliability, and functional safety. These

expectations are further raised by increasingly strict regulations [1–3]. Compliance with these standards, combined with intense market competition, has significantly increased the complexity of electric motor design, manufacturing, and quality inspection processes.

Modern electric motors are no longer simple electromechanical assemblies built only using stators and rotors. In most industrial applications, they are integrated with power electronics, sensors, control units, gearboxes, and mechanical actuators, forming complex mechatronic systems. Due to increasing system complexity, increasing production quantities, and tightening mechanical tolerances that achieve high precision, manufacturing processes are becoming increasingly sensitive to disturbances. Minor deviations—such as winding faults, rotor eccentricity, bearing defects, or assembly inaccuracies—can lead to excessive noise and vibration, reduced efficiency, accelerated wear, or premature failure [1,4–9]. Undetected faults can cause failure downstream systems, resulting in costly recalls, production downtime, safety incidents, and long-term damage to a manufacturer's reputation [10–13].

To avoid these risks, End-of-Line (EoL) quality control has become a crucial stage in electric motor production. EoL inspection serves as the final quality gate, ensuring that every manufactured motor meets functional, performance, and reliability requirements before being released to the market. Unlike in-process monitoring, which focuses on statistical trends and early detection of process deviations, EoL inspection must provide a reliable decision for each individual unit. In mass-producing industrial environments, inspection times are typically limited to only a few seconds per motor while maintaining extremely high fault detection sensitivity and low false-rejection rates [4,14–20].

Modern EoL inspection systems rely on non-invasive measurement techniques, including vibration and acoustic analysis, electrical signal evaluation, and rotational speed or torque measurements. These signals are acquired during short, standardized test cycles and provide crucial information about the mechanical, electrical, and electromagnetic behavior of electric motors. However, the resulting data are inherently high-dimensional, noisy, and often non-stationary, posing significant challenges for reliable interpretation [9,21–25]. Traditional EoL inspection systems address this complexity with handcrafted signal processing pipelines, where domain experts design features in the time, frequency, or time–frequency domains and define decision thresholds based on empirical knowledge and experience [6,24,26–28].

However, while such methods have proven effective in stable and well-defined manufacturing environments, they have fundamental limitations in modern manufacturing environments. Relying on expert-defined features and thresholds leads to long commissioning times and high maintenance effort. Furthermore, rule-based systems are difficult to adapt to the growing number of product variants, gradual process drift, and the capture of complex or subtle fault signals that do not result in simple threshold violations [11,13,29–31]. As manufacturing systems become more flexible and product lifecycles shorten, these limitations constrain the robustness, adaptability, and economic viability of traditional EoL quality control systems at an increasing rate.

In response to this, artificial intelligence (AI) has emerged as a transformative and powerful paradigm for industrial quality inspection. Advances in machine learning (ML), deep learning (DL), and transfer learning (TL) have enabled data-driven approaches that learn discriminative patterns directly from captured signals. Classical ML methods, such as decision trees, and ensemble algorithms have been widely explored for feature selection and classification tasks, offering improved robustness, reduced system complexity, and improved interpretability [14,15,32–34]. Deep learning methods, including convolutional and recurrent neural networks, further extend these capabilities by enabling automated

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feature learning from raw or minimally processed data, thereby reducing dependence on manual feature engineering and expert intervention [16,29,35–37].

Despite their growing use, AI-based EoL inspection systems face several practical challenges in industrial environments. These include limited availability of labeled fault data (especially for newly launched motor types), high class imbalance, strict real-time execution requirements, and the need for transparent and explainable decision-making. Transfer learning has therefore attracted increasing attention as a strategy to reuse knowledge from existing models, enabling faster commissioning, reduced data requirements, and improved performance in low-data regimes [38–42]. Together, ML, DL, and TL form a complementary set of techniques that address different aspects of scalability, adaptability, and data efficiency in intelligent EoL quality control systems [14–16,43–45].

This review provides a comprehensive review of the latest advances in intelligent End-of-Line quality inspection for electric motor production. It systematically examines traditional inspection methods and compares them with emerging AI-based methods, highlighting their advantages, limitations, and areas of application. Particular focus is placed on industrially relevant aspects, including non-invasive sensing, real-time constraints, commissioning effort, and robustness to production variability. By summarizing current research trends and identifying open challenges, this review aims to support both researchers and experts in the development and deployment of next-generation intelligent EoL quality inspection systems.

A graphical abstract is provided to visually summarize the transition from traditional rule-based inspection systems to intelligent AI-driven End-of-Line quality control approaches.

The remainder of this article is organized as follows:

- Section 2 presents a review methodology used in this study.
- Section 3 reviews conventional End-of-Line quality control practices in electric motor production.
- Section 4 compares traditional inspection approaches with AI-based methods, emphasizing their conceptual and practical differences.
- Section 5 surveys machine learning, deep learning, and transfer learning techniques applied in industrial quality inspection, with a focus on electric motors.
- Section 6 discusses open challenges, research gaps, and future directions for intelligent EoL quality control.
- Section 7 concludes the review.

2. Review Methodology

This review follows a structured yet pragmatic methodology for identifying, analyzing, and synthesizing relevant literature on EoL quality inspection based on AI for electric motor manufacturing. The goal is to provide a comprehensive overview of current methods, industrial challenges, and emerging research directions.

2.1. Literature Sources

The literature search was conducted using multiple scientific databases to ensure wide coverage of both academic research and industry-relevant studies. Primary sources included Scopus, Web of Science, IEEE Xplore, ScienceDirect and ResearchGate. These databases were selected for their extensive coverage of peer-reviewed journals and conference proceedings in the fields of manufacturing systems, signal processing, machine learning, and industrial automation.

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In addition, selected references were also identified using backward and forward citation tracking of key publications to capture important articles that were not directly found through keyword searches.

2.2. Search Strategy and Timeframe

The search strategy combined keywords related to EoL inspection, electric motor manufacturing, and artificial intelligence techniques. Representative search terms included the following keywords:

- Electric motor manufacturing;
- EoL quality inspection;
- Condition monitoring;
- Fault diagnosis;
- Fault detection;
- Machine learning;
- Deep learning;
- Transfer learning;
- Non-invasive inspection, etc.

The main timeframe we were looking at covered publications from 2015 to 2025, with a special focus on recent works published from 2020 onwards, reflecting the rapid development of AI-based inspection methods and their growing importance in the industry.

2.3. Inclusion and Exclusion Criteria

Publications were included if they met the following criteria:

- Peer-reviewed journal articles or conference papers;
- Focused on quality inspection, fault diagnosis, or condition monitoring relevant to electric motors or closely related rotating machinery;
- Discussed the application of signal-based methods using vibration, acoustic, electrical, or rotational measurements;
- Involved machine learning, deep learning, transfer learning, or hybrid AI approaches with relevance to industrial environments.

Studies were excluded if they:

- Focused solely on simulation or theoretical modeling without experimental or practical relevance;
- Addressed unrelated application domains with no transferable relevance to EoL inspection;
- Lacked sufficient methodological detail to support meaningful analysis.

2.4. Analysis and Synthesis Approach

The selected literature was qualitatively analyzed and classified into thematic categories corresponding to conventional review methods, feature-based machine learning, deep learning, transfer learning, and emerging artificial intelligence approaches. Particular focus was placed on the advantages, limitations, and practical aspects of application, such as data requirements, robustness, interpretability, and real-time performance.

Instead of focusing on quantitative meta-analysis, this review takes a comparative and critical synthesis approach that aims to identify repeated challenges, technological trends, and open gaps in research. These insights provide a basis for discussing future research directions and industrial applications of intelligent systems for EoL quality inspection, which are presented in the following chapters.

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3. End-of-Line Quality Control in Electric Motor Production

3.1. Role and Objectives of EoL Quality Inspection

The EoL quality inspection provides the final stage of quality inspection in the production of electric motors and is the last fault detection step before products are released to the market. Unlike monitoring during production, which focuses primarily on statistical process control and early detection of systematic deviations, EoL inspection must provide a reliable assessment for every individual motor within strict cycle-time constraints [7,15,20,46]. In mass production environments, inspection times are typically limited to a few seconds per unit, placing stringent requirements on both diagnostic accuracy and computational efficiency [11,17,18,43,47].

The main goal of EoL quality inspection is to verify that each motor meets predefined requirements for performance, capability, and reliability. This includes verifying proper electromechanical operation, noise and vibration compliance, and absence of hidden faults that could cause premature failure during operation [1,3–5,7]. Typical fault categories addressed during EoL inspection include mechanical defects such as bearing faults, rotor imbalance, and shaft misalignment; electrical faults such as winding short circuits, phase asymmetry, and insulation degradation; and assembly-related issues including loose components or improper mounting [6,9,27,48,49].

EoL inspection systems must therefore carefully balance sensitivity and selectivity. High sensitivity is necessary to detect even the smallest faults, while high selectivity is essential to reduce the number of false rejects, which would otherwise lead to unnecessary rework or rejects [7,31,50,51]. Achieving this balance is particularly challenging due to the natural variability in manufacturing processes and the increasing diversity of motor designs being produced on the same production lines [11,17,18,48]. Figure 1 shows an example of an EoL inspection system installed in a production environment.



Figure 1. Typical End-of-Line quality inspection for electric motor production.

3.2. Non-Invasive Measurement Techniques

To meet industrial requirements for speed, repeatability, and cost efficiency, EoL quality inspection systems rely primarily on non-invasive measurement techniques [16,19,25,52]. These techniques allow motors to be inspected without disassembly or physical modifica-

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tion, making them suitable for 100% inspection in automated production environments. Some of these techniques are illustrated in Figure 2.

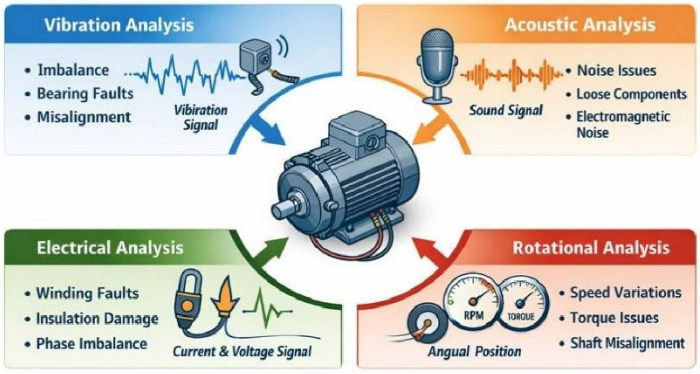


Figure 2. Overview of non-invasive measurement modalities in EoL quality inspection.

Among the most widely used sensing methods are vibration measurements, which are typically captured using accelerometers installed on the motor block or test bench. Vibration signals are highly sensitive to mechanical defects such as imbalance, misalignment, and bearing faults [21,23,24,27,49]. Acoustic measurements, captured using microphones, provide additional information about noise and can be particularly effective for detecting electromagnetic and mechanical anomalies that appear as acoustic or ultrasonic emissions [22,53–56].

In addition to mechanical and acoustic sensors, electrical measurements also play a key role in EoL inspection. Stator current and voltage signals can reveal electrical faults, asymmetries, and electromagnetic irregularities [48,57]. Furthermore, rotational parameters, such as speed, torque, and angular position, are often monitored to evaluate functional performance under controlled operating conditions [8,58–61].

These measurements are typically obtained during short, standardized test cycles that are designed to excite the relevant motor dynamics while reducing inspection time. However, the results are often high-dimensional, noisy, and non-stationary [24,62–64]. They can be influenced by many interacting physical events, including mechanical resonances, electromagnetic forces, and control system dynamics [21,48,65,66]. Therefore, obtaining reliable diagnostic information from non-invasive measurements represents a key challenge in EoL quality control.

To complement the individual descriptions of non-invasive sensing methods, a comparative analysis is needed to highlight their practical advantages and disadvantages in EoL quality inspection. In real manufacturing environments, the selection of a sensing method depends not only on its ability to detect faults, but also on its cost, robustness, and real-time feasibility under strict cycle time constraints [19,25,46,52]. Tables 1 and 2 provide a comparative overview of the most commonly used non-invasive measurement techniques for EoL quality control of electric motors, with a focus on detection sensitivity, cost-effectiveness, and suitability for industrial environments.

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Table 1. Comparison of detection capabilities of non-invasive measurement modalities [19,25,46,52].

Measurement Modality	Typical Sensors	Typical Detectable Faults	Detection Sensitivity
Vibration analysis	Accelerometers	Bearing defects, imbalance, misalignment, rotor eccentricity	High
Acoustic analysis	Microphones	Bearing faults, electromagnetic noise, rubbing, assembly defects	Medium–High
Electrical signal analysis	Current and voltage sensors	Winding faults, phase asymmetry, rotor bar defects, electromagnetic anomalies	Medium
Rotational measurements	Encoders, tachometers	Torque ripple, speed fluctuation, imbalance-related effects	Medium
Multi-sensor fusion	Combination of above	Combined mechanical and electrical faults	Very High

Table 2. Industrial feasibility of non-invasive measurement modalities for EoL inspection [19,25,46,52].

Measurement Modality	Cost-Effectiveness	Real-Time Suitability	Industrial Maturity	Key Limitations
Vibration analysis	Medium	High	High	Sensitive to mounting conditions; affected by structural resonances
Acoustic analysis	High	High	Medium–High	Sensitive to ambient noise; requires acoustic shielding
Electrical signal analysis	High	Very High	High	Limited sensitivity to purely mechanical faults
Rotational measurements	Medium	Very High	Medium	Often indirect fault indicators; requires precise synchronization
Multi-sensor fusion	Low–Medium	Medium	Medium	Increased system complexity and integration effort

The comparison highlights that each non-invasive method has its advantages and limitations when evaluated against industrial EoL requirements. Vibration and acoustic measurements provide high sensitivity to mechanical faults, while electrical and rotational measurements offer real-time feasibility and cost-effectiveness. Multi-sensor approaches achieve the highest diagnostic coverage but create additional complexity in integration and maintenance. These trade-offs highlight the importance of selecting measurement modalities in combination with appropriate AI-based analysis methods to achieve robust and scalable solutions for EoL quality inspection.

3.3. Industrial Constraints and Challenges

EoL quality inspection systems operate under a unique set of industrial limitations that heavily influence their design and performance. One of the most critical limitations is cycle time, as inspection must be completed within the takt time of the production line. This limits the complexity of data acquisition, signal processing, and decision-making algorithms, especially in mass production [14,31,67,68].

Another major challenge is production variability. Even motors that fully meet quality specifications show natural variation in measured signals due to tolerances in materials, assembly, and environmental conditions. Inspection systems must therefore separate ac-

ceptable variation from actual defects, which is becoming increasingly difficult as tolerances decrease and product diversity increases [2,3,7,8,29].

The availability of labeled fault data also presents a major challenge. In many industrial environments, faulty units are relatively rare, resulting in highly imbalanced datasets. This issue is particularly pronounced during the commissioning of new motor types or variants, for which only limited data is available. Moreover, creating labeled fault data can be expensive and time-consuming, as it may require destructive testing or controlled fault injection [31,41,67,69].

Finally, traditional EoL inspection systems often rely heavily on human expertise. Experts typically must select relevant features, define thresholds, and tune decision logic during commissioning and maintenance. This dependence leads to long ramp-up times, limited scalability, and challenges in transferring inspection systems across production lines [13,16,20,43,52]. Figure 3 summarizes key industrial constraints that arise during the design of an EoL quality inspection system.

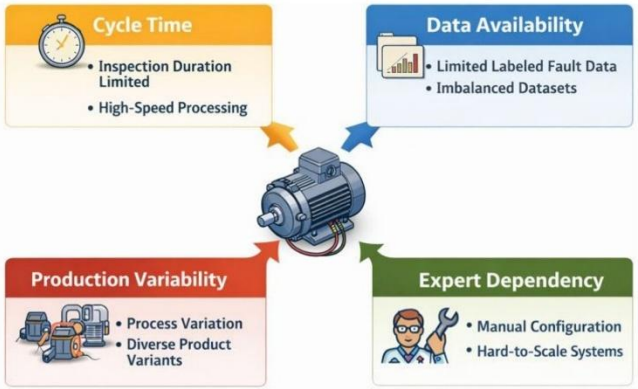


Figure 3. Key industrial constraints influencing EoL quality inspection system design.

4. Traditional vs. AI-Based Quality Inspection

Due to the increasing complexity of electric motor production and the limitations of conventional inspection systems, there has been a gradual shift toward data-driven and AI-based EoL quality inspection approaches [2,16,43,70]. This chapter contrasts traditional inspection methods with new machine learning-based methods, highlighting their principles, advantages, and limitations in industrial environments.

4.1. Convectional Inspection Approaches

Traditional EoL quality inspection systems are mostly based on signal processing combined with rule-based decision logic. In such systems, first, raw sensor signals (typically vibration, acoustic, or electrical measurements) are preprocessed, which includes filtering, resampling, normalization, or noise removal. A set of handcrafted features is then extracted from the processed signals [1,6,24,29].

Often-used features include statistical measures in the time domain (e.g., root mean square, variance, kurtosis), spectral characteristics in the frequency domain (e.g., harmonic amplitudes, sideband energy), and time–frequency features obtained through Fourier or wavelet transforms [6,27,55,56]. These features are selected based on expert knowledge of motor physics and known fault mechanisms. Final classification is typically performed using fixed thresholds, decision trees defined by experts, or simple statistical tests [4,7,10,51].

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The main advantage of conventional inspection methods is their simplicity and transparency. Feature definitions and decision rules are straightforward, making them easy to understand, validate, and verify. Moreover, computational requirements are generally low, enabling real-time in industrial environments [14,17,19].

However, these advantages come at the cost of limited flexibility and scalability. The development and commissioning of traditional inspection systems require extensive collaboration among experts to identify relevant features, tune thresholds, and validate performance. This process is time-consuming and must often be repeated when motor designs, materials, or production conditions change [11,13,43,46]. Additionally, handcrafted features may fail to capture complex, nonlinear fault signatures, especially when faults are difficult to detect or are masked by normal manufacturing variability [28,32,48,49].

Another limitation is the sensitivity to manufacturing drift and noise. Changes in sensor placement, environmental conditions, or upstream processes can significantly affect captured signals, leading to an increase in false-reject rates or missed faults. As production systems become more flexible and product lifecycles shorten, these limitations increasingly constrain the effectiveness of EoL inspection systems [2,13,51,68]. Figure 4 illustrates the sequential stages of a rule-based inspection pipeline.

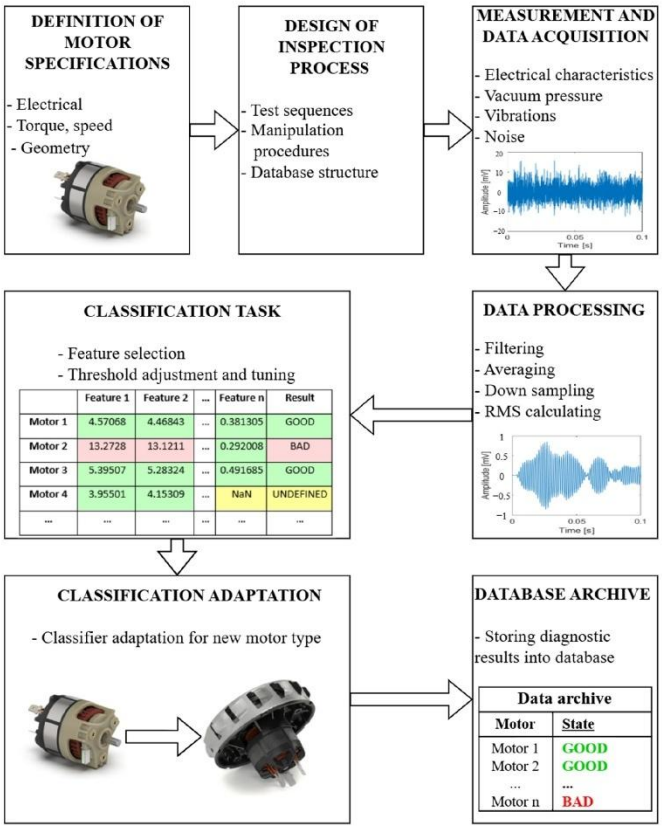


Figure 4. Overview of a conventional EoL quality inspection workflow for electric motors.

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4.2. The Use of Machine Learning in EoL Inspection

ML has appeared as a powerful alternative to rule-based inspection methods, as it allows for data-driven decision making. Instead of relying on fixed thresholds, ML models learn directly from labeled examples, allowing them to exploit multivariate correlations between features and improve robustness to noise and variability [2,11,29,43].

Early applications of ML in EoL quality inspection focused on supervised classifiers such as support vector machines, k-nearest neighbors, and logistic regression. These methods demonstrated improved fault detection performance compared to threshold-based systems, particularly in scenarios involving overlapping feature distributions or multiple fault classes [13,14,35,51,71]. However, their effectiveness still depended on the quality and relevance of the selected features.

Subsequently, ensemble methods such as random forests, bagging, and boosting algorithms, gained popularity in industrial inspection tasks. These methods combine multiple weak learners to improve generalization and robustness [12,13,34,35,51]. A key advantage of tree-based ensemble models is their ability to provide feature importance metrics, enabling systematic feature selection and dimensionality reduction. By identifying the most informative features, ML-based systems can reduce computational complexity, simplify diagnostic pipelines, and improve interpretability [14,15,72,73].

The use of ML methods has significantly reduced the dependence on manual threshold tuning and improved scalability across motor variants. Nevertheless, feature-based ML systems still require feature engineering and sufficient labeled training data. Their performance may degrade when they are applied to new motor types or operating conditions that differ significantly from the training dataset, highlighting the need for more adaptive learning strategies [14,15,35,39,41,69]. Figure 5 illustrates the integration of ML into a conventional EoL inspection workflow.

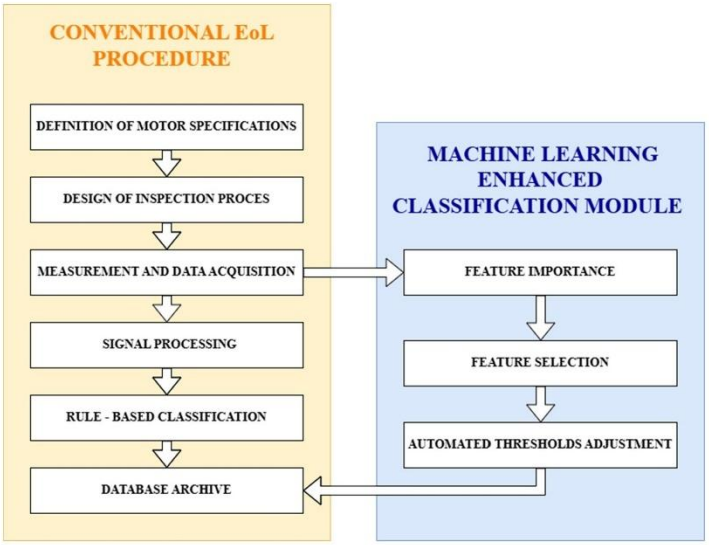


Figure 5. Integration of ML into conventional EoL quality inspection workflow.

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4.3. Limitations of Traditional and ML-Based Approaches

Although ML represents a significant advancement over traditional inspection methods, both approaches have certain limitations when applied in industrial EoL environments. A key challenge is the dependence on labeled fault data, which are often scarce, especially during preproduction or ramp-up phases. Fault data are typically imbalanced, with defective units representing only a small fraction of total production, making model training and evaluation difficult [11,14,31,39,74].

Another challenge is related to generalization and adaptability. Feature-based ML models may have trouble transferring knowledge across different motor families or production lines without retraining or manual adaptation [7,8,14,15,75]. This can result in repeated commissioning and limit the adaptability of inspection systems across global manufacturing environments.

Furthermore, the increased complexity of the system raises concerns about interpretability and trust. While conventional systems are transparent by nature, ML models may behave like black boxes from production engineers' perspective. Ensuring reliable operation, traceability, and compliance with industrial standards remains a key requirement [11,13,46,48].

4.4. Transition Toward Intelligent Inspection Systems

The limitations of both conventional and classical ML-based inspection methods have led to a shift toward intelligent EoL quality inspection systems that integrate more advanced AI techniques. These systems are designed to reduce human intervention, improve adaptability, and enhance fault detection performance in real industrial environments [11,13,14,70].

In fact, the rise of DL and TL has made it possible to automatically learn features directly from raw or minimally processed signals and has made it easier to reuse knowledge across different motor types [15,38,75–77]. These developments mark a paradigm shift from expert-driven inspection to data-driven, scalable, and increasingly autonomous quality inspection systems.

5. Machine Learning, Deep Learning, and Transfer Learning in Industry

The limitations of traditional feature-based inspection systems have led to the increasing use of advanced AI methods in industrial EoL quality inspection. In recent years, ML, DL, and TL have emerged as alternative methods for improving fault detection accuracy, reducing commissioning effort, and improving flexibility across product variants [14–16,32,37]. This section describes the role of these methods in industrial quality inspection, with a focus on electric motor production.

5.1. Deep Learning for Signal-Based Quality Inspection

DL has attracted significant attention in industrial environments due to its ability to automatically learn feature representations from raw or minimally processed data. Unlike traditional feature-based ML approaches, DL models do not require explicit manual feature engineering, making them especially suitable for complex signal analysis tasks in which it is difficult to analytically define fault features [11,48,78–80].

In the context of EoL quality inspection, DL is most commonly used to create time–frequency representations of vibration and acoustic signals. Spectrograms obtained from short-time Fourier transforms, wavelet transforms, or Mel-frequency filter banks convert one-dimensional time series into two-dimensional representations that capture both spectral and temporal characteristics [6,55,56,77,81]. Convolutional neural networks (CNNs) are then used to extract spatial patterns associated with different fault conditions [23,47,61,76,82].

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The use of Mel-frequency spectrograms (MFSs) has attracted increasing interest, as they provide a compact and perceptually motivated representation of frequency content. Originally developed for speech recognition [17,55,56,83], MFSs emphasize lower-frequency bands while reducing dimensionality, which can improve robustness and computational efficiency. When combined with CNNs, MFSs enable effective classification of subtle fault patterns in acoustic and vibration signals [16,54,84].

To capture temporal dependencies and dynamic behavior, CNNs are often combined with recurrent neural networks (RNNs), such as long short-term memory (LSTM) units or bidirectional gated recurrent units (BiGRUs) [16,54]. Hybrid architectures allow models to learn both local spectral features and long-term temporal dependencies, which are especially important in the diagnostics of rotating machinery [17,79,80,85,86]. Such architectures have proven to achieve a strong performance in detecting mechanical and electromagnetic faults under various operating conditions [9,21,36,61].

Despite their advantages, DL methods face several challenges in industrial environments. They typically require large labeled datasets for training, which may be difficult to obtain in practice [7,14,40,69]. Moreover, their high computational demands can limit their use in real time, and their black-box nature raises concerns about interpretability and trust [43,48,70,72]. Addressing these issues remains an active area of research in industrial AI. Figure 6 illustrates a DL-based approach for signal-driven EoL quality inspection that combines MFSs with a hybrid neural network architecture. The proposed pipeline replaces conventional handcrafted feature extraction and threshold-based decision logic with automated representation learning and data-driven classification. This approach, originally introduced in [16], serves as the methodological foundation for the DL framework considered in this work.

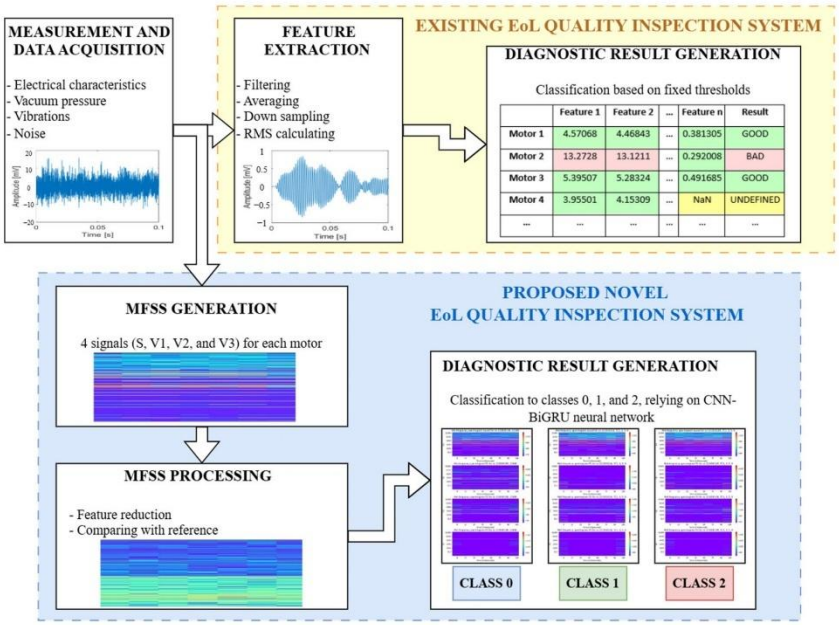


Figure 6. DL pipeline for signal-based EoL quality inspection [16].

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5.2. Transfer Learning for Industrial Applications

A constant challenge in industrial EoL quality inspection is the limited availability of labeled fault data, especially during the commissioning of new motor types or variants. In many cases, production data mainly consist of healthy units, while faulty units are rare or unavailable. TL has proven to be an effective strategy to address this challenge by reusing knowledge from related tasks or previously trained models [15,38,39,41,87].

TL can be applied at different levels. In feature-based ML systems, TL may involve reusing feature importance rankings, selected feature subsets, or optimized hyperparameters from one motor type to another. This approach reduces the need for extensive retraining and expert intervention when deploying inspection systems for new variants [14,15,29,31].

In DL applications, TL is often performed by initializing a neural network with weights pretrained on a related dataset and fine-tuning it using limited new data. Lower layers of the network, which capture general signal characteristics, can be reused, while higher layers are adapted to the specific fault patterns of the new motor type. This strategy significantly reduces training time and improves performance in low-data scenarios [15,38,44,78,81].

Although TL is widely used in fields such as computer vision and natural language processing, its application in industrial EoL quality inspection remains relatively unexplored. However, current studies suggest strong potential for reducing commissioning time, lowering data acquisition costs, and improving scalability across product families and production lines [15,39,70].

Key challenges related to TL include selecting appropriate input and output data, avoiding negative transfer when domains differ significantly, and ensuring that transferred models remain reliable and interpretable in safety-critical industrial environments [11,38,39,48,72]. Figure 7 illustrates the integration of ML into a conventional EoL inspection workflow.

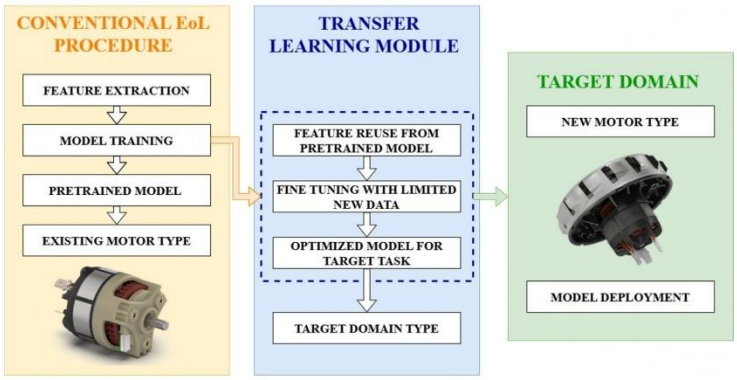


Figure 7. Integration of TL into conventional EoL quality inspection workflow.

5.3. Industrial Case Studies and Reported Deployment

Although ML, DL, and TL techniques show strong potential in research environments, their successful integration in industrial EoL inspection systems depends on several practical considerations. The most important is real-time performance, as inspection algorithms must operate within strict cycle-time constraints. This often necessitates model simplification, hardware acceleration, or hybrid architectures that combine lightweight ML models with more complex DL components [13,14,31]. Industrial case studies confirm that satisfying cycle-time requirements is a crucial for adoption. For example, AI-based EoL inspection

tests for highly varied production of geared motors have shown that algorithmic complexity must be carefully balanced with process flow constraints to ensure continuous operation without bottlenecks [17,18]. Similar conclusions have been reported for high-speed glass tube production lines, where real-time performance directly determines the feasibility of AI-based inspection solutions [67].

Robustness and reliability are equally important. Inspection systems must maintain consistent performance despite changes in production conditions, sensor noise, and environmental impacts. This requires careful validation, continuous monitoring, and, in some cases, regular model recalibration [7,11,20,46]. Real-world evidence shows that long-term robustness remains a key challenge, especially in highly diverse manufacturing environments. Reported industrial EoL applications highlight the need for continuous performance monitoring and adaptive maintenance strategies to prevent degradation due to 481 process variations, sensor aging, or mechanical tolerances [17,18,70].

Another important aspect is interpretability and transparency. Production engineers and quality managers must understand and trust inspection decisions, especially in regulated industries. Feature-based ML models and visualization techniques can provide diagnostic insight, while ongoing research in explainable AI (XAI) aims to improve the transparency of DL models [11,30,48,70]. Industrial studies of EoL highlight that transparent decision-making logic significantly improves acceptance by operators and quality engineers, particularly during commissioning and fault analysis. In practice, systems that provide interpretable intermediate outputs or feature relevance are easier to integrate into existing EoL inspection systems [61,70].

Finally, integration with existing automation infrastructure plays a crucial role in industrial application. AI-based inspection systems must be seamlessly connected with programmable logic controllers (PLCs), manufacturing execution systems, and quality databases. Easy installation, maintenance, and scalability across multiple production lines are essential for realizing the full benefits of intelligent EoL quality control [13,31,46]. The reported deployment frameworks for electric motor and rotating machinery inspection demonstrate that modular system architectures and standardized communication interfaces are key factors for integration with PLC- and MES-based production environments. Industrial case studies further show that scalability across multiple lines and sites can only be achieved when AI components are designed as flexible modules within the existing 501 automation infrastructure [61,70].

5.4. Emerging AI Concepts for EoL Quality Inspection

In contrast to conventional feature-based ML, DL, and TL, several new AI concepts are gaining importance as potential enablers for more robust, data-efficient, and useable EoL inspection systems. These approaches are particularly relevant for electric motor manufacturing, where diagnostic decisions must be made under strict cycle-time constraints, limited fault labeling, and frequent domain changes between different motor variants.

5.4.1. Physics-Informed and Physics-Guided AI

A key challenge of models based exclusively on data is their sensitivity to domain changes and dependence on large labeled datasets. Physically informed approaches address this by incorporating prior knowledge (e.g., failure mechanisms, vibration characteristics, or constraints derived from physical models) into learning objectives, architectures, or decision rules. A typical example is physics-informed deep learning for bearing fault detection, where physics-motivated rules are combined with CNN-based learning via customized loss functions, improving robustness when labeled fault data is limited [65]. Related physics-informed approaches incorporate physical reasoning directly into the structure of the

neural model; for example, by constraining the learning process for fault identification (e.g., rotor imbalance), which improves generalization and interpretability [66]. For industrial EoL inspection, physically informed methods are promising because they can reduce data requirements while improving stability under changing tolerances and operating conditions [65,88].

5.4.2. Semi-Supervised and Self-Supervised Learning

Industrial EoL datasets typically contain large amounts of healthy samples, while labeled faulty units are rare, making semi- and self-supervised methods attractive. Semi-supervised learning exploits limited labeled samples together with abundant unlabeled data and has been applied for the diagnosis of rotating machines using graphical neural models to learn a more robust class structure at low labeling rates [89]. Self-supervised learning extends this concept by learning representations from unlabeled data through virtual tasks (e.g., contrastive targets), followed by lightly supervised fine-tuning. Recent studies show that self-supervised contrastive learning can significantly improve the effectiveness of bearing fault diagnostics when labeled data is scarce—a realistic environment in industry for newly introduced products or ramp-up phases [90]. From an EoL perspective, these approaches support faster commissioning and reduce dependence on an extensive fault database [91–93].

5.4.3. Unsupervised Anomaly Detection for Open-Set Inspection

In practice, EoL systems must deal with unknown or previously unseen faults. Unsupervised methods address this by modeling "normal" behavior and detecting deviations without requiring labeled fault classes. Self-supervised anomaly detection has been evaluated on a vibration dataset from rotating machinery and is increasingly viewed as a practical complement to supervised classifiers, especially when fault coverage is incomplete or constantly changing [91,94–97]. In industrial EoL systems, such methods can act as a safety layer for detecting conditions that are not in line with distribution and trigger expert review or additional testing, instead of forcing a potentially unreliable multi-class decision.

5.4.4. Explainable AI and Human-in-the-Loop Diagnostics

Challenges to adoption in industry are often related to trust, explainability, and debugging AI decisions. XAI methods such as feature attribution, surrogate models, or explanation by example are becoming increasingly prevalent in machine fault diagnosis, in which they are used to help operators understand causes and increase their acceptance. Recent reviews and frameworks suggest that XAI is not just a model-side technique, but also an interface and workflow problem: explanations must be relevant to engineers and must align with maintenance and quality procedures [72]. For EoL inspection, XAI is particularly important for reducing false rejections, accelerating commissioning, and enabling systematic troubleshooting when deviations from the process occur [43,45].

5.4.5. Reinforcement Learning for Inspection

Although reinforcement learning (RL) is less mature when it comes to direct classification of EoL faults, it is becoming a more common tool for optimizing inspection and maintenance strategies in industrial production systems. Deep RL has been used to optimize inspection and maintenance planning in production line environments, providing a formal framework for balancing cost, availability, and intervention time [98]. For EoL quality control, RL is best viewed as a new layer on top of diagnostics—optimizing when to tighten thresholds, trigger additional measurements, or schedule recalibration based on risk and operational constraints.

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Overall, these emerging concepts point to a transition toward data-efficient, physics-aware, and development-oriented AI. However, the impact on industry will depend on standardized evaluation protocols, robust handling of changes in the domain, and transparent integration into factory automation and quality workflows. Recent research on deep TL for fault diagnosis highlights this trend toward flexibility and industrial readiness, further reinforcing the need for practical validation in realistic environments [40,44,69].

6. Research Gaps and Motivation for Further Work

Although significant progress has been made in EoL quality inspection for electric motor manufacturing, several critical research gaps remain, limiting the widespread industrial application of intelligent AI-driven inspection systems. Although ML, DL, and TL methods have shown promising results in controlled experimental environments, their integration in real-world manufacturing environments still faces methodological, practical, and organizational challenges [13,14,48,99,100]. This chapter summarizes the key limitations identified in the reviewed literature and outlines the motivation for further research.

6.1. Dependence on Expert Knowledge and Manual Configuration

A common limitation of both traditional and AI-based inspection systems is their persistent reliance on human experts during system design and commissioning. Feature-based ML pipelines typically require expert selection of signal preprocessing steps, handcrafted feature definitions, and decision thresholds. Even in systems that employ automated feature selection, expert intervention is often crucial to validate model behavior and ensure robustness under varying production conditions [10,28,29,99,101].

While DL reduces the need for manual feature engineering, it does not fully eliminate expert involvement. The selection of network architectures, hyperparameters, input representations, and training strategies remains largely heuristic and experience based. This dependence on domain expertise slows down commissioning, increases costs, and limits scalability, especially in environments with high variability and low production quantities, where frequent model adjustments are necessary [11,48,70].

6.2. Limited Data Availability and Class Imbalance

The lack of data remains one of the biggest challenges. In industrial environments, high-quality labeled datasets containing different types of faults are rare, especially in preproduction stages. Due to quality requirements, the number of faulty units is often deliberately reduced, resulting in a severe class imbalance and incomplete fault coverage [28,43,99,102].

Many studies rely on laboratory-generated fault data or artificially induced faults, which may not accurately reflect real industrial conditions. As a result, models trained on such data are often difficult to generalize when applied to production lines. While TL and data augmentation techniques have shown promising results in reducing these issues, systematic evaluations under realistic industrial environments are still limited [15,38,44,100,102].

6.3. Generalization and Robustness Across Motor Variants

Another challenge concerns the ability to generalize AI-based inspection systems to different motor types, variants, and operating conditions. Most published studies focus on a single motor type or a narrowly defined operating regime, limiting the applicability of their findings in real-world manufacturing environments [11,21,48,99,103].

Changes in motor geometry, materials, assembly tolerances, or sensor configurations can significantly change signal characteristics, leading to degraded model performance. Robust inspection systems must therefore accommodate changes in the domain and changing

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production conditions without requiring complete retraining. While TL offers promising solutions, there is still lack of standardized methodologies and validation protocols for assessing robustness [15,39,70,104,105].

6.4. Interpretability and Trustworthiness of AI Models

The limited interpretability of complex AI models remains a critical challenge in industrial environments, especially in safety-critical and regulated applications. DL models are often treated as black boxes, making it difficult to understand the logic behind classification decisions or diagnose fault modes [11,28,48,99,100].

Although visualization techniques and XAI methods have been suggested, their integration into industrial inspection workflows is still in its early stages. There is a clear need for approaches that balance predictive performance with transparency, enabling engineers to validate, debug, and trust AI-driven inspection systems [28,29,70,99,100].

6.5. Evaluation of Methodology and Benchmarking

The lack of standardized evaluation frameworks presents another challenge. Many studies report performance using limited datasets, single train–test splits, or metrics that do not fully capture industrial requirements such as false rejection rates, inspection cycle time, or long-term stability [14,31,43,99,100].

Robust evaluation strategies, including cross-validation, confidence interval estimation, and long-term monitoring, are rarely applied. Furthermore, direct comparisons between traditional inspection methods and AI-based approaches under identical conditions are rare, making it difficult to quantify the true added value of intelligent inspection systems [13,29,44,99,100].

6.6. Motivation for Future Research

The presented gaps highlight the need for research that goes beyond proof of concept and focuses on available, adaptable, and reliable industrial solutions. Future work should focus on reducing dependence on human expertise, improving data efficiency, and enhancing robustness across product variants. In particular, hybrid approaches that combine automated feature selection, DL, and TL offer a promising solution for establishing flexible EoL inspection systems that are capable of adapting to changing production demands [14,15,48,70,104,105].

Equally important is the development of transparent and interpretable AI models, along with more strict validation methods aligned with industrial standards. Addressing these challenges is essential to realizing the full potential of intelligent EoL quality control and ensuring its successful integration into modern manufacturing environments [13,28,98,99,106].

7. Conclusions

This review has surveyed the current state of EoL quality control for electric motor production, with a special focus on the transition from traditional inspection systems to intelligent AI-driven solutions. As electric motors become increasingly complex and their production volumes continue to grow, conventional rule-based inspection methods are increasingly unable to meet industrial demands for scalability, adaptability, and diagnostic reliability. In this context, AI has emerged as a key enabler for next-generation EoL quality inspection systems, capable of addressing both technical and organizational challenges.

The review began by highlighting the critical role of EoL quality inspection as a final safeguard against manufacturing faults, emphasizing the importance of non-invasive measurement techniques such as vibration, acoustic, and electrical signal analysis. Although these measurement methods provide rich diagnostic information, their effective use in the past has been based on manually crafted features and thresholds. Such approaches,

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although well established and widely deployed, exhibit limited robustness to process drift, struggle to deal with process variability, tightening tolerances, and increasing product diversity, which constrains their long-term viability in modern manufacturing environments.

ML methods have introduced more systematic and data-driven approaches by enabling automated feature selection, improved fault discrimination, and better interpretability compared to rule-based systems. Ensemble-based classifiers have demonstrated strong performance and robustness in industrial environments while supporting systematic reduction in feature sets and inspection complexity. However, these methods remain dependent on carefully engineered features and sufficiently labeled data, limiting their applicability in low-data regimes during early production phases or rapidly changing production environments.

DL approaches address several of these limitations by learning discriminative representations directly from raw sensor signals, reducing the reliance on manual feature engineering. Techniques based on CNN and RNN, often combined with time–frequency representations such as spectrograms, have shown superior fault detection performance in complex and noisy industrial scenarios. Nevertheless, their deployment in real-world EoL inspection remains challenged by data availability, computational constraints, and limited model interpretability, which are critical concerns in industrial and safety-relevant applications.

TL has proven to be a promising strategy to address the lack of data and commissioning challenges, particularly during preproduction phases or for new motor types. By utilizing knowledge gained from previously trained models, TL enables faster model adaptation, improved performance under limited data conditions, and reduced commissioning time. Despite these advantages, the lack of standardized TL methodologies, validation protocols, and robustness assessment frameworks highlights the need for further systematic investigation.

Across all reviewed approaches, several persistent challenges were identified. These include reliance on expert knowledge during system design, limited generalization across motor types and production lines, insufficient transparency of complex models, and a lack of standardized evaluation metrics aligned with industrial performance indicators such as false-rejection rates, cycle time, and long-term stability. Addressing these challenges is essential for the transition of AI-based EoL inspection from experimental applications to reliable, widespread industrial use or pilot deployments aimed at reliable and scalable industrial solutions.

To conclude, intelligent EoL quality control represents a critical component of modern electric motor manufacturing. The integration of ML, DL, and TL has the potential to significantly improve inspection accuracy, efficiency, and flexibility while reducing costs and the amount of human intervention required. Future research should focus on data-efficient learning strategies, explainable and trustworthy AI models, and rigorous evaluation methodologies grounded in industrial requirements. By addressing these challenges, intelligent EoL inspection systems can play a central role in ensuring high-quality, reliable, and sustainable electric motor production in increasingly complex manufacturing environments.

Supplementary Materials: The following supporting information can be downloaded at https://www.mdpi.com/article/10.3390/machines14020149/s1, Figure S1: EoL Quality Control of Electric Motor: Transition from Traditional to Smart AI Methods, PRISMA-ScR checklist used to guide this scopin review is also provided as Supplementary Material [107].

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence.
BiGRU	Bidirectional Gated Recurrent Unit.
CNN	Convolutional Neural Network.
DL	Deep Learning.
EoL	End-of-Line.
LSTM	Long Short-Term Memory.
MES	Manufacturing Execution System.
MFS	Mel-Frequency Spectrogram.
ML	Machine Learning.
PINNs	Physics-Informed Neural Network.
PLC	Programmable Logic Controller.
RL	Reinforcement Learning.
RNNs	Recurrent Neural Network.
SVM	Support Vector Machines.
STFT	Short-Time Fourier Transform.
TL	Transfer Learning.
XAI	Explainable AI.

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Chapter 3

Research Methodology

This chapter defines the common methodological framework used throughout the dissertation. All three original research articles included in Chapters 4–6 are based on the same industrial EoL quality inspection system, real production data, and comparable evaluation principles. The methodology described in this chapter combines and summarizes the experimental setups, data preparation procedures, and validation strategies described in [35], [36], [37], and also extends the previous work of the authors [8], [9], [38], [39], [40].

The purpose of this chapter is to ensure methodological consistency across all included articles, enable meaningful comparison of the proposed ML, TL, and DL approaches, and clearly separate shared methodological aspects from individual article-specific algorithms.

3.1 Data Sources and Acquisition

All data used in this dissertation is obtained from real industrial EoL quality inspection systems (shown in Figure 3.1), installed at fully automated electric motor manufacturing lines. The inspected products are brushless direct current (BLDC) motors produced by a European mass manufacturer Domel d. o. o. [35], [36], [37].

Two BLDC motor types were investigated in this dissertation, as illustrated in Figure 3.2 Motor type a) represents motor type 759, which was used in [35] and [37], while motor type b) represents motor type 720, which was used in [36]. The EoL inspection system is designed for 100% quality control, meaning that every produced motor undergoes the same standardized inspection procedure. The choice of motor type used was determined by the specific methodological requirements of each approach under investigation and by the availability of representative industrial data. Motor type 759 was used for the machine-learning and deep-learning studies because large volumes were produced, providing a dataset of appropriate size for model training, particularly for the data-intensive deep-learning approach. On the other hand, the transfer-learning study required several related motor subtypes in order to investigate transfer learning from a mass-produced source type to new target variants for which there was limited pre-production data available. At the time of the study, the motor type 759 data did not satisfy this requirement, while the motor type 720 provided the necessary combination of related subtypes. Therefore, the datasets, training and testing procedures were selected according to the specific requirements of each research goal instead of direct comparison between the three approaches.



Figure 3.1: The modular EoL inspection system integrated at Domel d. o. o., consisting of multiple test cells used for non-invasive inspection and data acquisition.

a) b)

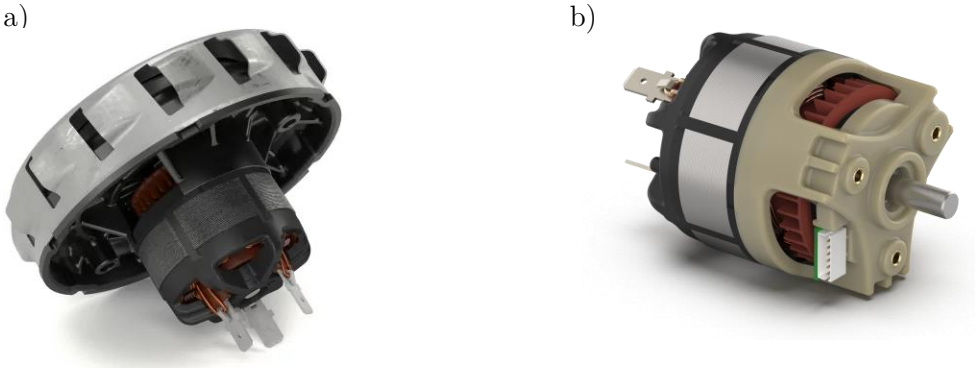


Figure 3.2: Brushless DC motors investigated in this dissertation. Motor a) represent motor type 759 [39] and motor b) represent motor type 720 [40].

During EoL inspection, each motor is exposed to one or more short test runs under predefined operating conditions (e.g., nominal or low rotational speed). Multiple non-invasive sensors are used to capture motor behavior, including a laser vibrometer that captures vibrations at three points on motor housing, microphones for acoustic measurements, and electrical sensors that measure current, voltage, and power. Depending on the inspection cell and motor type, additional process parameters (e.g., speed, torque, vacuum pressure, environmental conditions) may also be recorded [35], [36], [37].

The acquired signals are stored as high-resolution time-series data ("raw signals"). Sampling frequencies typically range from 10 kHz to 60 kHz, and signal durations are between 0.1 s and 1 s, resulting in time series containing between 1 000 and 10 0000 of samples per channel.

Actual condition labels are assigned at motor level according to the existing industrial quality inspection procedure. Motors are classified into categories such as GOOD, BAD, or UNDEFINED based on diagnostic rules, expert evaluation, and, where necessary, additional verification procedures. As presented in [35], [36], [37], faulty motors are

relatively rare compared to healthy ones, resulting in strongly imbalanced datasets that reflect real production conditions.

Due to the industrial background of the data used in this dissertation, the datasets and source code are not publicly available as they contain commercially sensitive information. However, both the data and the code are available from the author upon reasonable request, but only after approval from the industrial data owner and signing of an appropriate non-disclosure agreement (NDA). These restrictions are imposed by the industrial partner, who owns the data and related sensitive information.

3.2 End-of-Line Quality Inspection Setup

The EoL inspection systems discussed in this dissertation follow a modular architecture, which is built from three test cells. Each of these is responsible for specific tests or fault types. Although the exact configuration may vary between manufacturing lines, the basic principles of inspection remain the same [35], [36], [37]. Figure 3.3 shows a schematic overview of the EoL quality inspection process, which is the subject of this dissertation. Figure 3.3 shows the classic three-stage process:

1. Non-invasive measurement and data acquisition of signals (Figure 3.3, step 1),
2. Classical signal processing with manual feature extraction (Figure 3.3, step 2),
3. Diagnostic result generation based on fixed thresholds and expert-defined decision rules (Figure 3.3, step 3).

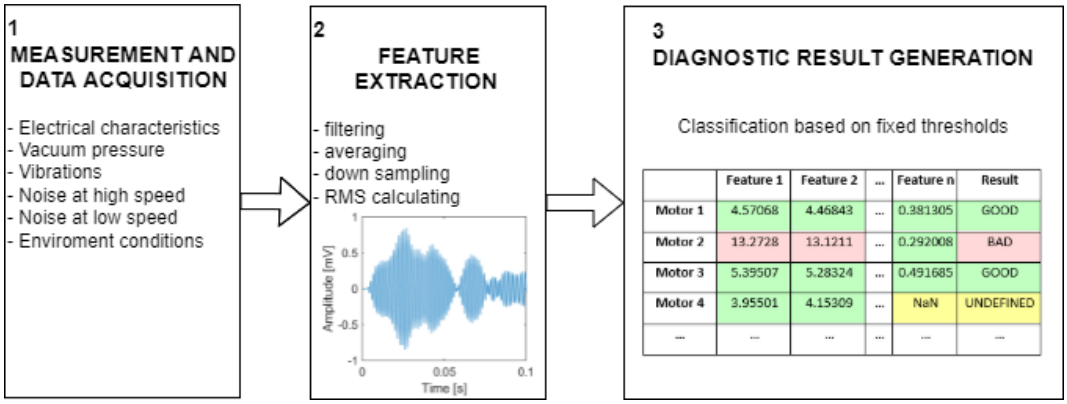


Figure 3.3: Conventional EoL quality inspection workflow used in industrial electric motor production.

3.2.1 Conventional signal processing and feature generation

In the existing industrial inspection system [35], [36], [37], raw signals undergo a sequence of classical signal processing steps. These typically include digital filtering, down-sampling, averaging, and frequency-domain analysis. The result of this processing is a fixed set of scalar features, where each feature represents a specific signal characteristic, such as root mean square (RMS) value within a frequency band or signal power at a selected frequency. Signal processing has already been described in detail in previous studies [8], [9], [39].

For the investigated motor types, this process results in approximately 80 features per motor. These features serve as inputs to rule-based diagnostic logic, where expert-defined thresholds determine whether a motor is classified as GOOD or BAD. The selection of relevant features and the tuning of their thresholds are traditionally performed manually

by skilled experts, which leads to long commissioning times and strong dependence on expert knowledge [35], [36], [37].

3.2.2 Data preparation for machine learning and transfer learning

Articles [35] and [36] that are part of the dissertation propose ML methods to reduce the dimensionality of the feature space and automate feature selection. For these approaches, sets (vectors) of features generated by data pre-processing algorithms, represent the input. Feature importance metrics derived from supervised learning models are used to identify the most informative features and to eliminate redundant or non-informative ones. In the TL scenario [36], knowledge in the form of feature selection and optimized model hyperparameters is transferred from a mass-produced motor subtype to new preproduction subtypes with limited data availability.

3.2.3 Data preparation for deep learning

Unlike feature-based approaches, [37] applies directly to raw vibration and acoustic signals. Instead of feature generation by data pre-processing and expert-based manual selection of relevant features, raw signals are automatically transformed into time–frequency representations using Mel-frequency spectrograms (MFSs). This conversion preserves both spectral and temporal information while significantly reducing data dimensionality.

To further improve data relevance and robustness, a multi-step data preparation procedure is applied, including removal of non-informative frequency bands, normalization, and comparison with reference spectrograms derived from healthy motors. This process allows DL models to focus on diagnostically relevant signal components while reducing sensitivity to noise and irrelevant variations [37].

Table 3.1 summarizes the key characteristics of the ML, TL, and DL approaches applied in this dissertation to provide a clear overview of the methodological differences and similarities between the three analyzed approaches. The table highlights the input data type, data preparation strategy, model architecture, and primary objective of each approach within the industrial EoL inspection system.

Table 3.1: Methodology overview.

Aspect	ML approach with feature selection (Chapter 4)	TL approach (Chapter 5)	DL approach (Chapter 6)
Input data	Engineered feature set	Engineered feature set	MFSs from raw signals
Data volume	Large	Large + small	Large
Model type	Tree-based and ensembles	Transfer of ML models	Neural network (CNN+BiGRU)
Main objective	Feature reduction Automatic selection of informative features, automatic elimination of redundant ones, automatic determination of feature thresholds	Data efficiency Speeding-up the commissioning of the quality control of new motor types	End-to-End learning Elimination of expert dependent data pre-processing

As shown in Table 3.1, the three approaches differ in data representation, learning strategy, and intended contribution to improving inspection performance. However, they are all based on the same industrial data acquisition system.

3.3 Evaluation Metrics and Validation Strategy

The evaluation strategy of newly applied methods is designed to reflect industrial requirements for reliability, robustness, and practical applicability. All evaluation criteria are based on and presented in [35], [36], [37].

3.3.1 Performance metrics

Model performance is primarily evaluated using classification accuracy, precision, recall, and classifier's accuracy metric (F1-score). Due to the strong class imbalance typical for EoL inspection data, special attention is placed on recall for faulty motors, as missed faults are the most critical industrial risk. Confusion matrices are used to analyze misclassification patterns and to evaluate trade-offs between false rejects and false accepts.

In [37], the statistical robustness of performance evaluations is additionally assessed using bootstrap resampling to compute confidence intervals for key metrics. In contrast, studies [35] and [36] report cross-validation-based point estimates without corresponding confidence intervals. This difference in how statistical uncertainty is treated reflects the validation procedures adopted in the original peer-reviewed studies and should be considered when comparing the performance metrics they report.

3.3.2 Validation procedures

For feature-based ML approaches [35], cross-validation is used to compare different classifiers and feature subsets, avoiding overfitting. Models are trained and tested on separate subsets of motors to ensure independence between training and evaluation data.

In the TL study [36], validation is performed by training models on a large dataset from a mass-produced motor subtype and evaluating them on preproduction subtypes with limited data. This approach directly reflects the intended industrial use case of fast commissioning for new motor types.

For DL models [37], training and validation are performed on separate motor sets, and oversampling techniques are applied to mitigate class imbalance. Model performance is evaluated on independent test data to evaluate generalization to unseen motors.

3.3.3 Industrial relevance

In addition to classification accuracy, all evaluation strategies consider practical industrial constraints such as computational efficiency, commissioning effort, and robustness to production variability. The conclusions in [35], [36], [37] are not limited to algorithmic performance but also consider the feasibility of integrating the proposed methods into existing EoL inspection workflows.

Chapter 4

Machine Learning Approach with Feature Selection

4.1 Introduction

In industrial EoL quality inspection, reliability and speed of decision-making are critical performance criteria. Inspection systems must operate within strict time constraints while maintaining high sensitivity to manufacturing faults. For this reason, many industrial inspection systems rely on classical ML methods that operate on predefined signal features. These approaches provide ideal trade-offs between computational efficiency, robustness, and interpretability. Despite this, the effectiveness of such systems depends heavily on the selection of relevant features, a process that is traditionally manual and requires extensive expert involvement.

Feature generation and selection has therefore become a central topic in ML for industrial quality control. Feature selection methods identify and retain only the most informative features, which reduces model complexity, improves generalization, enhances interpretability, and lowers computational requirements. Recent studies have shown that supervised feature selection techniques based on tree-based models and ensemble learning are particularly well suited for industrial datasets characterized by high dimensionality, redundancy, and noise [41], [42], [43]. These methods provide useful measures of feature importance that can simplify diagnostic procedure.

In manufacturing environments with high product variability, reducing the number of required features offers additional practical benefits. A smaller and more meaningful set of features can significantly shorten the commissioning time for new products, reduce the need for extensive parameter tuning, and simplify the necessary diagnostic hardware and software infrastructure. Moreover, interpretable feature importance rankings enable engineers to validate model decisions against their understanding of the system's physical principles, a critical requirement for the industrial acceptance of data-driven inspection systems [46], [47].

Despite these advantages, feature selection for EoL quality inspection remains challenging due to strong class imbalance, overlap in fault signatures, and variability in operating conditions. Many general-purpose feature selection methods fail to consider for these constraints, so they only offer limited benefits when applied directly to real production data. Therefore, there is a need for systematic investigations of feature selection strategies that are explicitly designed and validated for industrial EoL inspection systems.

This chapter introduces and explains the ML–based feature selection and classification approach [35]. This study evaluates multiple supervised learning algorithms, including decision trees and ensemble methods, to evaluate their ability to identify relevant

diagnostic features and reliably classify faults. Leveraging feature importance metrics derived from these models, the approach aims to optimize both the reliability and speed of EoL inspection while reducing dependence on expert-driven feature selection.

4.2 Optimization of Reliability and Speed of the End-of-Line Quality Inspection of Electric Motors Using Machine Learning

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Optimization of reliability and speed of the end-of-line quality inspection of electric motors using machine learning

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ABSTRACT

Consistently maintaining high-end product quality in the production process is challenging. End-quality inspection must be highly sensitive to detect even minimal deviations, while being fast and accurate. However, quality inspection systems often face calibration intricacies, are time-consuming, and rely heavily on expert knowledge. They handle substantial data flows and inspect numerous features, some of which contribute minimally to the final grade. To address these challenges, the paper proposes employing statistically supervised machine learning methods for classification. Decision trees, Random forests, Bagging, and Gradient boosting classifiers are recommended for feature selection and accurate diagnosis, particularly for electric motor classification. By utilizing the feature importance attribute for feature selection, the proposed approach compares model accuracies, reducing ramp-up and commission times significantly. The study found that all suggested classifiers achieved high accuracy in classifying electric motors in end-of-line quality inspection system. Moreover, they effectively reduced the number of features and optimize database operations. Utilizing a reduced feature set streamlined diagnostic algorithms, accelerated learning, and improved model interpretability, enhancing overall efficiency and comprehension. Furthermore, analysing the feature importance attribute could simplify diagnostic hardware and expedite quality inspection by eliminating unnecessary steps. Newly generated models can also verify expert decisions on feature selection and limit adjustments, enhancing efficiency in production processes.

ARTICLE INFO

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Quality inspection;
Fault detection;
Machine learning;
Feature selection and classification;
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Decision trees;
Random forests;
Bagging;
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1. Introduction

Electric motors are one of the most mass-produced devices and they are produced at highly automated manufacturing lines equipped with 100 % end-of-line (EoL) quality inspection, [1, 2]. Maintaining constant product quality, detecting faulty products and preventing them to be delivered to the customers or further built into devices and systems is highly important. With each production/integration step of faulty part, replacement costs increase substantially [1]. For this reason, a great attention is put to the design and implementation of fully automated EoL quality inspection systems. These must be reliable and at the same time fast enough not to hinder the production line pace. In the presented case, quality inspection of electric motors is performed in a non-invasive way, where several variables are measured during short test run of the motor. The measured variables comprise electric parameters (voltage, current and power), speed, torque, vibrations at different points of motor body and sound at different rotational speeds [1]. The

mentioned signals are sampled by high frequency (e.g. 50 kHz) and further processed by signal processing methods (e.g. Digital Filtering, Fast Fourier Transformation, etc.). This reduces the amount of data considerably while preserving relevant information, but still results in a high number of calculated parameters – features, representing basis for motor fault detection and isolation. High number of features can be impractical from several reasons: a) not all features carry useful information, b) some feature may carry the same information, c) comparing a high number of features against their thresholds values may be time consuming and finally, d) determining (learning) feature threshold values is demanding and time-consuming process.

With an ultimate goal of developing reliable and fast quality inspection methods, this paper deals with the problem of reduction of feature space to a limited subspace of relevant features, carrying enough information for motor quality inspection. The space of features can be reduced by implementing machine learning methods which select only the relevant features. Since not all relevant features contribute the same amount of information to final classification, additionally evaluation of feature selection describes the influence of each observed feature. Therefore, the features with the minimal influence can be eliminated from learning procedure. This can significantly decrease computational demand during learning (ramp-up and commission time) and operation phases. Moreover, in certain cases it can even lead to elimination of particular measurements (sensors), thus simplifying the inspection system hardware and software as well as speeding-up the EoL testing procedure. Study presented in this paper is based on the real industrial data derived from real EoL quality inspection systems installed at the production site of one of renowned European mass producer of electric motors. EoL quality inspection line, which is subject of this paper, was designed and implemented by the authors of the paper.

The paper is organized as follows: In Section 2, the subject of inspection and existing quality inspection procedure/system are briefly described. The structure of the measured data record and resulting feature set generated by the inspection of one motor is described. This is then followed by the Section 3, where machine learning algorithms (Decision tree, Random forest, Bagging and Gradient boosting) for feature selection are presented. In Section 4 the presented algorithms are evaluated and compared.

2. Problem description: Subject of inspection and quality inspection system

The subjects of inspection are brushless DC (BLDC) motors for domestic and automotive applications. An example of such motor used for vacuum cleaning applications, is shown on the Fig. 1. The addressed motors are manufactured by the renowned mass producer (Domel Slovenia, [3]). The production takes place at fully automated assembly line equipped with modular EoL quality inspection system, presented on the Fig. 2. More details can be found in [2], which describes similar system.



Fig. 1 Example of the BLDC motor (subject of EoL quality inspection)



Fig. 2 Modular EoL quality inspection system

The EoL quality inspection system assures "100 % quality inspection" meaning that each produced motor undergoes the test procedure. In general, the faults fall in two categories: electrical and mechanical. The latter can be further divided to rotor, bearing and turbine faults. Rotor and bearing faults are comprehensively elaborated in [4] whereas the explanation of turbine faults can be found in [1, 2]. The main steps of quality inspection procedure are described in following sections 2.1, 2.2 and 2.3 and in the Fig. 3.

2.1 Measurement and data acquisition

In the EoL quality inspection system, each motor is started several times and during short test runs various motor parameter are measured by the automatic measuring and data acquisition system (Fig. 3, square 1). The following parameters are measured by sensors: electric parameters (winding voltage and current, power, power supply current and voltage), vacuum pressure, rotation speed, vibrations at several points of motor body, sound at low and high rotational speed and also environmental conditions (ambient temperature and pressure) to compensate their effect on motor performance. The results of measurements are time series (waveforms) of particular parameter, and they represent ''raw signals''. Depending on observed parameter and derived features, signals are acquired at specific sampling frequency (typically 10-60 kHz) and measurement duration (typically from 0.1 up to 1 s), resulting in timeseries of various lengths (from 1000 samples to 30000 samples).

2.2 Feature extraction by signal processing

To reduce the amount of data and to extract the relevant information, raw signals are processed by signal processing methods, such as filtering (low-pass, high-pass, band-pass filters), downsampling, averaging, frequency analysis, etc. The outcome of signal processing is a set of ''features'', which are detailed in [4] and shown on the Fig. 3 (square 2). They are in general:

- Root-Mean-Square (RMS) values of band-pass-filtered waveforms;
- Power of signals at particular frequencies;
- Aggregated/actual values obtained from specific measurement equipment.

Details of feature extraction and signal processing algorithm are not described in this paper as they are subject of past research and development, elaborated in detail in [1, 5]. In this particular case the signal processing algorithm generates 80 features, where each feature is represented by floating-point numeric value.

2.3 Diagnostic result generation

Based on the on the values of the features, final diagnostic result of the inspected motor is generated by simple rules, as follows from the Table 1. For each feature it is checked if it is inside specified range.

Table 1 Diagnostic result generation

Measurements	Features	Diagnostic result
Completed	All features are within specified ranges	Motor GOOD
	One or more features are outside specified range	Motor BAD
Not completed, due to: • measurement faults • sensor faults • motor manipulation fault • motor transport faults • etc.		UNDEFINED

At the start of the production of new motor type, the motors from test-production set (series 0) are assessed as good or bad by the skilled experts. Based on experiences, the experts select features that are going to be used in diagnostic result generation. For this case-study system and motor type, 36 of total 80 features were chosen, and for each of chosen features two limit values (low and high) are set. In practice, all this is done manually by skilled experts. This is time-consuming and highly depends on expert skills. In addition, this method requires regular updates and fine-tuning of limit values when the mass production starts and production volumes increases [4].

Fig. 3 illustrates the entire procedure of measurement and data acquisition, feature extraction and diagnostic result generation. The whole process for one motor can be executed under 30 s, but due to parallel execution of diagnosis steps, the motor inspection rate is 10 s, which means that every 10 s one motor exists the EoL inspection system.

The described quality inspection algorithm successfully detects motors with insufficient quality, but it has some drawbacks:

- High number of original features (80) leads to high number of feature range limits that must be defined;
- Some features carry similar information (redundancy);
- Some features carry no useful information;
- Skilled expert is required to remove redundant features and features that carry no relevant information and to adjust limit values of feature in use. This is difficult and time consuming and becomes an issue during start of production and commissioning of new motor types.

Based on that there are four main goals of the study presented in this paper:

- Automatic selection relevant of features (removing redundant features and features that do not carry relevant information);
- Decrease the dependence on human expert skills;
- Automatic determination of feature limit values;
- Generating classification models with set of features that hold 95 % of useful information;
- Reducing ramp-up and commission time of the quality inspection system.

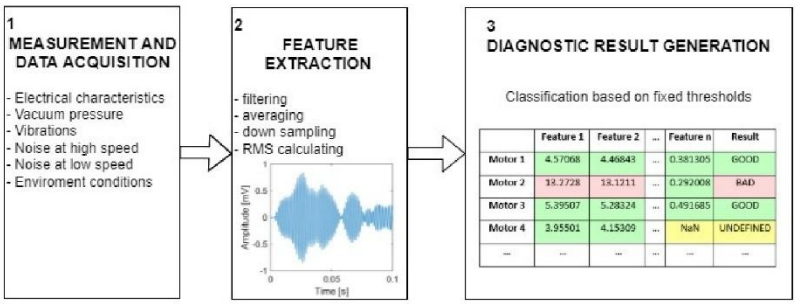


Fig. 3 Data transformation during the procedure

3. Feature selection using machine learning methods

In this section, dedicated machine learning methods will be used to automatically select the relevant features and set their threshold values. In general, feature selection is an effective way to deal with dimensionality [6] and it is often used in areas where a huge amount data is being obtained, such as identifying genes [7-9], image classification and analysing [10-13] text classification [14-16], in recent times also for monitoring manufacturing processes and quality control [17-19]. Feature selection aims to identify and retain the most relevant features while discarding redundant or uninformative ones by determining the "degree of usefulness" of a specific feature. By reducing the number of features, also the number feature limit values to be adjusted is reduced. The risk of the associated quality inspection errors [6] is also decreased. However, within the set of informative features, some may be significantly more informative than others.

The methods presented not only eliminate non-informative features but also sort the remaining features according to their informativeness. The goal of this paper is therefore to assess whether the quality inspection can be successfully performed by using only the limited number of the most informative features. Feature selection reduces the dimensionality of the data; therefore, data mining algorithms can be operated faster and more efficient [6]. Reduced amount of input data simplifies the interpretability of tree-like machine learning methods [20]. Additionally, such simplified classification methods and reduced input datasets decrease the ramp-up and commission time of quality inspection system and whole production line. Since some redundant and non-informative features are removed, sensors associated with removed features can potentially be eliminated. Optimization and reordering of the diagnostic steps based on feature importance can speed-up the quality inspection procedure.

3.1 Supervised machine learning classification methods

Supervised machine learning methods were selected since the labelled data for learning is available. These methods offer several advantages, including high reliability based on statistics, robustness, and reduction of the need for expert knowledge (e.g. knowledge about physical background of the system). However, in order to establish a supervised learning method, a sufficient amount of data from the production process is required. Therefore, these methods are suitable for manufacturing lines for mass production, like the one presented in this paper, where a lot of data is generated. In this paper 4 different methods were tested and compared:

- Decision tree classifier (DT);
- Random forest classifier (RF);
- Bagging classifier (BG);
- Gradient boosting classifier (GB).

The decision tree classifier partitions the instance space through a recursive process, forming a tree model where top nodes (roots) lack incoming edges, while internal nodes (test nodes) split the space based on attribute values. Internal nodes symbolize decision points, and bottom nodes (leaves) indicate decision outcomes [21, 22].

Random forests is a powerful ensemble learning method that combines multiple tree predictors. It belongs to family of averaging methods, meaning, the driving principle is to build several estimators independently and then to average their predictions [23-25].

Bagging, short for bootstrap aggregating, is a powerful and straightforward method for constructing an ensemble of classifiers. It also belongs to family of averaging methods. It combines multiple classifiers' outputs for improved accuracy by training each on a subset of instances randomly drawn from the training set [22, 26, 27].

Gradient boosting is a technique for improving the performance of weak learners [28]. It belongs to the family of boosting methods, meaning, base estimators are built sequentially, and one tries to reduce the bias of the combined estimator. It enhances weak learners sequentially, aiming to reduce the combined estimator's bias. The technique combines weak models for a powerful ensemble, particularly effective in decision trees [22, 25].

While the decision tree classifier (DT) stands alone, the remaining three classifiers (RF, BA,

GB) belong to the ensemble-based methods category. All methods here are "tree-like" classifiers and can be represented as decision trees using IF-THEN rules. The methods automatically generate IF-THEN rules for classification, including threshold values for each observed feature.

3.2 Data for learning and evaluation

To implement and test the methods, the data is needed. Data was generated by existing EoL quality inspection system (Fig. 2) during inspection of a total of 37440 motors. Generated data contains raw time series of measured signals and extracted features (mentioned 80 features), as follows from the Section 2. For machine learning algorithms, all features are used. The whole data set of features can be presented as 37440 × 80 matrix. The quality inspection results (1=Motor GOOD, 2 = Motor BAD, 0 = UNDEFINED) represents 37440 × 1 vector. The entire data set was divided into two parts: training data (75 % of all data) and testing data (25 % of all data). The situation is represented by the Table 2.

The data records of all 37440 motors were randomly distributed between training data and testing data to compensate for possible time drift of product quality. The same training and testing datasets were used during the training and testing of all 4 machine learning methods. Dataset remained unchanged throughout the entire training process. All involved features are named by symbols and anonymized to prevent the disclosure of sensitive technical data.

Table 2 Training and testing data arrangement

	F1	F2	...	F80	R	
M1	X	X	X	X	X	
M2	X	X	X	X	X	Training data (75 %)
...	X	X	X	X	X	
M28080	X	X	X	X	X	
M28081	X	X	X	X	X	
...	X	X	X	X	X	Testing data (25 %)
M37440	X	X	X	X	X	

M – motors, F – features, R – quality inspection results

3.3 Implementation

Fig. 4 illustrates the proposed process of feature selection.

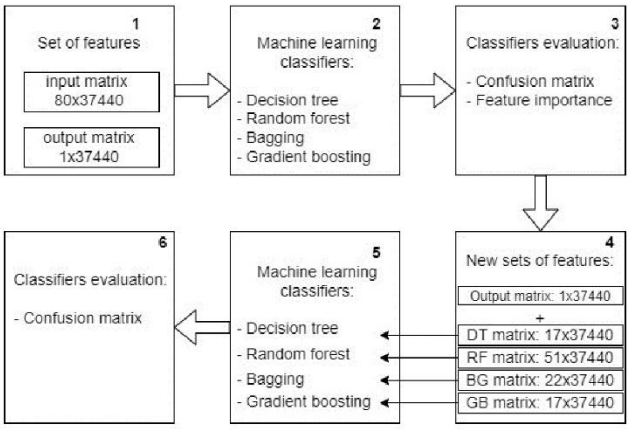


Fig. 4 Flow chart of the procedure

The process is carried-out in six steps:

1. Generation of original feature set (an input matrix of size 80 features × 37440 motors and output matrix of size one feature – grade × 37440 motors) obtained by data acquisition and signal processing, described in Section 2.
2. First machine learning to train the classifiers. Feature selection is utilized to eliminate redundant features. Depending on the type of classifier, the range of selected features is reduced to 38 (DT classifier), 78 (RF classifier), 42 (BG classifier), and 35 (GB classifier).
3. Evaluation of trained classifiers to present their performance and capability to evaluate features' classification impact and importance. From obtained results it followed:
   a. Set of features with 95 % informativeness additionally reduce space of features. Depending on the type of classifier, the range of selected features is additionally reduced to 17 (DT classifier), 51 (RF classifier), 22 (BG classifier), and 17 (GB classifier).
   b. Certain features, despite their low importance, still persist.
   Therefore, it was decided to check the performance of reduced classifiers with features that contains 95 % of all useful information.
4. Generation of reduced sets of training and testing data with features with 95 % of useful information for each classifier, output matrix remains the same from step 1.
5. Second machine learning to train the classifiers with new reduced dataset.
6. Evaluation of new classifiers and comparison to the results of classifiers from step 2.

All classification methods were implemented and tested in Python using the *scikit-learn* (sklearn) library. Cross-validation was employed during training (step 2 and step 5) to ensure robust model evaluation and to prevent model overfitting. For visualization and data manipulation, *matplotlib*, *numpy*, and *pandas* libraries were also utilized.

3.4 Presentation of the results and comparison of the methods

Following the training phases, the trained algorithms were evaluated using the testing data, and the predicted output classes (quality inspection result) were compared to the actual output classes. For each method, outcomes are presented in the form of well-known Confusion Matrix (CM). The CM provides numerical and visual representation of the classification algorithm's accuracy. It consists of columns representing the predicted output classes and rows representing the actual output classes. In the presented case, since there are three classes, the size of the CM is 3 × 3 as shown in the Table 3. The diagonal elements represent correctly classified instances, while the off-diagonal elements represent miss-classified instances.

Table 3 Confusion matrix structure

		PREDICTED		
		UNDEFINED	Motor BAD	Motor GOOD
ACTUAL	UNDEFINED			
	Motor BAD			
	Motor GOOD			

The CM provides valuable information about the miss-classification, but it does not directly capture the cost associated with each type of miss-classification. To address this, the Miss-classification cost matrix can be introduced. This matrix assigns specific costs to different types of miss-classifications, considering the relative importance or impact of miss-classifying different classes. The Miss-classification cost matrix has the same dimension as the Confusion matrix and consists

of numerical values, as shown in the Table 4. The diagonal elements of the Miss-classification cost matrix are set to zero (correct classification represent no cost). The off-diagonal elements represent the costs associated with miss-classified instances, with larger values indicating higher risks or costs associated with miss-classification. In our case the highest cost is associated with situation when actual faulty or undefined motor is recognized as good one and delivered to the customer (actual class BAD or UNDEFINED, predicted class GOOD). The cost of this miss-classification is set to 10. Bad motor that is predicted as undefined (and the opposite) presents low cost of miss-classification, therefore these cases are graded with 0.5. Good motor, ranked as bad or undefined, does not present any risk for the customer, but it represents an unnecessary waste of motors, therefore it is marked with 1.

To calculate the overall miss-classification cost, the CM the Miss-classification cost matrix are multiplied (element-by-element multiplication) resulting in new 3 × 3 matrix. Total cost is calculated by adding up all 9 elements of resulting matrix. This value provides a measure of the total cost incurred due to miss-classification. Ideally, a well-performing classifier would have a miss-classification cost close to zero, indicating minimal miss-classification and associated risks.

The accuracy of a classifier is a measure of its performance and is calculated as the ratio between the number of correctly classified elements and the total number of elements. The desired accuracy is close to 1 (100 %), indicating that almost all elements were classified correctly.

Table 4 Cost matrix

		PREDICTED		
		UNDEFINED	Motor BAD	Motor GOOD
ACTUAL	UNDEFINED	0	0.5	10
	Motor BAD	0.5	0	10
	Motor GOOD	1	1	0

4. Analysis of the results

During machine learning, all methods generated own IF-THEN rules for classification. In 3.1 it is explained that chosen methods are “tree-like” and can be explained with IF-THEN rules. In the Fig. 5, an example of the decision tree of the decision tree classifier is presented. The figure shows a diagnosis procedure with a tree-like set of rules and leaves. Since the generated decision tree is very extensive, one rule for the first branch is explained. At the enlarged part of the figure, the auto generated threshold value for one particular feature (BE_H2) is illustrated. At enlarged part the gini index value [6, 21, 29] is also illustrated and used as splitting criteria [6]. Further, at this branch 27064 samples are involved in classification process, where 600 of them are marked as UNDEFINED, 1355 as Motor BAD and 25109 as Motor GOOD.

Each of the methods generates similar decision tree scheme where rules are defined by observed features and their threshold values. Threshold values are set automatically during machine learning and since they are presented as real values. They can be easily checked and readjusted. Such examination of the decision tree structure of each classifier enhances comprehension of the decision-making process employed by each method. This understanding is particularly valuable in industrial applications where interpretability is paramount, as it allows users to gain insights and interpret the decision-making process with clarity.

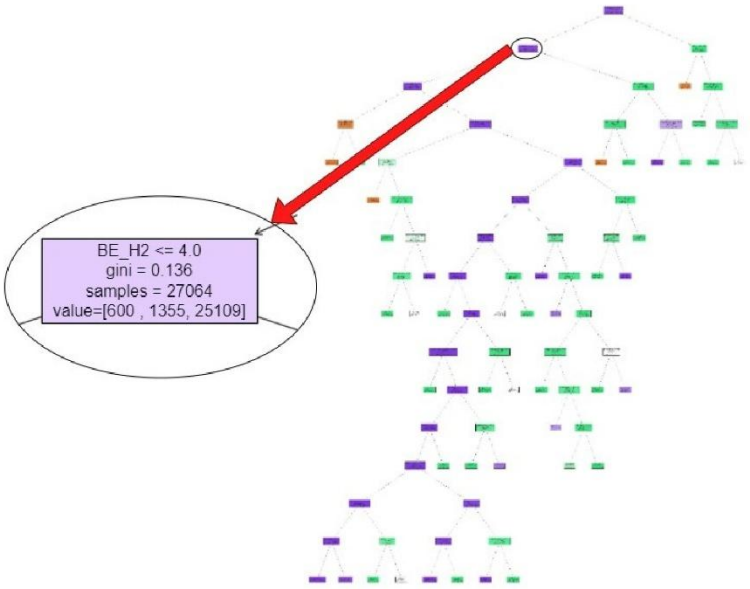


Fig. 5 Decision tree of the decision tree classifier

Results of feature selection are collected in Table 5, where the comparison between classifiers is presented. The results show that all methods successfully executed feature selection in the step 2 (Fig. 4). The *gradient boosting* classifier selected the lowest number of important features, meaning, this method requires the smallest amount of data for successful classification. The least successful method here is *random forest*.

However, the best performance shows the classifier with the lowest number of wrong classified motors and with the lowest miss-classification cost. Therefore, *bagging* overperformed all other classifiers and *gradient boosting* yield the worse performance. Fig. 6, Fig. 8, Fig. 10 and Fig. 12 present confusion matrices for each classifier, generated at step 2.

Table 5 Comparison of observed classifiers

	Decision tree	Random forest	Bagging	Gradient boosting
No. of selected features with original dataset after step 2	38	78	42	35
Number of features for 95 % informativeness	17	51	22	17
Influence of 10 most important features	92 %	69 %	88.6 %	91.4 %
Accuracy of classifiers with original dataset (step 3)	99.2 %	99.33 %	99.46 %	99.19 %
Accuracy of classifiers with reduced dataset (step 6)	99.16 %	99.33 %	99.46 %	99.16 %
No. of wrong classified motors of classifiers with original dataset (step 3)	75	53	51	76
No. of wrong classified motors of classifiers with reduced dataset (step 6)	79	53	51	79
Miss-classification cost of classifiers with original dataset (step 3)	426	477	312	679
Miss-classification cost of classifiers with reduced dataset (step 6)	430	468	348	637

Further insights into feature selection across different classifiers show that the most influential features hold the majority of information, useful for classification. Third row in the Table 5 shows a part of information contained in the 10 most important features of each method. In all methods (except RF) top ten features contain the majority of information and to achieve 95 % of data informativeness, 17-51 features are required. This comprehensive evaluation provides insights into the strength and weakness of each classifier, considering both accuracy and miss-classification cost. At the Table 6, where the 10 most influential features for each classifier in the order of importance are listed, it is shown that all classifiers recognize the majority of features as important (Figs. 14-17 visually illustrate the informativeness of each observed classifier for 10 most important features). At the Table 7 all features involved in machine learning are listed and in columns each of them is marked whenever it appears to be important for each classifier. With gravy are coloured rows of features that are important for all observed classifiers.

These findings can be highly beneficial for tuning classification parameters. Instead of adjusting the thresholds for all observed features, only the most influential features need to be addressed. Additionally, since some features do not contribute to the final classification decision, they do not need to be stored in the company database. This results in the reduced computational burden by focusing only on the most informative features, a smaller data flow between the local computer and the company database, reduces the potential for communication errors, and ultimately requires less storage space.

Table 6 List of 10 most important features for each classifier

	Decision tree	Random forest	Bagging	Gradient boost
1. important feature	BE_H1	BE_H2	BE_H1	BE_H1
2. important feature	BE_H2	BE_H1	BE_H2	BE_H2
3. important feature	BE_H3	BE_H3	BE_H5	VRC
4. important feature	VA	BE_H5	VRC	VA
5. important feature	VRC	BE_H4	VA	VA_H1
6. important feature	HW_H1S	BE_H6	HW_H1S	HW_H1S
7. important feature	VRL_H2	VRC	VA_H1	BE_H3
8. important feature	HW_H6	VA	BE_H3	BE_H6
9. important feature	AVR_V	HW_H1S	BE_H6	VRL_H2
10. important feature	VW_V	VA_H1	HW_H6	FR_H2

Table 7 All features involved in machine learning and their recognition as important for each classifier

Feature name	DT	RF	BG	GB
VA	X	X	X	X
VA_H1		X	X	X
VA_H2		X		
VA_H3		X		
VA_H4		X		
VA_H5		X		
VA_H6	X	X		
VA_H7		X		
VA_H8		X		
VA_H9		X		X
VA_H10		X		
VA_H11		X		
VA_H12		X		X
VA_H13	X	X		
VA_H14		X		
VA_H15	X	X		
AVR_U		X	X	X
AVR_V	X	X	X	X
AVR_W		X		
BM_U		X		
BM_V	X	X	X	X
BM_W	X	X		
FR_H1	X	X	X	X
FR_H2	X	X	X	X
BE_H0				
BE_H1	X	X	X	X
BE_H2	X	X	X	X
BE_H3	X	X	X	X
BE_H4	X	X	X	X
BE_H5	X	X	X	X
BE_H6	X	X	X	X
CP	X	X	X	
VW_U		X	X	X
VW_V	X	X	X	
VW_W	X	X	X	X
VRC	X	X	X	X
VRC_H1		X		
VRC_H2	X	X		
VRC_H3		X		
VRC_H4	X	X	X	

VRC_H5		X		X
VRC_H6		X		
VRC_H7		X		
VRC_H8		X		
VRC_H9	X	X	X	
VRC_H10		X		
VRC_H11		X		X
VRC_H12	X	X		
VRC_H13		X	X	X
VRC_H14		X		X
VRC_H15		X	X	X
VRL		X		
VRL_H1		X	X	
VRL_H2	X	X		X
VRL_H3		X		
VRL_H4		X		
VRL_H5		X	X	X
VRL_H6	X	X	X	X
VRL_H7		X	X	
VRL_H8		X	X	

VRL_H9	X	X	X	X
VRL_H10		X	X	X
VRL_H11		X		
VRL_H12		X	X	
VRL_H13	X	X		
VRL_H14		X		
VRL_H15		X		
MV	X	X	X	X
CW_U	X	X		
CW_V	X	X	X	
CW_W	X	X	X	
HW_H1S	X	X	X	X
HW_H18	X	X	X	X
HW_H2	X	X	X	X
HW_H2S	X	X	X	X
HW_H3	X	X	X	X
HW_H4	X	X	X	X
HW_H6	X	X	X	X
HW_H9		X	X	
REV				

At last, the performance of classifiers, trained with features of 95 % information (step 5), is evaluated (step 6). The result in Table 5 shows that the accuracies and performances of classifiers do not change a lot. However, despite the RF and GB classifier, the cost of miss-classification increased, meaning, those classifiers miss-classified performed slightly worse. (as shown at Fig 6-13). Despite minor fluctuations in accuracy, the overall performance remains relatively stable what indicate the robustness of chosen methods. However, the increase in miss-classification costs for certain classifiers indicates potential areas for optimization in future iterations.

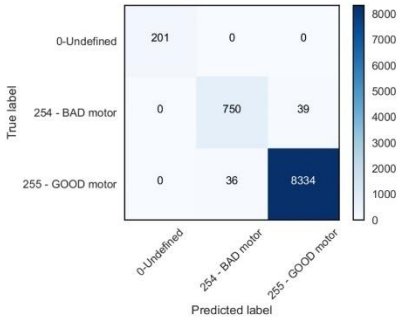


Fig. 6 Confusion matrix for decision tree classifier (38 features)

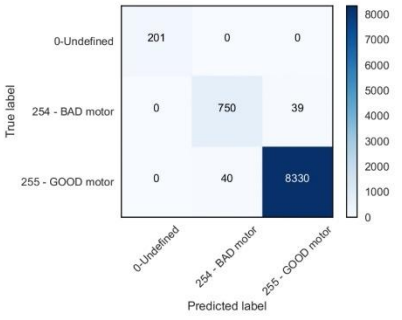


Fig. 7 Confusion matrix for decision tree classifier (17 features)

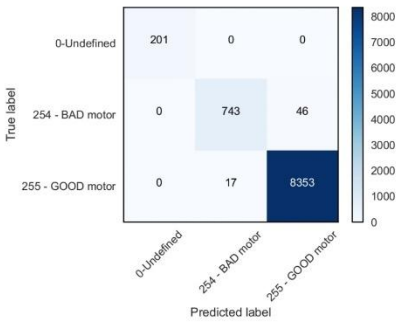


Fig. 8 Confusion matrix for random forest classifier (78 features)

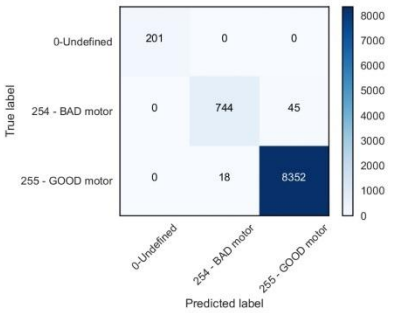


Fig. 9 Confusion matrix random forest classifier (51 features)

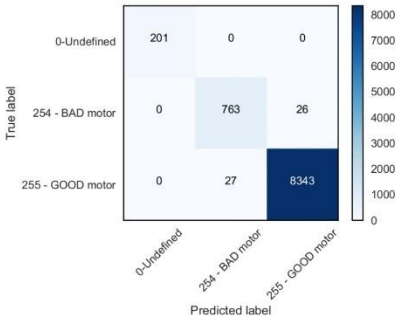


Fig. 10 Confusion matrix for bagging classifier (42 features)

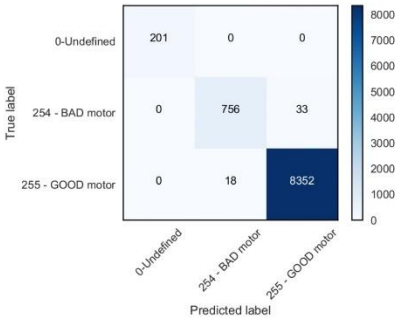


Fig. 11 Confusion matrix for bagging classifier (22 features)

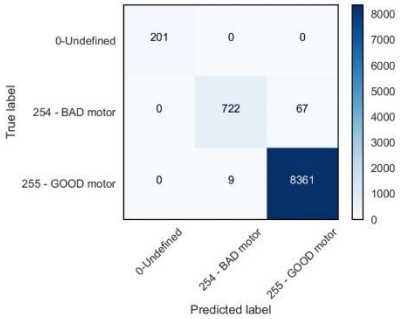


Fig. 12 Confusion matrix for gradient boost classifier (35 features)

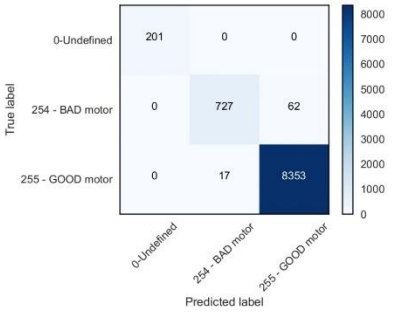


Fig. 13 Confusion matrix for gradient boost classifier (17 features)

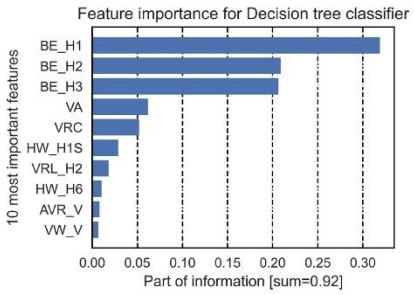


Fig. 14 Feature importance for decision tree classifier

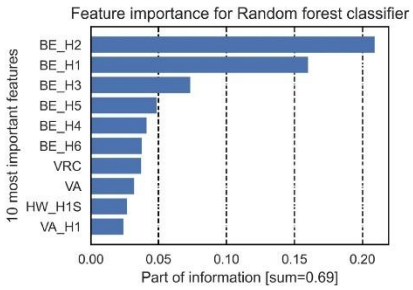


Fig. 15 Feature importance for random forest classifier

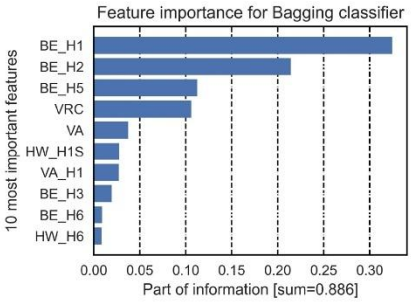


Fig. 16 Feature importance for bagging classifier

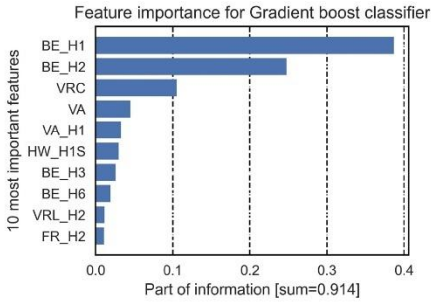


Fig. 17 Feature importance for gradient boost classifier

5. Conclusion

This study introduced and compared various classifiers for feature selection purposes used for automated end-of-line quality inspection of electric motors within the real manufacturing line. Decision tree, Random forest, Bagging, and Gradient boosting classifiers were implemented and assessed based on their complexity (number of selected features), accuracy, and the impact of the important features. Initial goal of the study was achieved successfully. All four tested classifiers demonstrated high accuracy, proving their suitability for electric motor classification in an end-of-line quality inspection system. All investigated classifiers successfully reduced the number of features and thus optimized the database operation. Further, the second step of feature selection, with a reduced dataset featuring features that hold 95 % of useful information, yielded high accuracy of trained classifiers. This reduced feature set simplifies the diagnostic algorithm, speeds-up its' learning, improves the interpretability of the observed models and makes them more understandable and explainable. In addition, new classification models, learned with reduced dataset, simplify the end-of-line quality inspection, decrease the ramp-up and commission time, eliminate unnecessary steps of diagnosis, reduce equipment complexity (in some cases eliminate the need for particular sensors), reduce costs, and minimize data flow. Consequently, company databases are optimized. Due to fully automated learning procedures, reliance on specialized experts is reduced. Developed classification models can also be used as a verification of experts' decision regarding feature selection and threshold values adjustment. In summary, this study encompasses insights into feature selection, practical implications for industrial applications considering methods robustness and comprehensive evaluation of different classifier, considering accuracy and miss-classification cost, aiding in decision making when selecting the most suitable classifier for specific application.

During research and implementation, two interesting and useful future topics of research were identified: 1. Transferability of classification models, and 2. Condition monitoring of production lines.

Within the first topic it could be investigated if classification models derived for one motor type could be used for quality inspection of similar motor types, or if they could increase learning procedure of new motor types. Based on the manufacturer's experiences, the diagnosis procedure across various manufacturing lines follows a similar approach, leading to the detection of similar faults and malfunctions across different products. Furthermore, common features are identified, suggesting that the feature selection process from observed classifiers of a particular motor type could be applied to other product. This transferability would be beneficial especially for small-series products. Some motor types are manufactured in small-series (e.g. up to thousand pieces per year), therefore it is challenging to establish accurate classification model with limited amount of learning data. Exploring the applicability of these findings across various motor types can speed-up the creation of quality inspection algorithms for new motor types in the future. As new motor types are developed frequently and produced in varying quantities, the transferability of the methods can establish a standardized approach to implement quality inspection algorithms for new motor types, reducing costs and thus enhancing the whole manufacturing process.

Second topics regards possibilities of condition monitoring of production line. In normal conditions (when there is no degradation of the manufacturing process) features importance attributes do not significantly change with time. On the other hand, an increase of importance of particular feature may indicate the issue of particular manufacturing operation or an issue of input material or components. Periodic evaluation of feature importance attributes can therefore help to detect faults or degradations of various steps of manufacturing process or issues with input materials and components.

Acknowledgments

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Chapter 5

Transfer Learning Approach

5.1 Introduction

One of the major practical limitations of data-driven EoL quality inspection systems is their strong dependence on large volumes of labeled data. During the production of electric motor, such data are typically available only for long-running, mass-produced motor types, while newly introduced or preproduction motor types are characterized by very limited datasets. The imbalance between data availability and inspection requirements presents a significant challenge for conventional ML approaches, as they often perform poorly in when trained on small or highly imbalanced datasets. Similar limitations of data-hungry models in industrial quality control have been widely reported in recent manufacturing and condition-monitoring studies [19], [20], [22], [23].

TL has emerged as an effective strategy for addressing these challenges by reusing knowledge acquired from related tasks or domains. Rather than training inspection models from scratch for each new product variant, TL allows models to leverage information learned from existing motor types. This reduces both data requirements and commissioning effort. Recent research has shown that transferring feature representations, model parameters, or decision boundaries can significantly improve classification performance in low-data regimes, particularly in industrial environments where fault samples are scarce and expensive to obtain [23], [29], [30], [46].

In the context of EoL quality inspection, TL is especially interesting because production lines often share common sensor equipment, test protocols, and basic physical principles for all motor families. These similarities create ideal conditions for knowledge transfer between different motor types, even when their geometries, power ratings, or application areas differ. Nevertheless, the practical application of TL in industrial EoL inspection is limited, and systematic studies under real manufacturing conditions are still rare. Open questions include which types of knowledge are most transferable, the effect of transfer on inspection reliability, and how to balance performance gains against the risk of negative transfer [47], [48], [49], [50].

This chapter introduces and explains the TL approach presented [36], which examines the use of supervised TL for ML–based EoL quality inspection of electric motors. The proposed approach focuses on transferring knowledge in the form of optimized model hyperparameters and feature importance information in the form of knowledge from a mass-produced motor type to newly introduced preproduction motor variants with limited data availability. Thus, the study directly addresses the industrial need for faster commissioning and reduced reliance on expert intervention during commissioning phases.

5.2 A Transfer Learning Approach for Machine Learning-Based End-of-Line Quality Inspection

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A transfer learning approach to machine learning-based end-of-line quality inspection

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ABSTRACT

Transfer learning is a powerful machine learning technique for accelerating the learning process of a new classification task by using knowledge from an existing and related classification task that has already been trained. This technique addresses situations where the necessary training and test data are unavailable or where data acquisition is costly, difficult, or impractical. Additionally, transfer learning significantly reduces training time compared to training from scratch. This study demonstrates the benefits of transfer learning in developing an end-of-line quality inspection system to produce brushless DC electric motors during preproduction. Decision Tree, Random Forest, Bagging, and AdaBoost classifiers were trained on a dataset of 10,000 instances from a mass-produced motor subtype (A). Knowledge in the form of hyperparameters and feature importance was transferred to classifiers for two preproduction subtypes (B and C), each with only 100 instances. The results show up to a 20 % improvement in classification accuracy and significantly lower misclassification costs when using transfer learning. The study highlights the importance of transfer learning as an effective approach for improving industrial classification tasks, especially in preproduction phases where datasets are typically small and imbalanced.

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1. Introduction

End-of-line (EoL) quality inspection contributes significantly to the manufacturing processes and to the overall quality of released products [1, 2]. With proper quality inspection, faulty products can be detected, diagnosed, and separated from good ones. Quality inspection can isolate and recognize faults of products; therefore, those products can either be repaired or recycled [1].

To establish quality inspection, extensive specific knowledge is required [2, 3]. This knowledge is usually possessed by experts, who gained it from past experiences and studies [1, 4]. With the advancement of artificial intelligence (AI), quality inspection systems can be established using machine learning (ML) methods [5]. These methods can significantly reduce dependence on expert knowledge. However, they require a vast amount of learning, testing and validating data.

The problem arises when the production of new product subtype starts, and there is not enough historical learning data, since the data has yet to be generated and collected during the production. Therefore, the ML process cannot start immediately, but only after the sufficient

amount of data is collected. The learning data must include instances of all expected classes, including rare errors, which may occur, for example, once in every 1,000 instances. Therefore, during the preproduction and test production stage (e.g., 100 instances of products), a sufficient amount of data is often not available.

However, when planning to manufacture the new product on existing production lines where structurally similar products have already been produced in large quantities, some knowledge from existing quality inspection algorithms can be utilized for the inspection of new product type in limited quantities. This procedure is called Transfer Learning (TL).

The study presented in this paper is based on real industrial data, obtained from an EoL quality inspection system of manufacturing line, installed at one of the European mass producers of electric motors. On the presented line, various motor types are produced, but this paper focuses on a particular motor class (referred to as 720). The research investigates whether the knowledge gained from motor classifiers for the mass-produced subtype can be transferred and applied to the ML of classifiers for similar preproduction motor subtypes, which have limited data quantities due to the early preproduction stage, where only a few (up to 100) units are produced.

This paper is organized as follows: Section 2 describes the problem, subject of inspection and existing quality inspection system. Section 3 discusses the transfer learning, studied methods and procedure. Section 4 presents the analysis of results, and finally, Section 5 provides the conclusion.

2. Problem description

The addressed EoL quality inspection system is part of the fully automated production lines at Domel, Slovenia, a renowned mass producer of electric motors. In this section, the subject of quality inspection and quality inspection systems are briefly described.

2.1 Subject of quality inspection

The subject of inspection is the brushless DC (BLDC) motor class named '720', and shown in Fig. 1. It is designed for battery-driven applications, such as electric garden tools, handheld tools, service robots, small appliances, and automotive uses. It is produced in many variants, defined by supply voltage (12-48 V), stack height (10-40 mm), nominal speed (3,000-45,000 rpm), power range (200-2,000 W), and the presence and type of control electronics [6].

This paper examines three subtypes of the motor class 720, referred to as A, B, and C. Subtype A has already been mass-produced, while the other two (B and C) were in preproduction stages, resulting in limited production quantities. The observed motor subtypes are produced at the same manufacturing line, and they have very similar structures but differ in only a few parameters (such as size, power, capacity, voltage, etc.).



Fig. 1 BLDC motor class 720 (subject of quality inspection)

2.2 Existing EoL quality inspection system

Production line is equipped with a modular End-of-Line (EoL) quality inspection system (Fig. 2) that inspects each produced motor. Each motor undergoes several short test runs to measure various parameters (electrical properties, rotation speed, vibrations, and sound at different speeds of rotation). In addition to motor parameters, the auxiliary variables are measured and used to compensate the effect of environment (air temperature, pressure and humidity). The measurements produce time-series waveforms, or "raw signals," sampled at 10-60 kHz for 0.1 to 1 second, resulting in several time series of different sizes (from 1,000 up to 30,000 samples).

To reduce data volume and, most importantly, to extract the relevant information, raw signals are processed by digital filtering, down-sampling, averaging, and finally, frequency analysis. Details about this have already been documented in [7] and in [8-10]. The result of signal processing is a set of features, where each feature is represented by a single floating-point scalar value. Typically, feature represents signal power at a particular frequency. In case of motor class 720 and selected subtypes, the quality inspection algorithm operates with 80 features, originating from sound, vibration, and electric signals. Based on the values of the observed features and their specified ranges, the inspected motors are categorized into three categories: GOOD, BAD and UNDEFINED. These categories are detailed in Table 1 and explained in [7]. Range of each feature (upper and lower threshold) is usually determined by experts, who also select the subset of features most relevant for the quality inspection.

Table 1 Diagnostic result generation [7]

Measurement status	Features	Diagnostic result
Completed	All features are within specified ranges	GOOD
	One or more features are outside specified range	BAD
Not completed, due to: • measurement faults • sensor faults • motor manipulation and transport faults etc.		UNDEFINED



Fig. 2 Modular EoL quality inspection system

Table 2 Key steps in the development of inspection system.

Step	Description	Executor
1. Selecting inspected parameters	Define inspection process, focusing on electrical, mechanical and performance tests.	Production engineers and experts
2. Designing the inspection process	Develop the workflow, including test sequences, manipulation procedures and database structure.	Production engineers and experts
3. Signal processing	Select and integrate appropriate sensors, capture real-time analog signals and convert them into digital data (details in [7-9] and [11])	Production engineers and experts
4. Data processing	Design algorithm to extract features from data to identify specific product characteristics. This process provides actual measurement value (details in [7-9, 11]).	Production engineers and experts
5. Classification task	Design algorithms to categorize inspected items into categories: GOOD, BAD, UNDEFINED. This step involves: 1. *Feature selection;* identify relevant features for inspection. 2. *Threshold adjustment and tuning;* setting and fine-tuning threshold values.	AI, ML (presented in [7])
6. Classifier adaptation	Adjust the inspection system to accommodate new product types or subtypes.	AI and ML (this study)
7. Data archive	Design system to store results in the company database, monitor manufacturing processes and detect trends such as system wear, degradation or material changes.	Production engineers and experts

The development of an EoL quality inspection system is a complex, challenging, and time-consuming process. Building such a system requires experts with specialized knowledge, and as a result, the system heavily relys on human expertise. To minimize reliance on experts, the ML approach was used to support *automated feature selection* and *automated feature threshold adjustment* [7]. The development process of the presented system follows the structured steps, outlined in Table 2.

3. Transfer learning for quality inspection

Transfer Learning (TL) is a ML technique where knowledge gained from training a model on one task (the source domain) is applied to a different but related task (the target domain) [12]. In this study, the idea of TL is to transfer knowledge from previously established quality inspection algorithms of mass-produced motor subtype (the source domain) to the new preproduction motor subtype that only has limited training data (the target domain). This approach can achieve the following goals:

- Develop a reliable quality inspection algorithm using a reduced amount of training data,
- Reduce ramp-up time and expedite the development of the quality inspection process.

3.1 TL basics

TL is effectively utilized in a wide range of applications like computer vision, especially for image classification tasks [13], natural language processing (e.g. BERT, GPT, and ELMo [14-16]), speech recognition [17], medical imaging [18], time-series forecasting [19] and robotics [20].

TL is usually applied with artificial neural networks and deep learning [12, 21] and it is less frequently used with ML classifiers such as Decision Trees and Ensembles (Random Forests, Bagging and AdaBoost). However, several studies [22-25] demonstrate that TL can also be applied to these classifiers in the following ways:

1. *Instance transfer:* In this approach, the suggested classifiers are trained on the source domain data and then applied to the target domain [24, 26]. The idea is that some data from source domain (instances from mass-production) are reweighted (their impact on the new model is reduced) and then directly reused for training new models with limited data (instances from preproduction). The success of transfer learning increases with the similarity between source and target domain. When instant transfer is performed, classifiers of source domain and target domain do not necessarily share any similarities, but they share some training data, as shown in Fig. 3, section a) in Target domain rectangle.
2. *Feature transfer:* This approach focuses on finding a list of relevant features of source domain and transferring them to the target domain [27, 28]. In the case of Decision Trees and Ensemble classifiers, this can be implemented by analysing the feature importance in the source domain. The assumption is that the feature importance in the target domain will closely resemble that of the source domain. When feature transfer is performed, the training data for classifiers of the source and target domain and the structure of classifiers remain independent. However, both classifiers share the same features, although their threshold values may differ (Fig. 3, section b in Target domain rectangle).
3. *Parameter transfer:* In this approach, the parameters of classifier are transferred from source to target domain [29]. In this case, instead of training from scratch, the initial splits and structures of source domain classifiers can be fine-tuned for purposes of target domain classification. In models like Decision trees and Ensembles, parameters such as weights, feature thresholds, estimators, and leaf node prediction as well as hyperparameters like splitting criteria, maximal depth, number of estimators, can be transferred. Parameters are values, learned during ML processes, while hyperparameters are pre-set values that control the structure and behaviour of the model [30]. When parameter transfer is performed, the training data of source and target domain remain independent, but the structure of the classifier (or part of it) can be the same. Please see Fig. 3, section c) in Target domain rectangle.

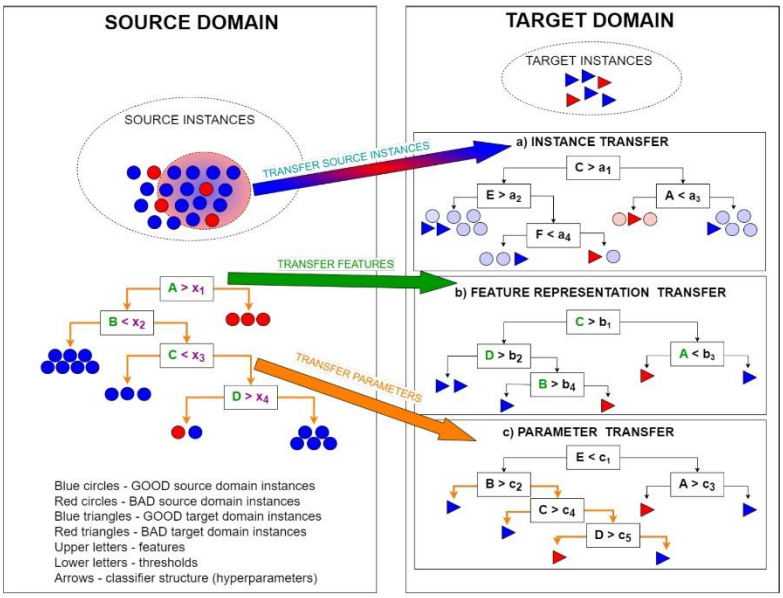


Fig. 3 Explained TL: a) Instance transfer, where source instances are added and mixed to target instances to ensure a sufficient amount of data (light colors represents lower weight), b) feature transfer, where all features (upper case letters) from source domain are transferred and used for target domain classification, however, they do not necessarily be on the same place, indicating different classifier structure, c) parameter transfer, where parameters that define classifier structure are transferred to target domain classifier (orange arrows represent part of structure that is defined by hyperparameters), one can notice that source and target structure of the decision tree are the same, but features at each node can be different.

In our case of EoL Quality Inspection system, *Decision Trees*, *Random Forests*, and *Bagging* and *AdaBoost* classifiers were applied to implement *Feature transfer* and *Parameter transfer*. For feature transfer, the most important features—determined through feature selection and feature importance metrics—were identified in the source domain (mass-produced motor subtype A) and transferred to the ML classifiers used in the target domain (preproduction subtypes B and C). For parameter transfer, hyperparameters were transferred. *Instance transfer* was not employed in this study due to several key limitations:

- The source and target domains are structurally similar, but not identical, which can lead to distributional shifts in feature behaviour and fault manifestation. Direct reuse or reweighting of source-domain instances in the target domain may introduce label noise or reduce classifier reliability.
- The dataset size imbalance is substantial. Subtype A includes 10,000 instances, whereas subtypes B and C contain only 100 each. This would likely bias the classifier toward the source domain, undermining generalization.
- The signal pre-processing already condenses raw sensor data into abstracted, denoised features, reducing the marginal value of reusing raw instances.
- Due to communication infrastructure limitations in the production environment, large-scale data manipulation is practically infeasible for the considered application.

While both feature and parameter transfer enhanced performance in this study, some trade-offs exist. By focusing on the most informative features, feature transfer enabled the creation of simplified, generalizable models, especially in cases where training data is limited. However, by eliminating less important features carries the risk of overlooking subtle fault indicators. By

reusing optimized hyperparameters, parameter transfer allows faster convergence. However, it may be less robust to changes in feature importance or domain shifts. The combined use of both methods helped mitigate these limitations and contributed to the development of reliable and robust classifiers for preproduction stage.

3.2 Chosen ML classifiers

To utilize TL, supervised ML classifiers were chosen due to the availability of labelled data. These classifiers provide several benefits, such as statistical reliability, robustness, and a decreased reliance on expert knowledge (e.g., understanding the physical background of the system). However, implementing supervised ML classifiers require a substantial amount of data from the production process. These classifiers are well-suited for manufacturing lines engaged in mass production. In this study, the following classifiers were used and compared:

- *Decision Tree classifier (DT)* involves recursive partitioning of the instance space into a tree structure. The top nodes, or roots, have no incoming edges, whereas internal nodes, or test nodes, divide the space based on attribute values. These internal nodes represent decision points and at the bottom ones-leaves-indicate decision outcomes [31, 32].
- *Random Forest classifier (RF)* is one of the most powerful ensemble learning techniques, combining several tree predictors. It belongs to a class of averaging methods where several independent estimators are built and their predictions averaged [33, 34].
- *Bagging (bootstrap aggregating) classifier (BG)* is a basic method used in creating an ensemble of classifiers. Similarly to averaging methods, bagging combines outputs of a number of classifiers with random training sets; therefore, improving accuracy [34, 35].
- *AdaBoost (adaptive boosting) classifier (AB)* is a widely used ensemble classifier that combines multiple weak classifiers to form a stronger classifier. It involves the repeated training of weak classifiers such that each iteration focuses on the instances previously misclassified, thereby improving model accuracy. In classification tasks, AdaBoost is quite effective at reducing bias and variance [34, 36].

The optimal structure of classifiers was determined through hyperparameter tuning, while feature selection and feature importance analysis generated a ranked list of relevant features, ordered from the most to the least important for classification. The feature selection process had already been discussed in [7] and is not the subject of this study.

Parameters are the internal variables that are automatically learned during the training process and directly control the model's predictions. Hyperparameters are the settings or configurations of the model that are set before the training and determine the structure of the model. In this study, hyperparameters are being tuned via hyperparameter optimizers to ensure the best classifier structure. Since SciKit learn python library was utilized, the following optimizers were available:

- Grid Search Cross Validation (CV) [37],
- Halving Grid Search CV [38],
- Halving Random Search CV [39],
- Parameter Grid [40],
- Parameter Sampler [37],
- Randomized Search CV [41].

In this work, hyperparameters were optimized using *Halving Random Search CV method* (with 10-fold Cross-Validation), which combines Halving Grid Search and Randomized Search. The process begins with a random set of hyperparameter combinations, after which the algorithm identifies the optimal combination. This method balances exploration and exploitation and is more efficient than traditional Grid Search [39].

Hyperparameters to be tuned for each classifier are listed in Table 3. Due to computational complexity, only the most influential hyperparameters (according to [31-35], [30]) are being tuned.

Table 3 List of transferable hyperparameters for each classifier.

DT	RF	BG	AB
Criterion	Bootstrap	Base estimator	Base estimator
Max depth	Criterion	Bootstrap	Learning rate
Max features	Max depth	Max features	N estimators
Min samples split	Max features	Max samples	
Min samples leaf	Min samples split	N estimators	
Splitter	Min samples leaf		
	N estimators		

Base estimator refers to the learning algorithm used to construct the ensemble in ensemble classifier such as Bagging and AdaBoost [36].

Bootstrap determines whether the entire dataset or a randomly sampled subset is used to build each tree in a Random Forest [42].

Criterion defines the function that measures the quality of a split in decision trees, with GINI impurity being a common choice for classification tasks [31].

Learning rate adjusts the contribution of each base learner within the ensemble, influencing how quickly the model adapts during training [43].

Max depth limits the maximum depth of the trees to prevent overfitting and complexity [31].

Max features sets the maximum number of features considered when splitting a node, when expressed as a float, it indicates a fraction of the total features [33].

Max samples specifies the fraction of samples drawn from the original dataset to train each base estimator [42].

Min samples leaf defines the minimum number of samples required to be present in a leaf node [31].

Min samples split defines the minimum number of samples necessary to split an internal node [31].

N estimators present the number of base estimators in the ensemble [33].

Splitter specifies the strategy employed to split each node during tree construction [33].

3.3 TL data

For machine learning, measured data of motor subtypes A, B, and C and were available. As mentioned, subtype A was mass-produced, so larger dataset was available. Each dataset (A, B and C) was divided into two parts: training data (75 % of all data) and testing data (25 % of all data). Instances for training and testing were selected randomly. The same training and testing subsets were used for all ML classifiers. A summary of the observed subtypes is provided in the Table 4.

In the table, 80 represents the number of features in the datasets, while 10,000 and 100 correspond to the number of inspected motors and the sizes of the respective datasets. The number 1 in the output array indicates a single output variable, i.e., the diagnostic result (GOOD/BAD). Each feature represents a pre-processed value, obtained from raw signals, measured by sensors during EoL testing. Noise and faults present during the manufacturing process are accounted for during signal processing, which includes filtering, down-sampling, normalization and feature extraction procedures. As a result, the datasets reflect meaningful, denoised inputs suitable for robust machine learning classification.

Table 4 Available data of observed motor subtypes.

Subtype	Input matrix	Output array	Production stage
A	80×10000	1×10000	Mass production
B	80×100	1×100	Preproduction
C	80×100	1×100	Preproduction

3.4 TL implementation

Fig. 4 outlines the complete procedure, which unfolds as follows:

1. *Data acquisition for mass-produced motor subtype.* The feature set of mass-produced motor subtype is obtained by data acquisition and signal processing, detailed in [7-9] and [11].
2. *Training classifiers.* The collected data of motor subtype A is used for training the classifiers. During training, best hyperparameters are determined using Halving Random Search, as explained in Subsection 3.2.

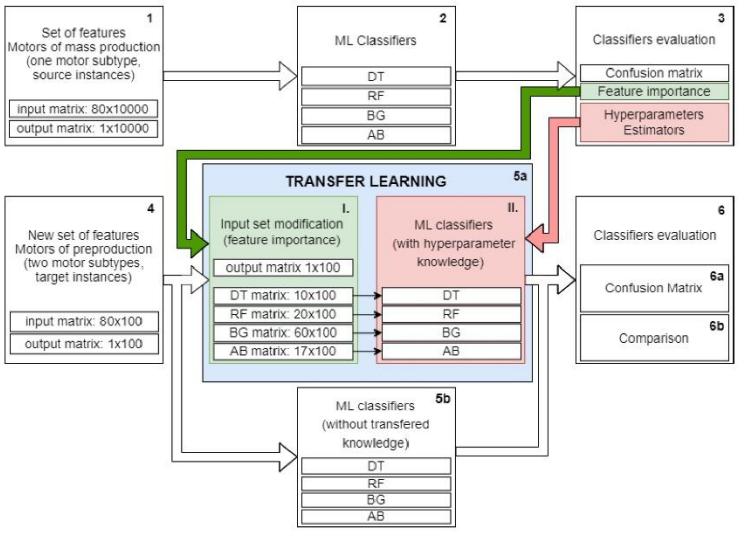


Fig. 4 Flow chart of the procedure

3. *Classifier evaluation*. Trained classifiers are evaluated across three main criteria:
   a) Confusion Matrix (CM) analysis addresses accuracy and performance [7].
   b) Evaluation of the importance of particular features of input data [7, 44]. The knowledge gained from this step is later utilized as feature transfer.
   c) Extraction of hyperparameters and estimators, and evaluation for new classifiers of preproduction subtypes. The knowledge obtained in this step is transferred through parameter transfer.

4. *Data acquisition for preproduction motor subtypes*. Like the procedure in step 1, the data of preproduction motor subtypes are collected and features extracted.

5. *Divergence into two training workflows*. At this point, procedure splits into two ways:
   a) *With transfer learning*. This procedure is executed in two steps:
      I. *Input set reduction (feature transfer)*. The dataset from step 4 is reduced based on feature importance evaluation for each classifier from step 3. This reduced dataset is then used in step 5a II. The size of new reduced input matrix for each classifier is shown in Fig. 4, rectangle 5a I.
      II. *Training with reduced dataset and transferred hyperparameters (parameter transfer)*. The optimal hyperparameters and estimators from step 3 are transferred to the new classifiers, which are then trained using reduced dataset from step 5a I. Each classifier utilized its own reduced dataset and corresponding transferred hyperparameters and estimators.
   b) *Without transfer learning*. Input data from step 4 is directly used for training classifiers, follows step 6. This involves creating classifiers without any transferred knowledge, solely for comparison purposes. Training procedure follows the step 2.

6. *Evaluation and comparison*. This procedure split into two steps:
   a) *Classifier evaluation through CM*. The performance (accuracy and miss-classification cost) of classifiers from step 5a and 5b are evaluated
   b) *Classifier comparison*. Classifiers from step 5a and 5b are evaluated and compared through accuracy and mis-classification cost value.

Note: Steps 4 to 6 must be repeated twice (for motor subtypes B and C). Also, note that classifier performance was evaluated using accuracy and cost value, where higher accuracy (closer to 1 is better) and lower misclassification cost value (closer to 0 is better) indicate a better classifier [7].

However, when dealing with imbalanced data, where typically only 3-10 % of motor instances (depending on the motor subtype) represent BAD motors, accuracy can be misleading. A classifier may achieve high accuracy simply by classifying all instances as GOOD. Therefore, CM and cost-sensitive learning have been employed, and the performance of classifiers is heavily influenced by the misclassification cost value [7].

4. Analysis of the results

4.1 Training the classifiers of mass-produced subtype (motor subtype A, source domain)

The classifier for the mass-produced motor subtype A was developed by steps 1-3 of Fig. 4. Its performance was evaluated based on accuracy and cost value, as shown in Table 5, rows *Accuracy* and *Miss-classification cost value*.

Next, the feature importance was assessed, and the insights were used to modify the input set for a new set of features (Step 5a I, Fig. 4). The number of important features influences the complexity of classifier. Classifier with fewer important features is simpler, but selecting too few features could result in undetected faults. Conversely, a high number of important features can result in an overly complex classifier. The number of important features transferred to the classifiers of preproduced subtypes is listed in Table 5, row *Number of important features.*

In Table 5, rows *Base estimator* to *Splitter* shows the optimal hyperparameter values for each trained classifier for motor subtype A. These values are the results of hyperparameter tuning process since they have been adjusted automatically. These optimized settings were then transferred to the classifiers for motor subtypes B and C (Step 5a II, Fig. 4).

Table 5 Specifications of classifiers for motor subtype A

	DT	RF	BG	AB
Accuracy	0.996	0.9956	0.9956	0.9932
Miss-classification cost value	91	92	101	152
Number of important features	10	20	60	17
Base estimator			Bagging	AdaBoost
Bootstrap		False	False	
Criterion	Gini	Gini		
Learning rate				1,2
Max depth	None	50		
Max features	0.8	0.5	0.8	
Max samples			0.8	
Min samples leaf	1	2		
Min samples split	2	10		
N estimators		200	200	50
Splitter	Best			

4.2 Training the classifiers of preproduced subtypes (B and C)

The classifiers of preproduced subtypes B and C were trained, evaluated, and compared according to 3.4 (steps 4 to 6). The results of the comparison are presented in Table 6.

The data in Table 6 demonstrate that classifiers with transferred knowledge (column "With TL") consistently outperform those without transferred knowledge (column "Without TL"), achieving higher accuracy (with three classifiers reaching 100 % accuracy) and significantly lower miss-classification cost. In contrast, classifiers without TL, due to high miss-classification cost are unsuitable for industrial purposes. The beneficial impact of TL is particularly evident for subtype C, where the DT improved accuracy from 76-96 % and miss-classification cost dropped from 15 to 1.

All evaluated classifiers with TL were found as effective and well-suited for industrial classification tasks. Among them, the DT classifier with the lowest miss-classification cost, stands out as the most appropriate. The BG and RF classifiers also prove as effective, offering slightly higher accuracy but also higher miss-classification cost for subtype C. On the other hand, the AB classifier with the highest miss-classification cost is somewhat less suitable. The performance of each individual classifier for each motor subtype is presented as CM in Figs. 5-20.

Table 6 Performance comparison of the classifiers for preproduction subtypes

Motor Subtype	Classifier method	Without TL		With TL	
		Accuracy	Miss-classification cost	Accuracy	Miss-classification cost
B	DT	0.92	2	0.96	1
	RF	0.92	2	1	0
	BG	0.96	10	1	0
	AB	0.96	10	1	0
C	DT	0.76	15	0.96	1
	RF	0.84	13	0.96	10
	BG	0.8	50	0.96	10
	AB	0.84	40	0.92	20

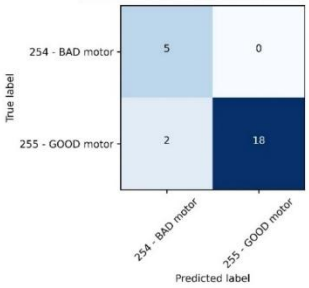


Fig. 5 CM for DT classifier without TL, subtype B

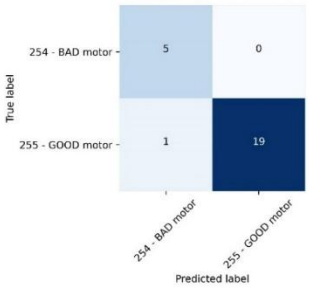


Fig. 6 CM for DT classifier with TL, subtype B

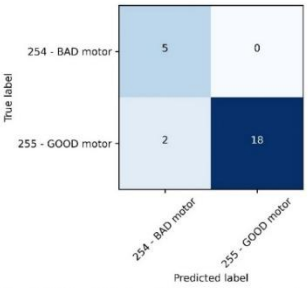


Fig. 7 CM for RF classifier without TL, subtype B

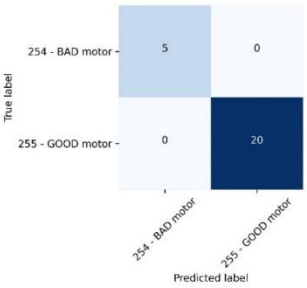


Fig. 8 CM for RF classifier with TL, subtype B

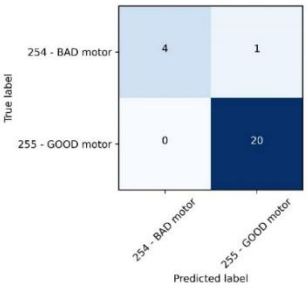


Fig. 9 CM for BG classifier without TL, subtype B

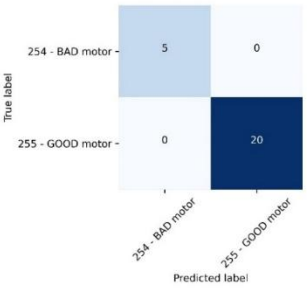


Fig. 10 CM for BG classifier with TL, subtype B

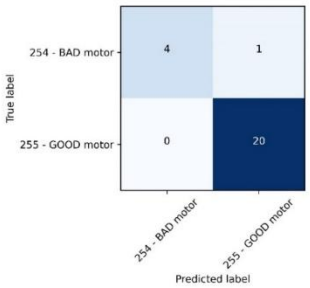


Fig. 11 CM for AB classifier without TL, subtype B

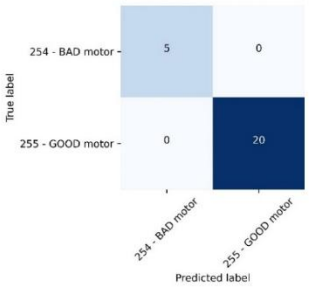


Fig. 12 CM for AB classifier with TL, subtype B

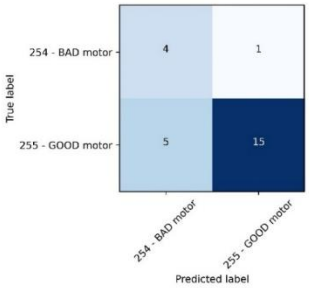


Fig. 13 CM for DT classifier without TL, subtype C

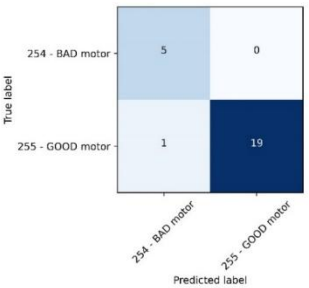


Fig. 14 CM for DT classifier with TL, subtype C

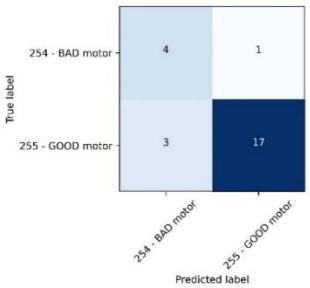


Fig. 15 CM for RF classifier without TL, subtype C

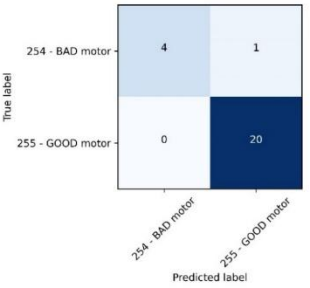


Fig. 16 CM for RF classifier with TL, subtype C

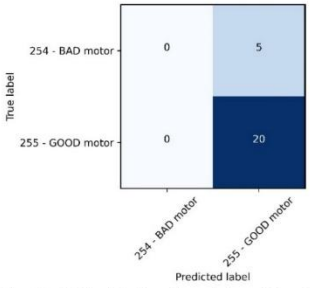


Fig. 17 CM for BG classifier without TL, subtype C

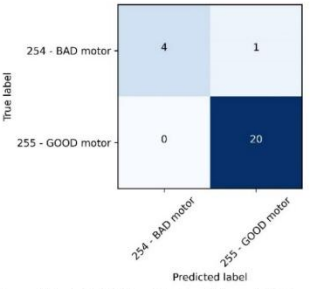


Fig. 18 CM for BG classifier with TL, subtype C

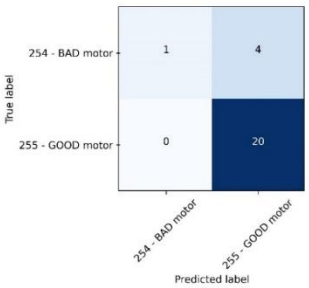


Fig. 19 CM for AB classifier without TL, subtype C

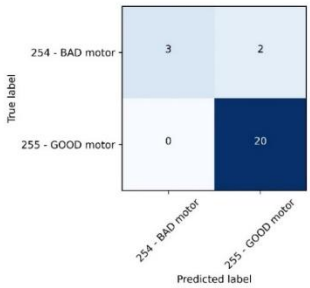


Fig. 20 CM for AB classifier with TL, subtype C

5. Conclusion

In this study, Decision Tree, Random Forest, Bagging, and AdaBoost classifiers were used for EoL quality inspection in the mass production of electric motors. The primary goal is to classify each produced motor as Good or Bad based on acquired electric parameters, vibration and sound during a short test run. The mentioned four classifiers were initially trained on a large dataset of 10,000 instances originating from the motor subtype, which is mass-produced. The knowledge gained during training was then transferred to the new classifiers for the new preproduced motor subtypes, where available training data were limited to only 100 instances per subtype.

The results clearly demonstrate the substantial advantages of employing TL in commissioning automated EoL quality inspection systems for electric motors. By leveraging TL, reliable classifiers for quality inspection systems were developed for new motor subtypes using significantly reduced datasets. This enables the establishment of quality inspection systems earlier in the preproduction phase, prior to the accumulation of extensive data. As additional data for new motor subtypes become available, the EoL inspection system can be continuously refined and improved.

In addition to improving model accuracy and enabling early deployment, the proposed approach has minimal impact on inference time and production latency. Classifiers operate on preprocessed features extracted during existing signal processing routines, and the tree-based models used are computationally lightweight; therefore, classification can be performed within milliseconds. This ensures real-time or near-real-time decision-making without disrupting the production flow.

This study focused on three structurally similar motor subtypes from the same production line. However, the approach is expected to generalize well to other motor types produced within the company. Most production lines at Domel share similar manufacturing processes, diagnostic procedures, and feature structures. Therefore, the TL framework presented here, holds the possibility for broader applicability across different motor types and even other production lines, provided appropriate pre-processing and feature selection are performed.

The TL-based classifiers are integrated into a larger diagnostic pipeline that includes safety measures and fail-safes to reduce the risk of misclassifying critical detects. Generally, motors that are marked as "UNDEFINED" or that are close to decision thresholds are marked for manual examination or further testing. Additionally, redundant sensing channels (such as vibration, sound and electrical signals) are employed in the inspection process to improve the reliability of fault detection. The impact of possible misclassifications is lessened by these built-in safeguards, especially in high-risk fault cases.

Overall, the findings confirm TL as a robust and efficient technique for improving classification performance in industrial applications, particularly in situations involving imbalanced or limited datasets.

Acknowledgments

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Chapter 6

Deep Learning Approach

6.1 Introduction

As explained in Chapters 1–3, conventional EoL quality inspection systems for electric motors primarily rely on manually engineered signal features and expert-defined decision logic. While these approaches are well-established in industrial environments, they have limited adaptability, long commissioning times, and reduced sensitivity to complex or weak fault signals, especially in highly integrated motor assemblies [51], [52], [53]. These limitations become more pronounced as product complexity increases and production environments demand faster and more robust inspection solutions [43], [45].

Recent developments in DL offer a novel solution for industrial EoL inspection systems by enabling models to learn discriminative representations directly from raw or minimally processed signals. Unlike classical feature-based methods, DL approaches reduce dependence on manual feature engineering and expert knowledge while improving the ability to capture nonlinear and time-varying signal characteristics that are typical for electromechanical systems under real operating conditions [37], [54], [55], [56]. Nevertheless, applying DL in industrial EoL inspections remains challenging due to data imbalance, limited fault samples, computational constraints, and the necessity of robust performance in noisy production environments.

This chapter introduces and explains the context of DL–based EoL inspection approach [37]. This approach uses Mel-frequency spectrograms (MFSs) and a hybrid convolutional–recurrent neural network architecture to address the challenges of EoL inspections. The proposed method operates directly on vibration and acoustic signals acquired during standard EoL test cycles. It transforms these signals into time–frequency representations that preserve diagnostically relevant information while reducing data dimensionality and sensitivity to noise.

The idea originates from the fact that Mel-frequency spectrograms provide visual appearance of sound spectra and its dynamics (changes by the time) in terms of images. Humans can then actually see the difference in sound from the image. To automatize the procedure, image recognition algorithms can be used.

Unlike the feature-based ML [35] and the TL strategy [36], the DL approach [37] focuses on End-to-End learning (E2E), where feature extraction and classification are performed together within a single neural network model. By combining CNNs for spatial feature extraction with BiGRUs for temporal modeling, the method is specifically designed to capture both spectral patterns and their temporal evolution during the EoL test cycle.

Special attention is given to industrial constraints that are often overlooked in academic DL studies. These constrains include severe class imbalance, limited fault data, and the requirement for high classification reliability under production variability. The approach

addresses these issues by using data reduction techniques, reference spectrograms derived from healthy motors, and statistically robust evaluation strategies. This ensures that the reported performance is representative of real manufacturing conditions [37]. Similar trends toward data-efficient and robust DL-based inspection have been reported in recent industrial studies published within the last five years, confirming the relevance of this research direction [53], [59], [60].

In this dissertation, this chapter focuses on the DL aspect of the proposed intelligent EoL quality inspection framework. Along with the feature-based ML methods [35] and the TL strategy [36], it contributes to a comprehensive investigation of how different AI approaches can address different challenges in industrial quality inspection.

6.2 End-of-Line Quality Control Based on Mel-Frequency Spectrogram Analysis and Deep Learning

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End-of-Line Quality Control Based on Mel-Frequency Spectrogram Analysis and Deep Learning

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Abstract

This study presents a novel approach to the end-of-line (EoL) quality inspection of brushless DC (BLDC) motors by implementing a deep learning model that combines MEL diagrams, convolutional neural networks (CNNs) and bidirectional gated recurrent units (BiGRUs). The suggested system utilizes raw vibration and sound signals, recorded during the EoL quality inspection process at the end of an industrial manufacturing line. Recorded signals are transformed directly into Mel-frequency spectrograms (MFS) without pre-processing. To remove non-informative frequency bands and increase data relevance, a six-step data reduction procedure was implemented. Furthermore, to improve fault characterization, a reference spectrogram was generated from healthy motors. The neural network was trained on a highly imbalanced dataset, using oversampling and Bayesian hyperparameter optimization. The final classification algorithm achieved classification metrics with high accuracy (99%). Traditional EoL inspection methods often rely on threshold-based criteria and expert analysis, which can be inconsistent, time-consuming, and poorly scalable. These methods struggle to detect complex or subtle patterns associated with early-stage faults. The proposed approach addresses these issues by learning discriminative patterns directly from raw sensor data and automating the classification process. The results confirm that this approach can reduce the need for human expert engagement during commissioning, eliminate redundant inspection steps, and improve fault detection consistency, offering significant production efficiency gains.

Keywords: end-of-line quality inspection; fault detection; vibration control; condition monitoring; deep learning; convolutional neural networks; bidirectional gated recurrent units; Mel-frequency spectrograms

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1. Introduction

Electric motors are among the most widely produced devices worldwide. To reduce their production costs, they are typically produced on highly automated manufacturing lines. These lines are equipped with 100% end-of-line (EoL) quality inspection systems to check each produced motor for several possible faults and to prevent faulty motors from reaching the market or end-users [1,2].

The presented study is associated with the Slovenian company Domel d.o.o., one of the largest mass-producers of electric motors for vacuum cleaners and other applications [3]. Their motors are integrated into numerous high-end products, thanks to their comprehensive EoL inspection systems. Every manufacturing line at the company has to

be equipped with a 100% EoL quality inspection process [1,4–6]. Each produced motor undergoes a quality inspection process to verify the quality, absence of faults, and compliance with costumer requirements. The diagnostic process involves a series of tests assessing electrical, vacuum, vibrational, and acoustic characteristics from which a diagnostic report is generated for each motor [2,5].

Motors are becoming more and more complex and they demand specialized diagnosis approaches. Additionally, motor types produced at the same manufacturing line may differ substantially and require unique diagnostic procedures. Therefore, the current solution relies on a variety of sensors and the expertise of skilled experts in order to establish proper diagnosis procedures for each motor type [2,5].

In this study, we propose a diagnostic approach that relies on vibrational and acoustic signals. The selected manufacturing line captures vibration signals (V1, V2, and V3) at three points of the motor (P1, P2, and P3) using a laser vibrometer and acoustic signal (S) using the microphone. Signals are captured during short test runs at nominal (full) rotational speed. This manufacturing line is one of the newest at the company. However, the core principles of the manufacturing processes and diagnostic procedures remain very similar to those in older systems. Notably, when this line was developed, several technical upgrades were implemented to support future improvements, including the integration of machine learning and artificial intelligence in diagnostic workflows.

In the current automatic diagnostic system, these signals undergo traditional signal processing and feature-generating steps. During commissioning, relevant features are selected and their thresholds defined by skilled experts [5]. Despite the robustness of this approach, there are limitations in scalability and adaptability. Feature engineering and threshold setting require domain expertise and are highly specific to motor types and fault conditions. These limitations restrict the ability of traditional systems to generalize across varied conditions or detect emerging failure patterns [4,5,7,8].

This study explores a time–frequency analysis combined with artificial intelligence for fault detection and recognition. Specifically, we propose the use of Mel-frequency spectrograms (MFSs) as input features and neural networks as the classification model, to simplify data processing and improve fault classification performance.

Recently, data-driven methods and machine learning techniques have made progress on industrial quality inspection tasks. Many of the mechanical and assembly-related faults in electric motors can be detected using vibration and acoustic signals. Traditionally, diagnostic systems rely on signal pre-processing steps: filtering, resampling, scaling, Fourier transform, wavelet transforms, etc., followed by classical classification methods using decision trees, support vector machines (SVM), k-nearest neighbours, etc. [4,5,7,8]. These approaches demonstrate solid accuracy and cost-efficiency, but they are typically optimized for specific fault types and depend heavily on specific expertise for feature extraction and threshold settings.

To overcome these limitations, the presented research investigates the use of a combination of convolutional neural networks (CNNs) and bidirectional gated recurrent units (BiGRUs), applied to a time–frequency representation of signals (MFSs). MFSs, originally developed for speech and audio analysis, have become popular in fault detection systems because of their ability to compactly represent relevant frequency content while preserving temporal resolution. CNNs, trained on MFSs, have achieved notable results in fault detection and often outperform classical methods [9–11].

However, the integration of such systems in industrial applications also faces several challenges. These include the limited availability of labelled data, interpretability of model decisions, and integration with existing inspection workflows. In recent years, self-supervised and semi-supervised learning methods have emerged as powerful tools

to address some of these issues. For example, catenary support rod area masked image modelling (CSRM-MIM) [12] has demonstrated effective self-supervised pretraining for detecting structural faults in railway systems, and multi-modal imitation learning has been successfully applied to arc detection in complex industrial environments [13]. In parallel, focusing enhanced networks (FENets) and physics-informed neural networks (PINNs) are gaining attention for their ability to incorporate domain knowledge, which enhances interpretability and performance in safety-critical monitoring systems [14]. These developments highlight a growing trend toward more adaptable, interpretable, and data-efficient AI models.

The main contributions of this work are summarized as follows:

- A deep learning-based classification model using a CNN–BiGRU architecture trained on MFSs generated from acoustic and vibration signals of BLDC motors.
- An evaluation strategy that includes bootstrap resampling to estimate 95% confidence intervals, providing a more robust estimate of model reliability.
- The use of t-SNE visualization to analyse feature resolution and improve the interpretability of the learned representations in the output space.

The remainder of the paper is organized as follows:

- Section 2 describes the problem and outlines key challenges.
- Section 3 presents the proposed fault detection approach.
- Section 4 explains the data preparation and feature reduction process.
- Section 5 describes the neural network architecture and training procedure.
- Section 6 presents classification results and performance evaluation.
- Section 7 concludes the paper and discusses future directions.

2. Problem Description

2.1. Motor Description

The focus of this study is on brushless DC (BLDC) motors. These motors are produced in many variants. However, we focus on the particular variant with 18 V DC supply voltage, 600 W electric power, and a nominal speed of 38,500 RPM. The motor is shown on the Figure 1. This motor type was selected because the study targets the manufacturing line at its early stage of operation, for which sufficient and relevant data for only this motor type were available. Moreover, this was the first motor type to be mass-produced on the line, making it the most suitable candidate for initial analysis.



Figure 1. BLDC motor class 759 [15].

2.2. Existing EoL Quality Algorithm and Inspection System

A modular EoL quality inspection system (Figure 2) is installed at the end of the manufacturing line for the inspection of each produced motor. The EoL system consists of three test cells: TC 1, TC 2, and TC 3. Each cell is responsible for evaluating specific aspects of motor performance. During the inspection, each motor undergoes a series of short test runs. In TC 1, electrical characteristics and rotational speed are measured. In TC 2, vibration and acoustic emissions at nominal speed are checked, while TC 3 focuses on detecting bearing and friction faults during a low-speed run. At the time when data for the purposes of this study were collected, only TC 2 had the capability to record and save raw data into files suitable for further analysis. TC 2 was also the most stable and reliable test cell in terms of operation and data handling, which made the recorded data more consistent and trustworthy for subsequent processing.



Figure 2. Modular EoL quality inspection system.

The measurements result in high-resolution time series data, referred to as raw signals, sampled at rates between 10 and 60 kHz over time spans ranging from 0.1 to 1 s and containing between 1000 and 30,000 samples.

In the current diagnostic procedure, vibration and sound signals undergo a series of signal processing steps (digital filtering, down-sampling, and frequency–domain analysis) to extract meaningful information. As result, a fixed set of features is created, where each feature represents signal (vibration or sound) power at a specific frequency. For the observed motor subtype, a set of 82 features is created. According to the feature values, motors are then classified into one of three quality categories—good, bad, or undefined. In addition to overall classification, the feature values can find the root cause of faults. Details of diagnostic result generation are described in [5] and summarized in Table 1.

Table 1. Diagnostic result generation [5].

Measurement Status	Features	Diagnostic Result
Completed	All features are within specified ranges.	Good
	One or more features are outside specified range.	Bad
Not completed	Missing features.	Undefined

The development of such an inspection system is both complex and resource-intensive. Among other requirements, it requires a specific expertise to select relevant features and

determine their acceptable ranges. To reduce this dependency on expert knowledge, our recent work [5] introduced machine learning approaches for automated feature selection and threshold tuning.

Unlike previous approaches, this study considers raw, rather than processed, vibration and acoustic signals that were captured during EoL testing. By using time–frequency representations (MFSs) of raw signals, the proposed method enables a neural network to directly learn discriminative patterns from the data. This approach aims to simplify the development process, reduce expert reliance, and improve adaptability to variations in motor subtypes.

Figure 3 illustrates a comparison between existing and proposed EoL quality inspection systems. Both systems begin with measurement and data acquisition. However, existing system proceeds with manual feature extraction and diagnostic result generation, both of which depend heavily on expert experience and domain knowledge.

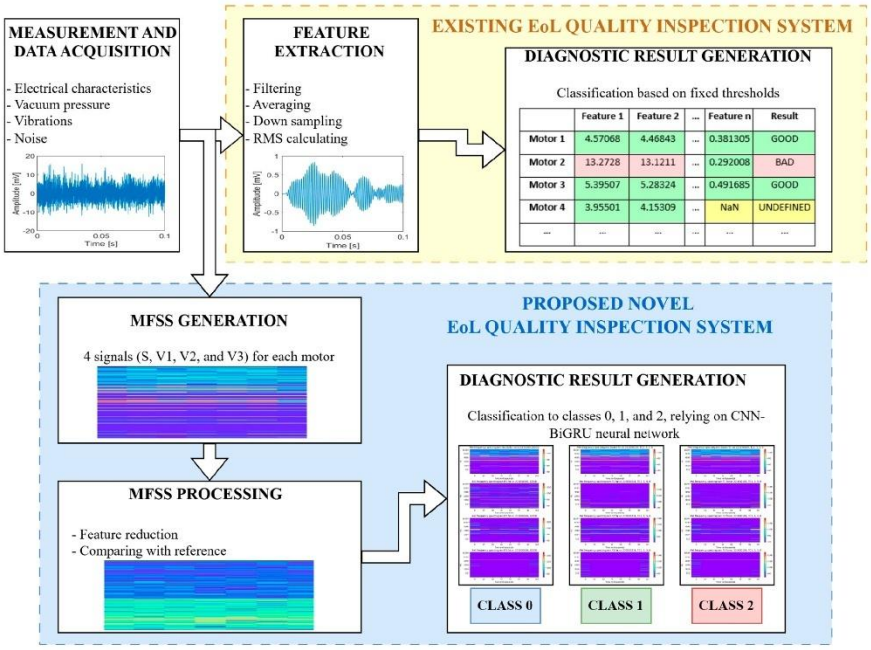


Figure 3. Comparison of existing and proposed novel EoL quality inspection system.

In contrast, the proposed system replaces manual feature extraction with automatic MFSs generation, followed by the statistical processing of the MFSs, and ends with diagnostic classification using a CNN-BiGRU neural network. This architecture facilitates a more automated and scalable diagnostic pipeline.

3. Proposed Novel EoL Quality Inspection Algorithm

3.1. Overview

This method is based on raw vibration and acoustic signals, captured at TC 2, and it is composed of two primary parts:

- MFSs are used to transform raw time-series signals into 3D time–frequency representations that can be presented as a colour image;
- A hybrid deep learning architecture that combines a CNN and a BiGRU network.

3.2. MFSs

An MFS is a time-frequency representation of an acoustic or vibrational signal, mapped to the Mel scale. The Mel scale transforms linear frequencies into a scale that approximates the sensitivity of human hearing. MFSs are usually used for purposes of speech recognition and music information retrieval [16,17]. In general, an MFS represents signal power as a function of frequency and time. The diagram shows the power spectrum as a function of time and it is useful for the observation of the dynamic changes within the signal. The x-axis represents the time within the data series and the y-axis represents the frequency. The signal power scalar (the subject of z-axis) is represented by the colour scale (RGB), giving the diagram the appearance of a colour image. An example is shown in Figure 4. Image recognition algorithms can, in principle, be used for the analysis of MFSs [18]. For the analysis, signal power (scalar) can be used, rather than its 3-component RGB representation, which is only used for visual interpretation.

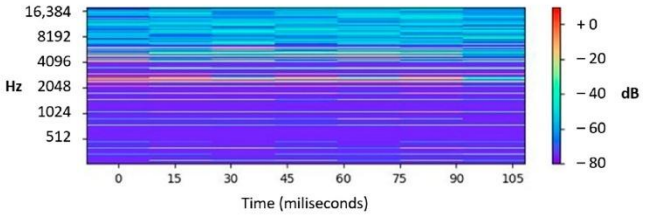


Figure 4. An example of a Mel frequency spectrogram used in this study.

Lately, MFSs were proven to be highly effective in the fault diagnosis of rotating machinery [9,19,20]. In motor diagnostics, MFSs enable the extraction of spectral and temporal features from the raw signal. Compared to traditional feature engineering (which usually relies on the extraction of power bands or harmonics), they provide an information format suitable as input into neural networks.

Compared to linear spectrograms or wavelet transforms, they provide several advantages for fault diagnosis in rotary machines [21]:

- Efficient dimensionality reduction while preserving perceptually and diagnostically relevant features;
- Enhanced sensitivity in the low- and mid-frequency ranges (up to 5 kHz), where mechanical issues such as imbalance, misalignment, and bearing defects usually occur;
- Increased robustness to noise and minor variations in signal phase or speed.

According to recent research, MFSs, combined with CNNs, outperform traditional hand-engineered features in diagnosing faults in electric motors, gearboxes, and rotating machinery [21,22]. Their adaptability for mechanical fault detection tasks is demonstrated by their successful application in vibration and acoustic analysis [23].

3.3. Neural Network Architecture: CNN–BiGRU

In order to classify motor conditions based on MFSs, this study proposes a hybrid neural network architecture, combining CNNs with BiGRUs.

CNNs are typically used to extract hierarchical features and local patterns from image-like inputs such as spectrograms. The convolutional layers use multiple filters that detect

frequency components and local spectro-temporal features, such as localized bursts of frequency activity or persistent harmonics, associated with specific fault types. These are critical for identifying motor faults [20,24,25]. CNNs reduce the dimensionality of inputs and preserve crucial spatial structures. That is why they are suitable for analysing the complex patterns in vibration and acoustic data.

However, signals generated by faulty motors often contain evolving patterns over time. To address this issue, a BiGRU layer is proposed. BiGRUs are a type of recurrent neural network, which is capable of learning long-range dependencies in sequential data by bidirectionally processing input sequences [26]. This allows the model to consider both past and future contexts in the time domain, improving sensitivity to dynamic signal changes and the ability to detect fault patterns [23,27]. This eliminates the need for a feature extraction process or manual threshold tuning and allows classification to be established directly from raw signal data.

The combination of CNN-BiGRU allows powerful spatial feature extraction with effective temporal modelling. This enables the learning of discriminative features for fault detection directly from the Mel spectrograms, without relying on extensive pre-processing designed by human experts. Several recent studies have demonstrated that CNN-BiGRU models outperform standalone CNN or recurrent architectures in rotating machinery diagnostics, bearing fault detection, and acoustic signal classification tasks [28–31]. The effectiveness of this combination has already been demonstrated in various studies that involve audio classification, anomaly detection, and fault diagnosis [32,33].

4. Data Preparation

4.1. Data Structure

The dataset used in this study was collected during the production of 1505 pieces of BLDC motors at the manufacturing line. For the purpose of this study, only data acquired at TC 2 was used: vibrations (V1, V2, and V3), and sound (S). Signals were sampled at the nominal motor speed (38,500 RPM) with a sampling frequency of 60 kHz over 100 ms windows, resulting in 6000 samples per signal. No pre-processing (filtering, resampling, scaling, etc.) was used. Figure 5 illustrates examples of raw signals, which served as the direct input to the proposed diagnostic system.

Each motor had already undergone standard diagnostic procedures at the end of the manufacturing line and was classified based on fault detection outcomes. The final classification used in this study is derived from fault localization across the test cells, as follows:

- Class 0: motors with no detected faults (good);
- Class 1: motors with faults detected in TC 2;
- Class 2: motors with faults detected in TC 3.

It is important to note that no faults were detected in TC 1 for this dataset, therefore it was excluded from class definition. Additionally, an extreme class-imbalance was observed. As expected, the majority of produced motors belonged to class 0 (approximately 95%), while only a few were classified as faulty (around 5%). The class distribution is presented in Table 2.

Table 2. Class distribution.

Class	Number of Motors	Part [%]
0	1422	94.49
1	16	1.06
2	67	4.45

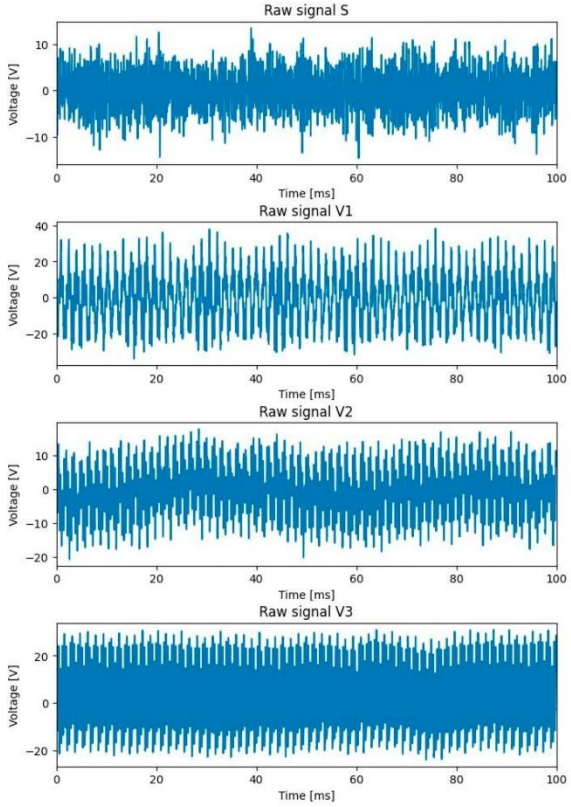


Figure 5. Raw signals for S, V1, V2, and V3, used as input.

4.2. MFS Generation

In this study, MFSs were generated directly from the raw time–domain signals (Figure 5) without any pre-processing. This approach provides the full frequency content preservation of the signals. For each of the signals (V1, V2, V3, and S), an MFS was created using a standard short-time Fourier transform (STFT)-based method followed by Mel-scale conversion. The spectrogram generation process was configured to retain sufficient resolution for identifying subtle variations in frequency patterns, associated with mechanical faults.

The parameters for MFS computation were chosen carefully to balance time and frequency resolution and to satisfy computational limitations. Those parameters are shown in Table 3. MFSs were created in the Python 3.13 programming language, using the librosa library. For improved visualisation and interpretability, the power spectrum magnitude of all MFSs in this study were converted to a logarithmic scale using decibel (dB) scaling. This transformation enhances the contrast of spectral features by compressing the dynamic range of signal power, making low- and high-energy components more visually recognizable.

Table 3. MFS parameters.

Name of Parameter	Brief Explanation	Value
sampling rate	The sampling frequency of raw input data [Hz], determined by hardware.	60,000
nfft	The length of the FFT window; defines frequency resolution. Set empirically.	2000
win_length	The length of the window for FFT analysis (same or smaller than nfft). Set equal to nfft for maximum frequency detail without truncation.	2000
hop_length	The number of samples between windows (hop); controls the time resolution of the MFS. Tuned empirically to balance the resolution and training stability.	1000
centre	The positioning of the window (symmetric analysis).	True
pad_mode	How the signal at the edge is completed. "Reflect" mirrors the signal at the edges, minimizing boundary artefacts and preserving continuity [34].	Reflect
power	The exponent magnitude of the Mel-frequency spectrogram (1—energy and 2—power).	2
n_mels	The number of Mel-frequency bands. Chosen empirically	2048
fmin	Low frequency limit; set by experts from the industrial partner.	20
fmax	High frequency limit; set by experts from the industrial partner.	18,000

4.3. MFS Processing and Dimensionality Reduction

MFSs preserve the majority of spectral–temporal information. However, not all frequency bands are informative and necessary for classification. Furthermore, their high dimensionality can lead to redundancy, noise, and unnecessary computational complexity and slow down the machine learning process. To address this, a 6-step procedure was created for data reduction where non-informative frequency bands were detected and removed from the dataset:

1. Step 1: MFS creation. In this step, raw time–domain signals of each motor (V1, V2, V3, and S, explained in Section 4.1) are converted into 4 MFSs, according to parameter settings from 0. The results of this step are 4 MFSs of size 2048 (frequency bands) × 7 (time frames) for each motor. The measured latency for generating all 4 MFSs for one motor is approximately 0.1231 s, which is acceptable and suitable for the requirements of the studied industrial application. Together, 1505 × 4 MFSs were created as shown in Figure 6.

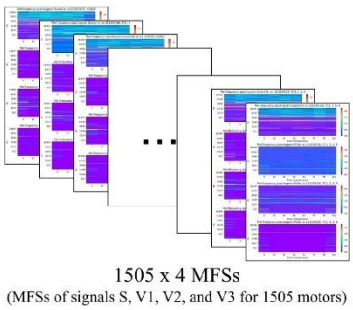


Figure 6. Step 1: MFS creation.

2. Step 2: Merging MFSs of the same type. In this step, all MFSs of the same type but from all motors (for example, all MFSs of sound) were merged into 4 MFSs. These MFSs were

a size of 2048 × 10,535, meaning 2048 frequency bands and 10,535 timeframes, calculated as a sum of all timeframes of all 1505 motors. Figure 7 shows the merged MFSs.

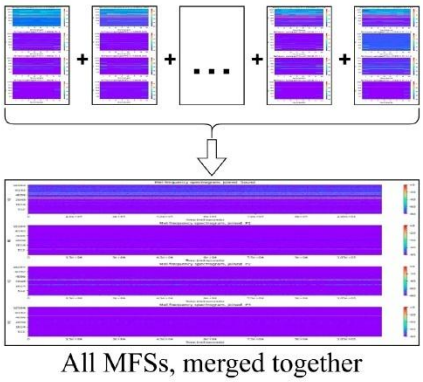


Figure 7. Step 2: Merging MFSs of the same type.

3. Step 3: Feature reduction. In this step, a feature reduction process was applied to identify and remove non-informative frequency bands from the merged MFSs. Several statistical methods were used to evaluate the distribution and variability of values across each frequency band, including histogram analysis, standard deviation, peak analysis, and kurtosis assessment. Frequency bands were classified as non-informative and excluded from further analysis based on the following criteria:
    - Low variance: Bands with values confined to a narrow range (e.g., all values falling within a single histogram bin) and exhibiting very low standard deviation were considered uninformative. Such low variability is typically associated with background noise or redundant data that contribute minimally to classification accuracy. This principle is widely supported in the feature selection literature, where low-variance features are routinely filtered out to improve learning performance and generalization ability [35,36].
    - Lack of multimodality: Bands with distributions showing only one prominent peak or no significant peaks were assumed to lack distinctive features. Informative spectral regions, especially in fault diagnosis tasks, often exhibit multimodal behaviour due to the presence of multiple signal patterns or transient components. This behaviour has been observed in fault analysis using wavelet transforms and is emphasized in machine health monitoring literature [37,38].
    - Low kurtosis (<3): Bands with a kurtosis value below 3 were identified as statistically flat (platykurtic), indicating the absence of outliers or sharp peaks. Such distributions generally lack impulsive components, which are important indicators of mechanical faults in vibration and acoustic signals. The threshold of kurtosis <3 was chosen based on standard statistical definitions [39,40] and reinforced by prior studies in predictive maintenance and condition monitoring [41,42]. Although not universally prescriptive, this threshold was also verified empirically in our study bands, as kurtosis values above 3 were more frequently observed to contain features contributing to successful fault classification, while those below this threshold consistently lacked discriminative power.

These combined statistical criteria enabled the effective detection of irrelevant or redundant frequency bands. Using this approach, nearly 70% of the total bands were elimi-

nated, significantly reducing input dimensionality while preserving informative content (Figure 8). The results of feature reduction are presented in Table 4.

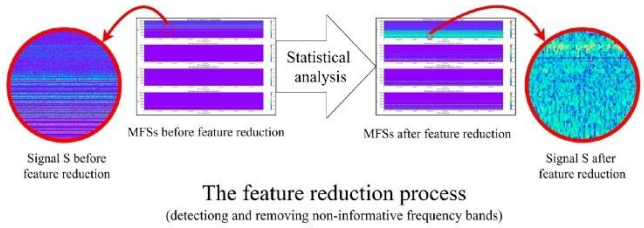


Figure 8. Step 3: Feature reduction process.

Table 4. Number of frequency bands before and after feature reduction.

Signal	Number of Frequency Bands Before Reduction	Number of Frequency Bands After Reduction	Part of Informative Frequency Bands
S	2048	678	0.33
V1	2048	381	0.19
V2	2048	701	0.34
V3	2048	709	0.35
Together	8192	2469	0.30

4. Step 4: Creating new MFSs with only informative frequency bands. From the MFSs from step 1 we eliminated non-informative frequency bands, which were detected as non-informative after step 3. For each signal, we obtained a new dataset of reduced features for each motor, as shown in Table 5. These MFSs with reduced datasets (Figure 9) were used in continuing work.

Table 5. Size of reduced MFSs for each signal.

Signal	Size of Dataset [Features × Time Frames]
S	678 × 7
V1	381 × 7
V2	701 × 7
V3	709 × 7

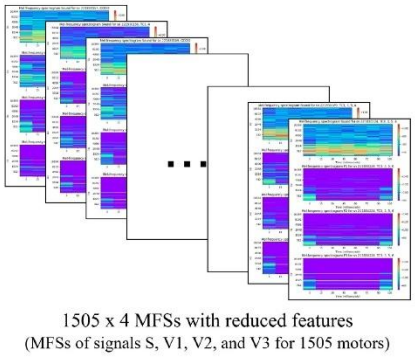


Figure 9. Reduced MFSs.

5. Step 5: Creating the reference MFSs. Next, we selected all MFSs of good motors (class 0). From this group, we calculated an average MFS for each signal. These MFSs represent the typical time–frequency characteristics of non-faulty motors and serve as a baseline profile of a healthy motor. These average MFSs, illustrated in Figure 10, are also referred to as reference MFSs. This step was critical for step 6 where a direct comparison of the MFSs of each individual motor to the reference good motor was performed.

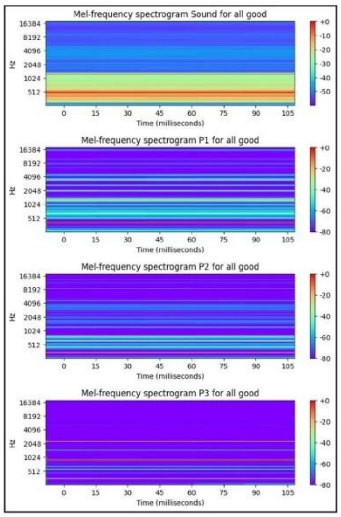


Figure 10. Reference MFSs.

6. Step 6: Comparing MFSs of an individual motor to reference MFSs. The MFSs of each individual motor from step 4 were compared to the reference MFSs, as shown in Figure 11, and explained with (1). The comparison results reveal the difference between the individual motor and the normal state. This approach allowed for an easy identification of the time–frequency regions that differ from normal behaviour. This difference was used in further machine learning processes. This method is quite common in anomaly detection when fault data are sparse or highly imbalanced. Usually, it simplifies the interpretability of the model and increases the robustness of the classification. This approach also enabled more sensitive and targeted fault detection [43,44].

$$\mathrm{MEL_D(i)} = \mathrm{MEL(i)} - \mathrm{MEL_R}\ (\mathrm{i} = 1 \ldots 1505) \quad (1)$$

At the end of the process, MFSs of the reduced datasets were generated. These MFSs served as inputs for the subsequent machine learning processes. Figure 12 shows the MFSs before dimensionality reduction of motors of class 0. Figure 13 shows its corresponding MFSs after feature reduction. Similar, Figure 14 illustrates the MFSs before dimensionality reduction of class 1 and Figure 15 illustrates its corresponding MFSs after feature reduction. Finally, Figure 16 represents the MFSs before feature reduction of class 2 and Figure 17 its corresponding MFSs after feature reduction.

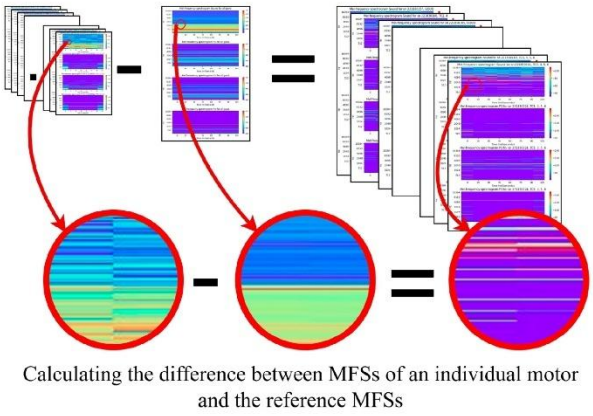


Figure 11. Comparing MFSs of an individual motor to the reference MFSs.

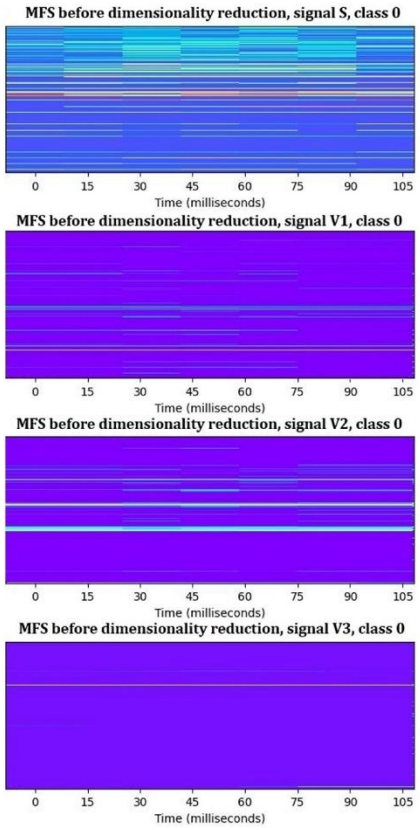


Figure 12. MFSs before dimensionality reduction of motors of class 0.

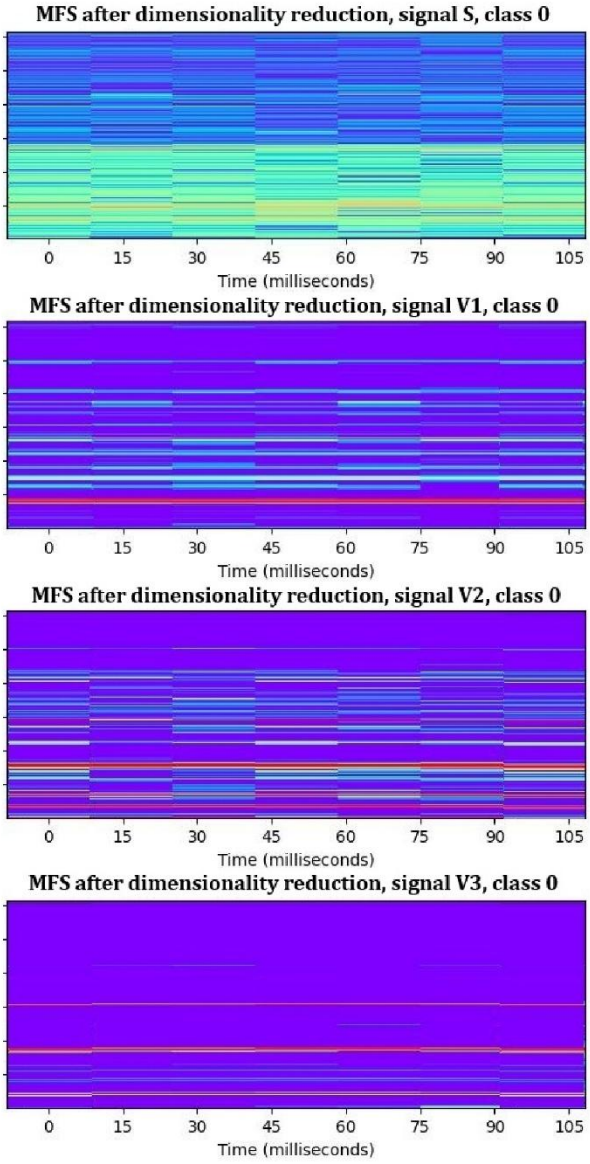


Figure 13. MFSs after dimensionality reduction of motors of class 0.

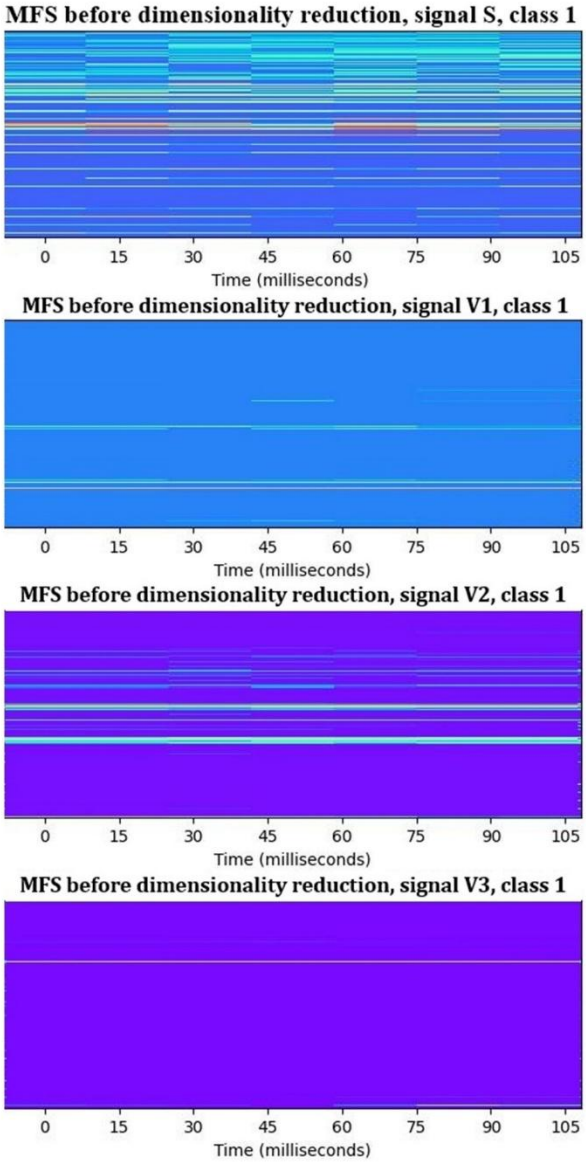


Figure 14. MFSs before dimensionality reduction of motors of class 1.

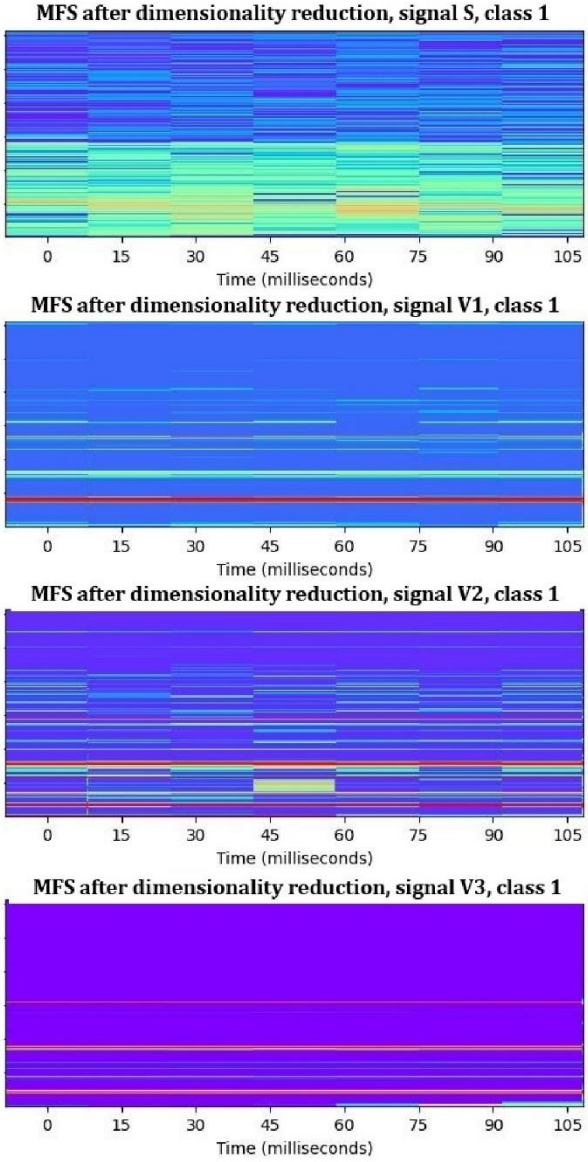


Figure 15. MFSs after dimensionality reduction of motors of class 1.

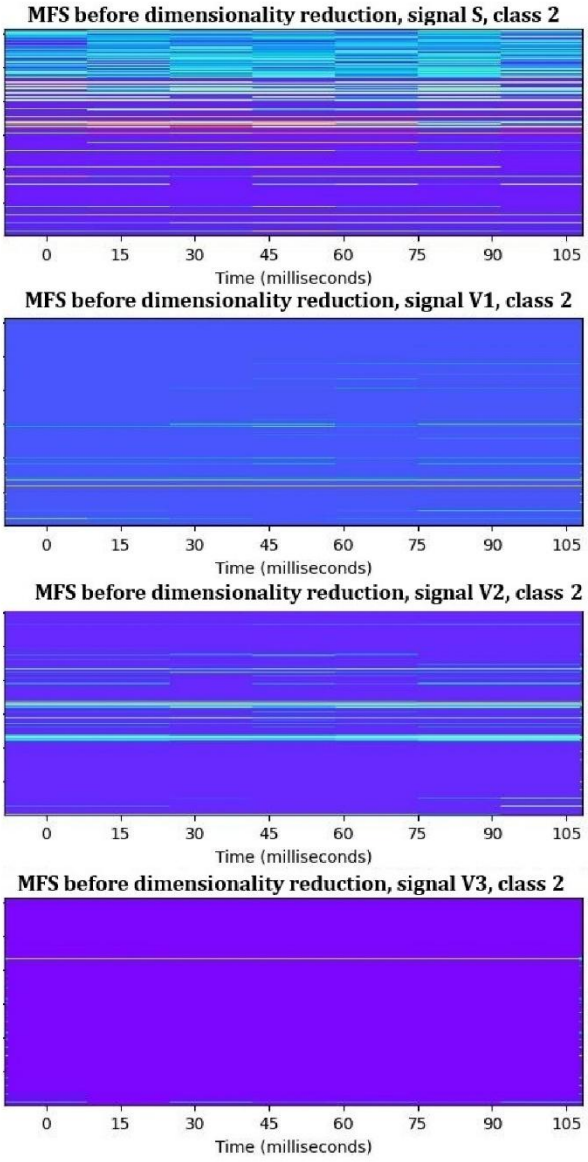


Figure 16. MFSs before dimensionality reduction of motors of class 2.

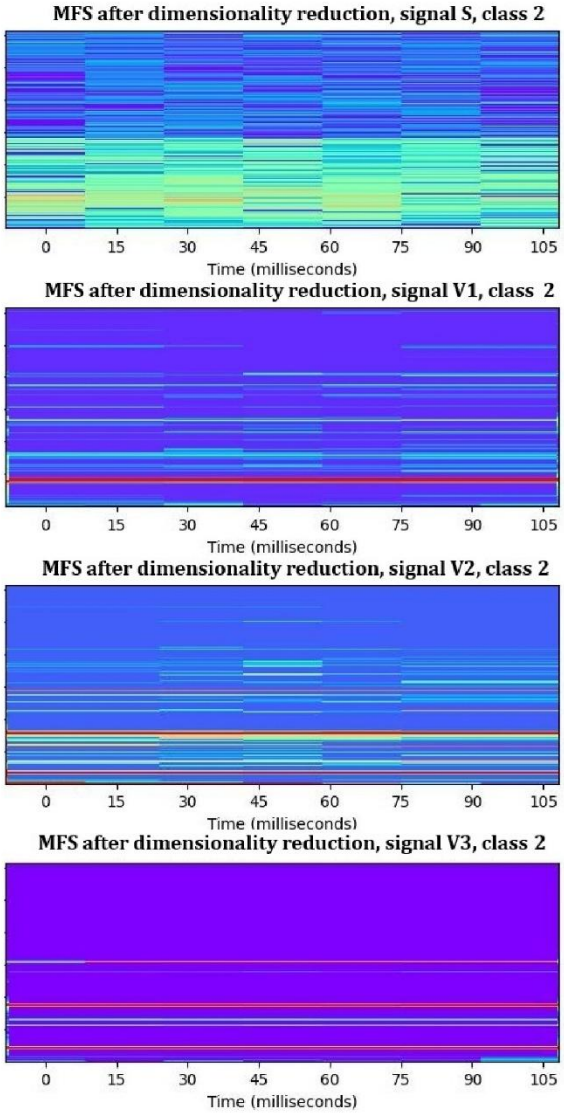


Figure 17. MFSs after dimensionality reduction of motors of class 2.

Importantly, the feature reduction process successfully preserved the essential structure within each class, maintaining critical visual information despite dimensionality simplification. Although non-informative features were eliminated and visual separation between classes was enhanced, the distinction between motor classes based on the visual inspection of MFSs alone remained challenging, even for experienced human experts.

5. Neural Network Architecture and Training

For the purposes of the classification, a hybrid neural network architecture combining CNNs and BiGRUs was employed. The combination of CNNs and BiGRUs has already been explained in Section 3.3 (CNNs are well-suited for extracting local patterns and hierarchical features from image-like inputs, while BiGRUs are suitable for capturing temporal dependencies and sequence dynamics). Based on previous research and empirical testing, the designed architecture includes two CNN and two BiGRU layers.

As explained in Section 4.1, the dataset consisted of 1505 motors, each labelled as one of three classes (class 0—good, class 1—fault in TC2, and class 2—fault in TC3). Figure 18 explains the data manipulation. At the start, the source dataset was split into a test set (ca. 33% of motor instances) and a training set (ca. 67% of motor instances).

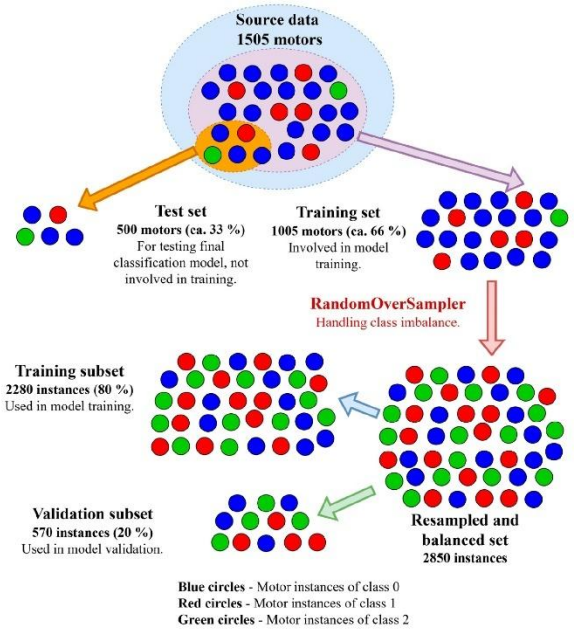


Figure 18. Dataset explanation.

The test set remained untouched and was exclusively used for final model evaluation. In the training set, the imbalance was fixed and the set was then used for training the neural network and hyperparameter tuning. Because of the high class imbalance (the low presence of class 1 and 2), we implemented balanced training using the RandomOverSampler method. This oversampling method duplicates minority class samples to balance the class distribution. Among the tested techniques, the RandomOverSampler yielded the most consistent and reliable results for our task. The test set remained imbalanced, presenting real-world distribution.

To optimize the network (the number of neurons in each layer, kernel sizes in CNN, dropout rates, etc.), we employed Bayesian optimization via a Tuner search. This method builds a probabilistic model of the objective function and selects hyperparameters that are most likely to improve model performance based on prior evaluations. Compared to

other methods, Bayesian optimization is more efficient and converges faster to optimal parameters [45].

6. Results

A neural network that could successfully classify motors into three classes (0, 1, and 2) was created after the training process was finished. Larger convolutional kernels and layers with relatively few neurons were combined to create the final architecture that performed the best. This suggests that a seemingly simpler network architecture, capable of analysing broader signal patterns, was more effective for this task. Dropout layers were added to prevent overfitting, and batch normalization was used to accelerate and stabilize training. This architecture reflects a well-balanced approach between model complexity and generalization ability. The details of the model are presented in Table 6.

Table 6. Neural network architecture and hyperparameter configuration used for classification.

Layer (Type)	Output Shape	Details
Input	(None, 7, 2469, 1)	Size of MFS
First Conv2D	(None, 7, 2469, 32)	First 2D convolutional layer with 32 filters, ReLU activation, and kernel size (7×7)
First Batch Normalization	(None, 7, 2469, 32)	Normalizes activations, improves training stability
First Max Pooling 2D	(None, 3, 1234, 32)	Down samples feature maps by 2×2
First Dropout	(None, 3, 1234, 32)	Prevents overfitting, dropout value 0.5
Second Conv2D	(None, 3, 1234, 64)	Second 2D convolutional layer with 64 filters, ReLU activation, and kernel size (7×7)
Second Batch Normalization	(None, 3, 1234, 64)	Further normalization post-convolution
Second Max Pooling 2D	(None, 1, 617, 64)	Further spatial reduction
Second Dropout	(None, 1, 617, 64)	Additional dropout, dropout value 0.5
Reshape	(None, 1, 39,488)	Flattening spatial data into time sequence
First Bidirectional BiGRU	(None, 1, 128)	First BiGRU layer (2×64 units) capturing bidirectional context
Second Bidirectional BiGRU	(None, 128)	Second BiGRU layer (2×64 units), flattening to vector
First Dense	(None, 64)	Fully connected layer
Third Dropout	(None, 64)	Final dropout before output, dropout value 0.4
Second Dense	(None, 3)	Final layer for 3-class classification (Softmax)

To evaluate the accuracy and robustness of the trained neural network, we performed a classification on the test set (explained in 0). The classification performance is shown using a confusion matrix (Figure 19). High values along the diagonal indicate correct classifications and off-diagonal values represent misclassifications. The matrix highlights the model's strong performance on the majority class (class 0) and its ability to correctly identify minority classes (classes 1 and 2), despite class imbalance. This indicates that the model handles class imbalance effectively, particularly demonstrating a reliable recognition of minority classes (classes 1 and 2), despite their low support.

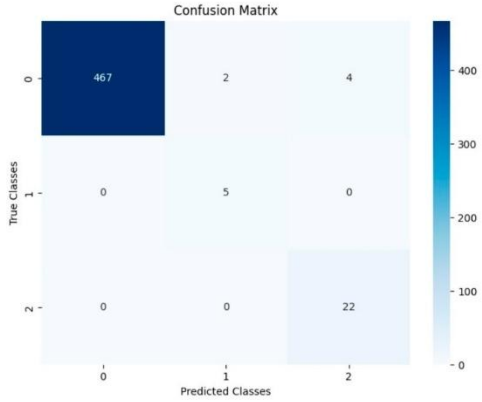


Figure 19. Confusion matrix of test set predictions.

Detailed evaluation metrics of the classification model's performance are presented in Table 7 and the metrics in Table 8 provide more insights into the general effectiveness and class-specific behaviour of the model. The performance was evaluated through following metrics:

- Precision—the proportion of motors classified into a class that truly belong to that class;
- Recall—the proportion of motors of a given class that were correctly identified;
- F1 score—the harmonic mean of precision and recall, offering a balanced view of both metrics;
- Support—the number of motor instances per class;
- Accuracy—the overall percentage of correct predictions across all classes;
- Macro average—the unweighted average of precision, recall, and F1 score across all classes (not accounting for class imbalance);
- Weighted average—The average of precision, recall, and F1 score across all classes (weighted by the number of instances per class, thus incorporating class imbalance).

Table 7. Classification results on the test set (per class). Values in brackets indicate 95% confidence intervals estimated via bootstrap resampling.

Class	Precision	Recall	F1 Score	Support
0	1 [0.99, 1]	0.99 [0.98, 1]	0.99 [0.98, 1]	473
1	0.71 [0.55, 1]	1 [0.80, 1]	0.83 [0.67, 1]	5
2	0.85 [0.75, 1]	1 [0.92, 1]	0.92 [0.84, 1]	22

Table 8. Overall evaluation of neural network performance. Values in brackets indicate 95% confidence intervals estimated via bootstrap resampling.

Metrics	Precision	Recall	F1 Score	Support
Accuracy			0.99 [0.98, 1]	500
Macro average	0.85 [0.75, 0.95]	1 [0.99, 1]	0.91 [0.82, 0.98]	500
Weighted average	0.99 [0.98, 1]	0.99 [0.98, 1]	0.99 [0.98, 1]	500

To provide a more statistically robust evaluation, 95% confidence intervals for each evaluation metric were computed using bootstrap resampling (1000 iterations). This method estimates the variability in model performance by repeatedly sampling the test set and recalculating metrics, offering a clearer picture of metric reliability.

Notably, class 0, which has the highest support (n = 473), achieves near-perfect scores across all metrics—precision, recall, and F1 score—indicating the model's strong reliability on the majority class. The narrow confidence intervals [0.99, 1.00] suggest that this performance is highly stable and consistent across resampled test sets.

For class 1, despite the perfect recall (1.00), the precision has a much wider confidence interval [0.55, 1.00]. This indicates that while the model consistently identifies all class 1 instances, it sometimes misclassifies samples from other classes as class 1. This variability is primarily due to the very small support size (5), which amplifies statistical uncertainty. The F1 score of 0.83 with an interval of [0.67, 1.00] shows this balance between perfect recall and fluctuating precision.

Class 2, with slightly more support (n = 22), also shows excellent recall (1.00) and strong precision (0.85), with a narrower confidence interval [0.75, 1.00] compared to class 1. This implies more consistent performance, with fewer misclassifications and better stability than class 1.

The model achieves an overall accuracy of 0.99, with a very tight 95% confidence interval [0.98, 1.00], confirming that the performance is statistically robust and generalizes well across the test distribution. The macro average metrics show additional insights: while precision and F1 score show some variability, recall remains consistently high. This suggests that the model rarely misses true instances across any class, even though precision may fluctuate for smaller classes. In contrast, the weighted average shows minimal variability across all metrics. This reflects the model's overall stability, driven by its strong and consistent performance on the dominant class 0.

Together, these confidence intervals underscore that while the model is highly reliable overall, caution should be exercised when interpreting performance on underrepresented classes, especially class 1, due to inherent statistical uncertainty from the small sample size.

Additionally, a t-distributed stochastic neighbour embedding (t-SNE) projection of the Softmax outputs was generated (Figure 20). t-SNE is a nonlinear dimensionality reduction technique that visualizes high-dimensional data (such as class probabilities) in two dimensions. Each point represents a sample and colours correspond to the predicted class: blue (class 0), green (class 1), and red (class 2.) This plot helps to illustrate how confidently and distinctly the model clusters the classes in its output space. Tight, well-separated clusters generally indicate high confidence and low overlap between class predictions, whereas scattered or overlapping regions may signal confusion between classes. The distinct clustering observed in the t-SNE plot confirms the model's confidence and clarity in class separation, consistent with the high classification scores reported earlier.

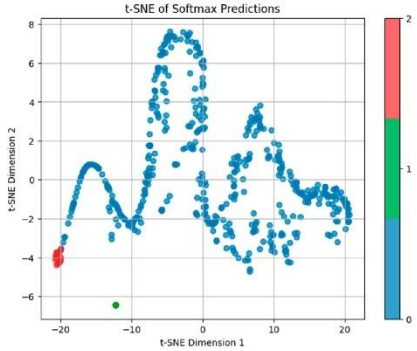


Figure 20. t-SNE visualization of the Softmax output layer for test set predictions.

7. Conclusions

The classifier developed in this study has demonstrated excellent efficiency and accuracy in the classification of BLDC motors into three classes (class 0, class 1, and class 2). It performed well, especially in terms of precision and recall. Most importantly, no false negatives were detected (no faulty motors were misclassified as good), which means that no faulty motor is delivered to the market or to the end-users. The rate of false positives (good motors misclassified as faulty) was very low, but not zero, which means a minor operational inconvenience. Beyond high precision and recall, the classifier's internal feature representation—illustrated through t-SNE—suggests strong class separation and high confidence in its decision boundaries.

Interestingly, the classifier showed the ability to find faults, originally detected in TC3. Using the existing classification algorithm (explained in Section 2.2), it is not possible to detect these faults from the acoustic and vibrational signals of TC2. The confusion matrix confirmed that the algorithm not only detects faults but also localizes them between those originating in TC2 and TC3. This suggests that diagnostic insights traditionally dependent on TC3 can now be inferred from TC2, potentially enabling earlier or more integrated fault detection within the existing TC2 framework. This internal clarity, combined with robust generalization to minority class scenarios, highlights the model's reliability in diverse and potentially imbalanced real-world conditions.

An important limitation of this study is the absence of motors with faults in TC1, which prevents the trained network's ability to recognize such faults. Expanding the dataset to include instances with faults at TC1 would be crucial for full coverage of all possible fault classes.

Another limitation is related to model interpretability. While CNN-BiGRU architecture learns discriminative features from raw signals, it functions as a black box. Therefore, it is unclear which specific signal components (frequencies, time intervals, etc.) are most influential in the model's decision-making. This limits traceability and explainability, which are critical for gaining trust in industrial AI systems.

In future work, it would be valuable to analyse the individual contribution of each input signal (V1, V2, V3, and S) to the overall classification performance. This could lead to further dimensionality reduction by removing redundant or low-impact features, potentially simplifying the hardware configuration for future deployments.

Additionally, the transferability of the trained model to other similar types of motors produced on the manufacturing line should be investigated. Techniques such as domain adaptation or transfer learning [46,47] could enable the model architecture to serve as a foundation for new classifiers, tailored to different motor variants.

Future work should also address model interpretability. Applying explainable AI (XAI) techniques such as Grad-CAM, SHAP, or layer-wise relevance propagation (LRP) can help to identify which features are most influential in the decision-making process. These insights can enhance trust, support model validation, and guide future optimizations.

Moreover, it would be beneficial to compare the performance of the proposed CNN-BiGRU architecture with other deep learning models, such as CNN-LSTM, transformer-based models, or lightweight 1D CNNs [48,49]. These comparisons could identify architectures that offer better accuracy, lower computational cost, or improved generalization to unseen motor types and fault conditions.

This study demonstrates the potential of deep learning models (CNNs combined with BiGRUs) for raw-signal-based industrial fault detection. By eliminating the need for manual feature engineering and expert-driven pre-processing, the proposed system enables faster, more scalable, and more adaptable diagnostics. Moreover, the ability to detect TC3 faults using only TC2 data suggests the potential for reducing system complexity and inspection time in the manufacturing line. Moreover, a combination of broader datasets,

interpretability tools, and generalization strategies will be critical for transforming this model into a fully functional, explainable, and adaptable industrial AI solution.

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Data Availability Statement: The data that support the findings of this study are not publicly available due to confidentiality agreements with the manufacturer but are available from the corresponding author upon reasonable request.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

EoL	End-of-Line
BLDC	Brushless DC
BiGRU	Bidirectional Gated Recurrent Unit
CNN	Convolutional Neural Network
CSRM-MIM	Catenary Support Rod area Masked Image Modelling
FENet	Focusing Enhanced Network
LRP	Layer-wise Relevance Propagation
MFS	Mel-Frequency Spectrogram
PINNs	Physics-Informed Neural Networks
SVM	Support Vector Machines
STFT	Short-Time Fourier Transform
TC1	Test Cell 1
TC2	Test Cell 2
TC3	Test Eell 3
t-SNE	t-distributed Stochastic Neighbour Embedding
XAI	Explainable AI

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Chapter 7

Research Findings

This chapter summarizes the findings of the three original research articles [35], [36], [37], presented in Chapters 4–6. Each article addresses a different methodological approach to intelligent EoL quality inspection: DL, ML with feature selection, and TL. Their combined results provide deeper insights into the design, deployment, and practical limitations of AI-based inspection systems in real industrial environments. Therefore, the purpose of this chapter is not to repeat the results of each article, but rather to integrate them into a cohesive evaluation of their strengths, weaknesses, and industrial applicability.

7.1 Comparison of Approaches

A comparison of the three approaches shows that no single AI approach outperforms the others consistently across all industrial requirements. Instead, each method addresses a different subset of the challenges inherent to EoL quality inspection and was therefore evaluated using datasets and validation protocols that were appropriate for its specific research purpose. Table 7.1 provides a structured methodological and application-oriented, rather than direct numerical, comparison of the investigated AI approaches, presenting their relative performance and practical characteristics in relation to key industrial criteria such as data requirements, interpretability, commissioning speed, computational demand, and fault detection ability.

Table 7.1: The comparison table.

Criterion	ML approach with feature selection	TL approach	DL approach
Accuracy	High	High (at small dataset)	Very high
Interpretability	High	High	Medium
Data requirement	Moderate	Low	High
Commissioning speed	Medium	Fast	Slower
Scalability	Medium	High	High

The ML approach based on supervised feature selection offers a more interpretable and computationally efficient solution. By identifying and retaining only the most informative diagnostic features, this method reduces system complexity, accelerates learning, and improves transparency in decision-making processes. These advantages are particularly

valuable in industrial environments, where explainability, commissioning speed, and system maintainability are critical. Similar findings concerning the significance of feature selection in industrial quality control have been described in recent manufacturing AI literature [59], [60], [61].

The TL approach improves performance and data efficiency. By reusing knowledge from mass-produced motor types, it enables the reliable inspection of new or pre-production motor variants under significant data scarcity. This directly addresses one of the most significant industrial challenges: the long commissioning times for new products. Recent work on TL in manufacturing and condition monitoring confirms its effectiveness in reducing data requirements and improving robustness in low-data regimes [62], [63], [64].

The DL approach based on MFSs has the greatest ability to capture complex, nonlinear, and time-varying fault patterns directly from raw sensor data. Its end-to-end learning approach eliminates the need for manual feature engineering and is effective at detecting subtle fault patterns that are difficult to express using manual tuned features. Similar findings have been reported in recent studies on DL for rotating machinery diagnostics and industrial signal analysis [65], [66], [67]. However, this approach requires sufficient training data, and attention to computational constraints, which may make it impractical for some production scenarios.

7.2 Integration of Results

The results of the three studies, viewed together, suggest that intelligent EoL quality inspection should not rely on a single methodological approach, but rather on a flexible framework that can adapt to different production phases and limitations.

Feature-based ML methods are ideal for stable, high-volume production environments that prioritize interpretability and quick deployment. TL extends these methods by enabling quick adaptation to new motor variants without the need for extensive data collection or expert intervention. Although DL approaches are more resource-intensive, they provide superior fault detection capabilities in complex systems and can be valuable once sufficient data has been collected. They also eliminate the need for data pre-processing and feature engineering.

This multifaceted approach aligns with current trends in industrial AI, where hybrid and staged inspection strategies are becoming more popular to balance performance, transparency, and operational limitations [59], [63], [65]. Therefore, the findings of this dissertation support the idea that intelligent EoL inspection systems should be designed as modular, flexible solutions instead of static diagnostic systems.

7.3 Limitations and Practical Implications

Although the investigated approaches show potential, they also reveal significant limitations that must be considered for industrial application. DL models are sensitive to data imbalance and require careful validation to ensure robustness under production variability. While interpretable, ML models based on feature selection may miss fault patterns that are not well captured by predefined features. TL methods depend on the similarity between the source and target motor types and may result in negative transfer if this assumption is inaccurate.

From a practical perspective, the results demonstrate the importance of aligning the selection of AI methods with the production context, available data, and organizational constraints. Recent studies have shown that the successful industrial adoption of AI

requires high classification performance as well as maintainability, explainability, and integration with existing automation infrastructure [66], [68], [69], [70].

7.4 Summary

This chapter combines the results of three original research articles and shows that ML, TL, and DL provide solutions that work well together to address the challenges of EoL quality inspection in electric motor manufacturing. Instead of competing with each other, these complementary approaches form a toolkit that can be combined strategically to improve reliability of inspections, reduce required effort for commissioning, and increase flexibility. The dissertation also proves that AI in industrial inspection systems is not a single-method solution but a structured framework combining interpretability, data efficiency, and representation learning.

Chapter 8

Conclusions

In conclusion, this dissertation discusses the findings in the context of the hypotheses formulated in Chapter 1. It addressed the challenges of end-of-line (EoL) quality inspection in electric motor manufacturing by systematically investigating the potential benefits of machine learning, transfer learning, and deep learning approaches using real industrial data. The results obtained in Chapters 4–6 allow for a clear evaluation of the hypotheses' validity.

Hypothesis 1 states that manual feature selection can be replaced with automated feature selection using machine learning techniques. This reduces the need for human expert activities, and leads to improved classification accuracy and reduced computational complexity in EoL inspection. The results presented in Chapter 4 confirm this hypothesis. Supervised machine learning models equipped with feature importance metrics were demonstrated to effectively identify the most informative features from extensive, expert-defined feature sets. By reducing feature dimensionality while preserving or improving classification accuracy, the proposed approach decreased system complexity and computation time. Additionally, the resulting models became more explainable, enabling transparent validation of diagnostic decisions. These results show that automated feature selection can replace expert-driven feature engineering in industrial EoL inspection systems effectively.

Hypothesis 2 states that the commissioning of quality inspection systems for new product subtypes can be significantly accelerated by applying TL to small preproduction datasets of new product subtypes using large-scale production datasets of existing product subtype. The results presented in Chapter 5 confirm this hypothesis. Using the TL strategy to transfer optimized hyperparameters and relevant features from a mass-produced motor type to preproduction variants led to improved classification accuracy and reduced misclassification costs under low-data conditions. These findings show that reliable inspection performance can be achieved with significantly fewer labeled samples. This shortens commissioning time and reduces dependence on extensive data collection during early production phases. These results confirm that TL is an effective and practical solution for scalable EoL inspection systems.

Hypothesis 3 stated that data preprocessing and feature engineering designed by experts could be eliminated by introducing DL models that operate on MFSs using a hybrid CNN–BiGRU architecture. The results presented in Chapter 6 confirm this hypothesis. The proposed DL model successfully learned discriminative representations directly from spectrograms of raw vibration and acoustic signals without relying on handcrafted features or manually designed thresholds. The hybrid CNN–BiGRU architecture effectively captured both spectral characteristics and their temporal evolution during EoL test cycles. Compared to traditional threshold- and feature-based ML approaches, the DL model

showed superior ability to detect complex and subtle fault patterns under realistic industrial conditions.

Overall, confirming all three hypotheses shows that intelligent, data-driven methods can significantly improve the quality of EoL inspections in electric motor manufacturing. Still, the dissertation shows that no single method is optimal in all cases. Feature-based ML offers interpretability and computational efficiency; TL enables rapid commissioning in the face of limited data; and DL provides superior representational power for complex fault identification. These methods' combined strengths suggest that future industrial inspection systems should adopt flexible, modular AI architectures, which can be tailored to specific production constraints and lifecycle phases.

From an industrial perspective, the results confirm that AI-based EoL inspection can significantly reduce dependence on high-skilled human experts during commissioning, shorten ramp-up times for new motor types, and improve robustness of inspections in the presence of production variability. Since all of the proposed methods were validated using real manufacturing data obtained from operating production lines, the findings can be applied directly to industrial environments.

In summary, this dissertation contributes to the field of intelligent industrial quality control by providing a systematic and experimental investigation of ML, TL, and DL approaches for EoL inspection of electric motors. This work supports transitioning from expert-driven, rule-based inspection to adaptive, scalable, data-driven quality inspection systems that can meet the demands of modern, large-scale manufacturing.

Chapter 9

Future Works

This dissertation presents results that demonstrate the significant improvement in EoL quality inspection in electric motor manufacturing that can be achieved through ML, TL, and DL. While these approaches address several key industrial challenges, they also create opportunities for further research focused on improving robustness, scalability, and long-term industrial applicability.

An important area for future research is developing integrated, adaptive inspection systems that combine multiple AI methods. The results show that feature-based ML, TL, and DL offer different advantages depending on the production phase, data availability, and inspection demands. Future inspection systems could dynamically select or combine these approaches, allowing for efficient commissioning during the early stages of production and more advanced diagnostics as data becomes more available.

Another relevant research direction is improving the interpretability of AI-based inspection systems, particularly DL models. While the proposed neural network approach demonstrated strong diagnostic performance, further research is needed to make model decisions more transparent. Increasing explainability would lead to greater industrial acceptance, allow for more efficient root-cause analysis, and help engineers refine production processes.

Data efficiency remains a critical challenge in industrial quality inspection. Future work could explore learning models that reduce dependence on labeled fault data, such as semi-supervised or self-supervised learning. These approaches could take advantage of the large amounts of unlabeled data produced during regular production, improving model performance without the need for more labeling.

The long-term robustness and lifecycle management of AI-based inspection systems are also important research topics. End-of-line quality inspection hardware setup changes over time due to upgrades, aging equipment, and design changes, all of which may degrade inspection system performance over time. Investigating online learning and concept drift detection could allow these systems to adapt continuously while maintaining reliable performance.

Finally, future studies could extend the proposed methodologies to other types of electric machines or complex electromechanical systems. Validating these approaches across different products and fault conditions would demonstrate their flexibility and support their adoption in a wider range of industries.

In summary, the work presented in this dissertation provides a solid foundation for intelligent, data-driven EoL quality inspection. Future research could further reduce human involvement, improve adaptability, and enable the development of fully autonomous inspection systems for modern industrial environments.

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Biography

Jernej Mlinarič was born on October 6th, 1996, in Celje, Slovenia. In 2015, he graduated from Šolski center Rogaška Slatina (gymnasium). He continued his studies at the Faculty of Electrical Engineering and Computer Science (FERI), University of Maribor, where he enrolled in the mechatronics study program. He obtained his bachelor's degree in 2018 with the thesis "Development of Safety Systems for Power System Control of an Electric Bike" and completed his master's degree in 2020 with the thesis "Diagnostics and Prognostics of Electromechanical Systems Based on Mechanical, Electrical, Vibrational and Acoustic Signals." In 2020, he was accepted into the Young Researcher Programme and began his doctoral studies at the Jožef Stefan International Postgraduate School. He is currently employed as a junior researcher at the Department of Systems and Control, Jožef Stefan Institute, under the supervision of Asst. prof. Dr. Gregor Dolanc. His research focuses on fault detection, condition monitoring, and diagnostics and prognostics of electromechanical systems in industrial environments, with particular emphasis on End-of-Line quality inspection, machine learning, deep learning, and transfer learning approaches applied to real manufacturing data. His work has resulted in publications in international scientific journals and contributions to applied industrial research projects.