machines

MDPI

Review

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

Jernej Mlinarič [1,*] and Gregor Dolanc [2]

[1] Jozef Stefan International Postgraduate School, Jamova cesta 39, 1000 Ljubljana, Slovenia
[2] Jozef Stefan Institute, Jamova cesta 39, 1000 Ljubljana, Slovenia
* Correspondence: jernej.mlinaric@ijs.si

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

Academic Editor: Ahmed Abu-Siada

Received: 30 December 2025
Revised: 16 January 2026
Accepted: 19 January 2026
Published: 28 January 2026

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 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.

https://doi.org/10.3390/machines14020149

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.

https://doi.org/10.3390/machines14020149

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

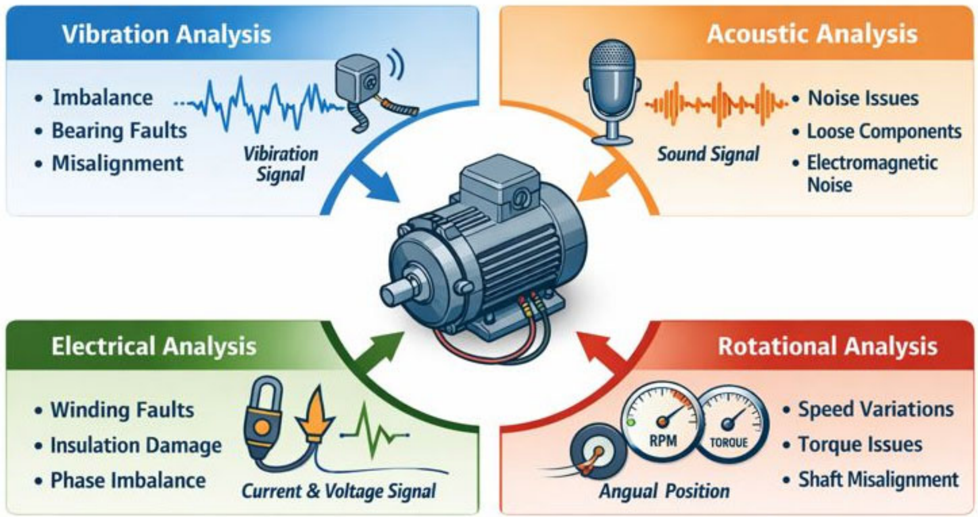

Figure 2. Overview of non-invasive measurement modalities in EoL quality inspection.

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.

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 acceptable 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.

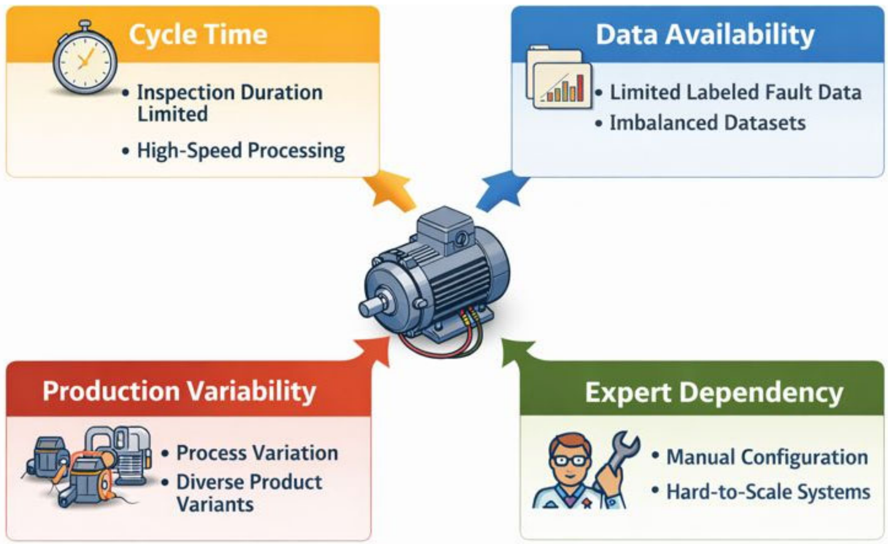

Figure 3. Key industrial constraints influencing EoL quality inspection system design.

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].

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.

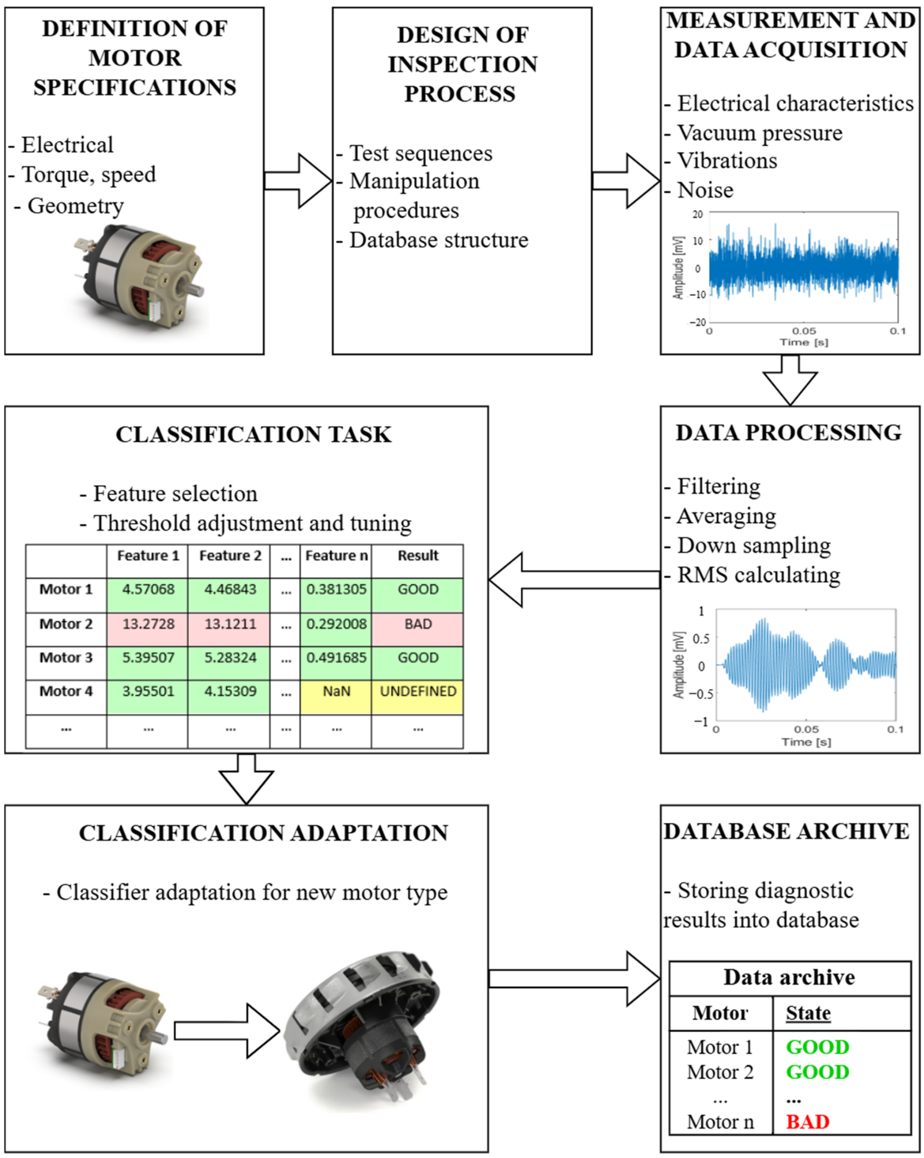

Figure 4. Overview of a conventional EoL quality inspection workflow for electric motors.

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.

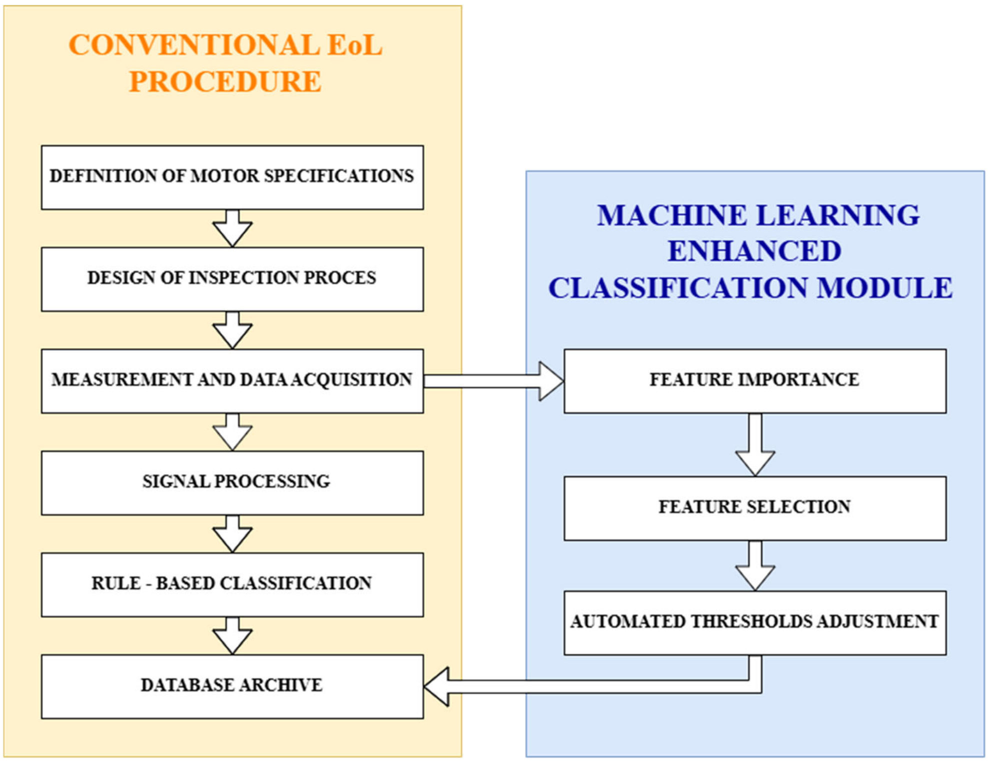

Figure 5. Integration of ML into conventional EoL quality inspection workflow.

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].

https://doi.org/10.3390/machines14020149

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.

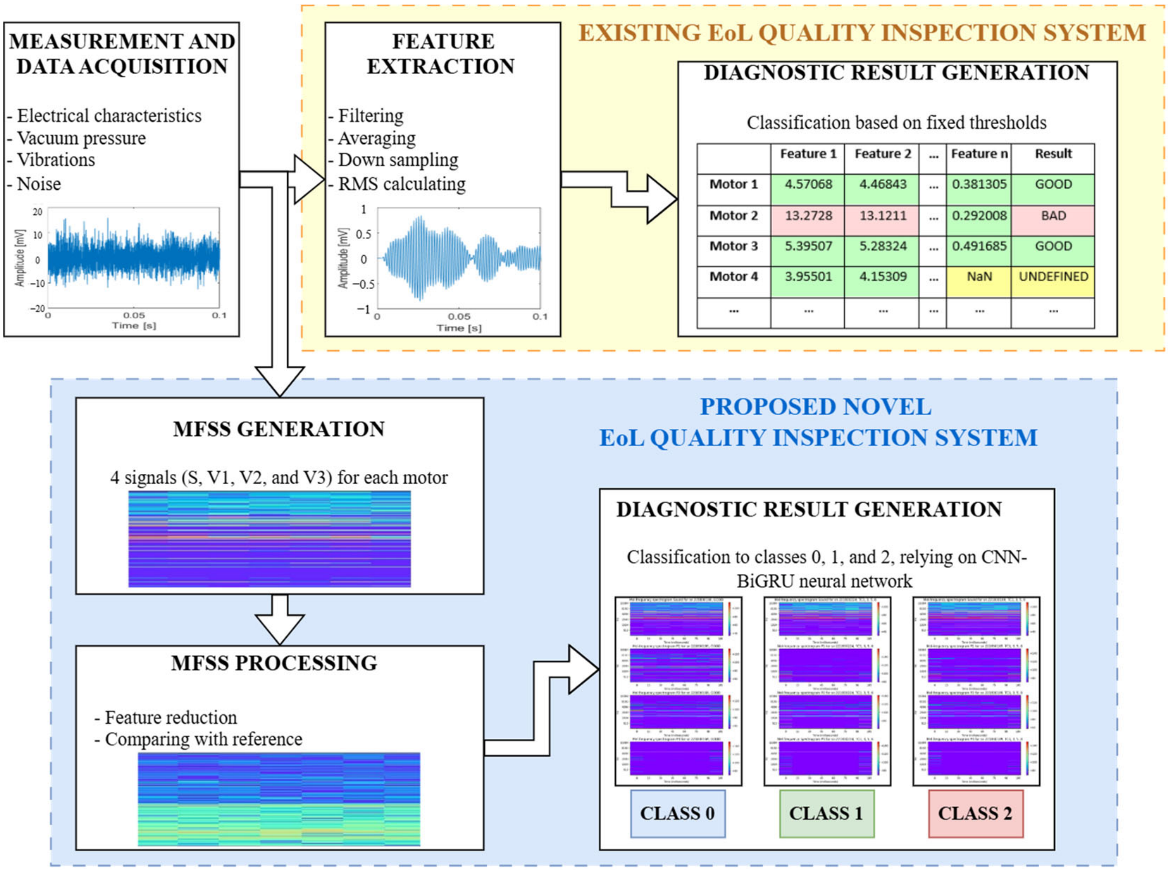

Figure 6. DL pipeline for signal-based EoL quality inspection [16].

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.

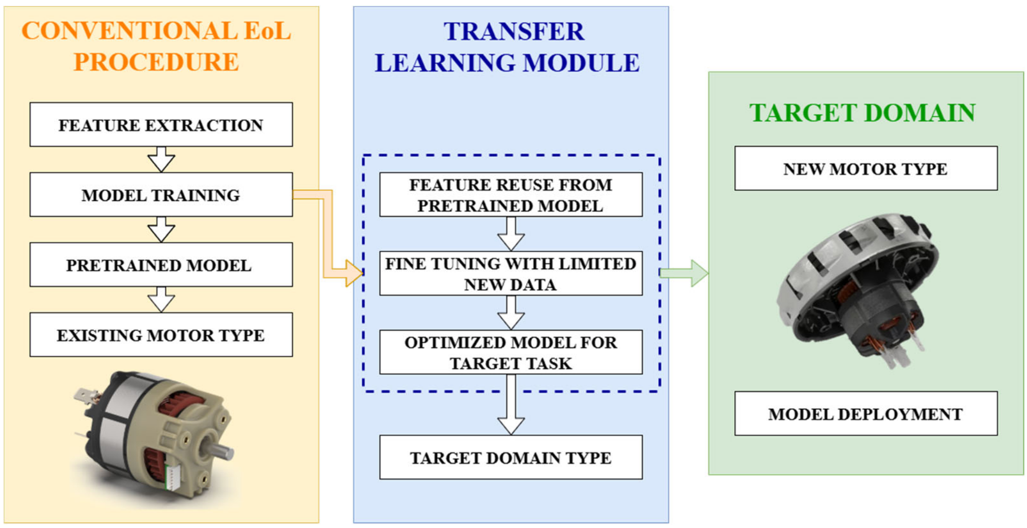

Figure 7. Integration of TL into conventional EoL quality inspection workflow.

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.

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 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, 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].

Author Contributions: Conceptualization, J.M. and G.D.; methodology, J.M. and G.D.; software, J.M.; validation, formal analysis, G.D.; investigation, J.M.; resources, J.M.; data curation, J.M.; writing—

original draft preparation, J.M.; writing—review and editing, G.D.; supervision, G.D. All authors have read and agreed to the published version of the manuscript.

Funding: The authors are grateful for the financial support of the Slovenian Research and Innovation Agency through grant P2-0001 and L2-4454.

Data Availability Statement: The PRISMA-ScR checklist supporting this scoping review is provided as Supplementary Material [107]. 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:

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.

References

1. Tavner, P.J.; Ran, L.; Penman, J.; Sedding, H. *Condition Monitoring of Rotating Electrical Machines*; IET: London, UK, 2008.
2. Arinez, J.; Chang, Q.; Gao, R.; Xu, C.; Zhang, J. Artificial Intelligence in Advanced Manufacturing: Current Status and Future Outlook. *J. Manuf. Sci. Eng.* **2020**, *142*, 110804. [CrossRef]
3. Issa, R.; Clerc, G.; Hologne-Carpentier, M.; Michaud, R.; Lorca, E.; Magnette, C.; Messadi, A. Review of Fault Diagnosis Methods for Induction Machines in Railway Traction Applications. *Energies* **2024**, *17*, 2728. [CrossRef]
4. Benko, U.; Petrovčič, J.; Mussiza, B.; Juričić, Đ. A System for Automated Final Quality Assessment in the Manufacturing of Vacuum Cleaner Motors. *IFAC Proc.* **2008**, *41*, 7399–7404. [CrossRef]
5. Benko, U.; Petrovčič, J.; Juričić, Đ. In-depth fault diagnosis of small universal motors based on acoustic analysis. *IFAC Proc.* **2005**, *38*, 323–328. [CrossRef]
6. Yan, R.; Gao, R.X.; Chen, X. Wavelets for fault diagnosis of rotary machines: A review with applications. *Signal Process.* **2014**, *96*, 1–15. [CrossRef]
7. Popsi, N.; Anik, A.; Verma, R.; Viana, C.; Iyer, K.; Kar, N. Influence of Electric Motor Manufacturing Tolerances on End-of-Line Testing: A Review. *Energies* **2024**, *17*, 913. [CrossRef]
8. Galfarsoro, U.; McCloskey, A.; Zarate, S.; Hernández, X.; Almandoz, G. Influence of Manufacturing Tolerances and Eccentricities on the Electromotive Force in Permanent Magnet Synchronous Motors. *IEEE Trans. Ind. Appl.* **2025**, *61*, 7046–7060. [CrossRef]
9. Niu, G.; Dong, X.; Chen, Y. Motor Fault Diagnostics Based on Current Signatures: A Review. *IEEE Trans. Instrum. Meas.* **2023**, *72*, 1–19. [CrossRef]
10. Juričić, Đ.; Petrovčič, J.; Benko, U.; Musizza, B.; Dolanc, G.; Boškoski, P.; Petelin, D. End-Quality Control in the Manufacturing of Electrical Motors. In *Case Studies in Control: Putting Theory to Work*; Springer: London, UK, 2013; pp. 221–256.
11. Liu, R.; Yang, B.; Zio, E.; Chen, X. Artificial intelligence for fault diagnosis of rotating machinery: A review. *Mech. Syst. Signal Process.* **2018**, *108*, 33–47. [CrossRef]

12. Alsahaf, A.; Petkov, N.; Shenoy, V.; Azzopardi, G. A framework for feature selection through boosting. *Expert Syst. Appl.* **2022**, *187*, 115895. [CrossRef]
13. Azamfirei, V.; Psarommatis, F.; Lagrosen, Y. Application of automation for in-line quality inspection, a zero-defect manufacturing approach. *J. Manuf. Syst.* **2023**, *67*, 1–22. [CrossRef]
14. Mlinarič, J.; Pregelj, B.; Boškoski, P.; Dolanc, G.; Petrovčič, J. Optimization of reliability and speed of the end-of-line quality inspection of electric motors using machine learning. *Adv. Prod. Eng. Manag.* **2024**, *19*, 183–196. [CrossRef]
15. Mlinarič, J.; Pregelj, B.; Boškoski, P.; Petrovčič, J.; Dolanc, G. A transfer learning approach to machine learning-based end-of-line quality inspection. *Adv. Prod. Eng. Manag.* **2025**, *20*, 277–290. [CrossRef]
16. Mlinarič, J.; Pregelj, B.; Dolanc, G. End-of-Line Quality Control Based on Mel-Frequency Spectrogram Analysis and Deep Learning. *Machines* **2025**, *13*, 626. [CrossRef]
17. Wißbrock, P.; Pelkmann, D.; Tölle, B. Automate Quality Prediction in an End-of-Line Test of a Highly Variant Production of Geared Motors—Discussion of a Full Concept. *PHM Soc. Eur. Conf.* **2021**, *6*, 10. [CrossRef]
18. Wißbrock, P.; Koschek, L.; Ren, Z.; Nejdl, W. Enhancing quality inspection of highly variant geared motors. *Appl. Acoust.* **2025**, *235*, 110687. [CrossRef]
19. Schmitt, J.; Bönig, J.; Borggräfe, T.; Beitinger, G.; Deuse, J. Predictive model-based quality inspection using Machine Learning and Edge Cloud Computing. *Adv. Eng. Inform.* **2020**, *45*, 101101. [CrossRef]
20. Nunes, C.; Nunes, R.; Pires, E.; Barroso, J.; Reis, A. A Machine Learning Tool to Monitor and Forecast Results from Testing Products in End-of-Line Systems. *Appl. Sci.* **2023**, *13*, 2263. [CrossRef]
21. Junior, R.F.R.; Areias, I.A.d.S.; Campos, M.M.; Teixeira, C.E.; da Silva, L.E.B.; Gomes, G.F. Fault detection and diagnosis in electric motors using 1d convolutional neural networks with multi-channel vibration signals. *Measurement* **2022**, *190*, 110759. [CrossRef]
22. Fahad, A.; Luo, S.; Zhang, H.; Shaukat, K.; Yang, G.; Wheeler, C.A.; Chen, Z. A Brief Review of Acoustic and Vibration Signal-Based Fault Detection for Belt Conveyor Idlers Using Machine Learning Models. *Sensors* **2023**, *23*, 1902. [CrossRef]
23. Janssens, O.; Slavkovikj, V.; Vervisch, B.; Stockman, K.; Loccufier, M.; Verstockt, S.; Van de Walle, R.; Van Hoecke, S. Convolutional Neural Network Based Fault Detection for Rotating Machinery. *J. Sound Vib.* **2016**, *377*, 331–345. [CrossRef]
24. Zhang, C.; Mousavi, A.; Masri, S.; Gholipour, G.; Yan, K.; Li, X. Vibration feature extraction using signal processing techniques for structural health monitoring: A review. *Mech. Syst. Signal Process.* **2022**, *177*, 109175. [CrossRef]
25. Alotaibi, M.; Honarvar, B.; Khan, M. Non-Invasive Inspections: A Review on Methods and Tools. *Sensors* **2021**, *21*, 8474. [CrossRef] [PubMed]
26. Antoni, J. Fast computation of the kurtogram for the detection of transient faults. *Mech. Syst. Signal Process.* **2007**, *21*, 108–124. [CrossRef]
27. Wang, Y.; Xiang, J.; Markert, R.; Liang, M. Spectral kurtosis for fault detection, diagnosis and prognostics of rotating machines: A review with applications. *Mech. Syst. Signal Process.* **2016**, *66–67*, 679–698. [CrossRef]
28. Sánchez, R.; Macancela, J.; Ortega, L.; Cabrera, D.; Márquez, F.; Cerrada-Lozada, M. Evaluation of Hand-Crafted Feature Extraction for Fault Diagnosis in Rotating Machinery: A Survey. *Sensors* **2024**, *24*, 5400. [CrossRef]
29. Guyon, I.; Elisseeff, A. An introduction to variable and feature selection. *J. Mach. Learn. Res.* **2003**, *3*, 1157–1182.
30. Wyłomańska, A. Statistical tools for anomaly detection as a part of predictive maintenance in the mining industry. *Eur. Math. Soc. Mag.* **2022**, *124*, 4–15. [CrossRef]
31. Wang, J.; Song, Y.; Cui, P.; Li, Y. A data-driven method for performance analysis and improvement in production systems with quality inspection. *J. Intell. Manuf.* **2021**, *34*, 455–469. [CrossRef]
32. Tama, B.; Vania, M.; Lee, S.; Lim, S. Recent advances in the application of deep learning for fault diagnosis of rotating machinery using vibration signals. *Artif. Intell. Rev.* **2023**, *56*, 4667–4709. [CrossRef]
33. Chen, R.; Dewi, C.; Huang, S.; Caraka, R. Selecting critical features for data classification based on machine learning methods. *J. Big Data* **2020**, *7*, 52. [CrossRef]
34. Ngo, G.; Beard, R.; Chandra, R. Evolutionary bagging for ensemble learning. *Neurocomputing* **2022**, *510*, 1–14. [CrossRef]
35. Zhang, Y.; Li, X.; Gao, L.; Chen, W.; Li, P. Intelligent fault diagnosis of rotating machinery using a new ensemble deep auto-encoder method. *Measurement* **2020**, *151*, 107232. [CrossRef]
36. Feng, Z.; He, W.; Qin, Y.; Ma, X. Rotating machinery fault diagnosis using hybrid deep neural networks with raw vibration signals. *IEEE Trans. Ind. Electron.* **2020**, *67*, 4143–4153.
37. Das, O.; Das, D.B.; Birant, D. Machine learning for fault analysis in rotating machinery: A comprehensive review. *Heliyon* **2023**, *9*, e17584. [CrossRef]
38. Jialin, S.; Qiang, Y. A Survey on Transfer Learning. *IEEE Trans. Knowl. Data Eng.* **2010**, *22*, 1345–1359.
39. Weiss, K.; Khoshgoftaar, T.M.; Wang, D. A survey of transfer learning. *Big Data* **2016**, *3*, 9. [CrossRef]
40. Feisa, T.T.; Gebremedhen, H.S.; Kibrete, F.; Woldemichael, D.E.; Ageze, S.D.; Nega, H.D. A Comprehensive Review of Deep Transfer Learning for Intelligent Fault Diagnosis in Rotating Machines. *Eng. Rep.* **2025**, *7*, e70494. [CrossRef]

41. Chen, H.; Luo, H.; Huang, B.; Jiang, B.; Kaynak, O. Transfer Learning-Motivated Intelligent Fault Diagnosis Designs: A Survey, Insights, and Perspectives. *IEEE Trans. Neural Netw. Learn. Syst.* **2023**, *35*, 2969–2983. [CrossRef]
42. Michau, G.; Fink, O. Unsupervised transfer learning for anomaly detection: Application to complementary operating condition transfer. *Knowl.-Based Syst.* **2020**, *216*, 106816. [CrossRef]
43. Tercan, H.; Meisen, T. Machine learning and deep learning based predictive quality in manufacturing: A systematic review. *J. Intell. Manuf.* **2022**, *33*, 1879–1905. [CrossRef]
44. Li, W.; Huang, R.; Li, J.; Liao, Y.; Chen, Z.; He, G.; Yan, R.; Gryllias, K. perspective survey on deep transfer learning for fault diagnosis in industrial scenarios: Theories, applications and challenges. *Mech. Syst. Signal Process.* **2022**, *167*, 108487. [CrossRef]
45. Surucu, O.; Gadsden, S.A.; Yawney, J. Condition Monitoring using Machine Learning: A Review of Theory, Applications, and Recent Advances. *Expert Syst. Appl.* **2023**, *221*, 119738. [CrossRef]
46. Azamfirei, V.; Granlund, A.; Lagrosen, Y. Multi-Layer Quality Inspection System Framework for Industry 4.0. *Int. J. Automot. Technol.* **2021**, *15*, 641–650. [CrossRef]
47. Zhang, X.; Wang, L.; Xu, X.; Tang, J. Fault diagnosis of rotating machinery using deep convolutional neural networks with wide first-layer kernels. *Knowl.-Based Syst.* **2019**, *165*, 105–114.
48. Zhao, R.; Yan, R.; Chen, X.; Mao, K.; Wang, P.; Gao, R.X. Deep learning and its applications to machine health monitoring. *Mech. Syst. Signal Process.* **2019**, *115*, 213–237. [CrossRef]
49. Garcia-Calva, T.; Moriñigo-Sotelo, D.; Fernández-Cavero, V.; Romero-Troncoso, R. Early Detection of Faults in Induction Motors—A Review. *Energies* **2022**, *15*, 7855. [CrossRef]
50. Movahed, P.M.; Taheri, S.; Razban, A. A bi-level data-driven framework for fault-detection and diagnosis of HVAC systems. *Appl. Energy* **2023**, *339*, 120948. [CrossRef]
51. Martinez, P.; Ahmad, R. Quantifying the Impact of Inspection Processes on Production Lines through Stochastic Discrete-Event Simulation Modeling. *Modelling* **2021**, *2*, 406–424. [CrossRef]
52. Sarvesh, S.; Zeid, A. Artificial Intelligence-Based Smart Quality Inspection for Manufacturing. *Micromachines* **2023**, *14*, 570. [CrossRef]
53. Piczak, K.J. Environmental sound classification with convolutional neural networks. In Proceedings of the IEEE International Workshop on Machine Learning for Signal Processing (MLSP), Boston, MA, USA, 17–20 September 2015.
54. Zavrtanik, V.; Marolt, M.; Kristan, M.; Skočaj, D. Anomalous Sound Detection by Feature Level Anomaly Simulation. In Proceedings of the IEEE International Conference on Acoustics, Speech and Signal Processing, Seoul, Republic of Korea, 14–19 April 2024.
55. Davis, S.; Mermelstein, P. Comparison of parametric representations for monosyllabic word recognition in continuously spoken sentences. *IEEE Trans. Acoust. Speech Signal Process.* **1980**, *28*, 357–366. [CrossRef]
56. Logan, B. Mel frequency cepstral coefficients for music modeling. In Proceedings of the International Symposium on Music Information Retrieval (ISMIR), Plymouth, MA, USA, 23–25 October 2000; International Society for Music Information Retrieval: Cambridge, MA, USA, 2000.
57. El Hachemi Benbouzid, M. A review of induction motors signature analysis as a medium for faults detection. *IEEE Trans. Ind. Electron.* **2000**, *47*, 984–993. [CrossRef]
58. Azevedo, G.O.d.A.; Fernandes, B.J.T.; Silva, L.H.d.S.; Freire, A.; de Araújo, R.P.; Cruz, F. Event-Based Angular Speed Measurement and Movement Monitoring. *Sensors* **2022**, *22*, 7963. [CrossRef] [PubMed]
59. Chen, W.; Yang, Z.; Chen, C.; Luo, W. Load-Dependent Rotating Performance of Motorized Spindles: Measurement and Evaluation Using Multi-Zones Error Map. *IEEE Access* **2019**, *7*, 180482–180490. [CrossRef]
60. Gomez, J.; Khelf, I.; Bourdon, A.; André, H.; Rémond, D. Angular modeling of a rotating machine in non-stationary conditions: Application to monitoring bearing defects of wind turbines with instantaneous angular speed. *Mech. Mach. Theory* **2019**, *136*, 27–51. [CrossRef]
61. Kim, H.; Frommknecht, A.; Bieberstein, B.; Stahl, J.; Huber, M.F. Automated end-of-line quality assurance with visual inspection and convolutional neural networks. *Tech. Mess.* **2023**, *90*, 196–204. [CrossRef]
62. Lee, H.; Son, S.; Jeong, D.; Sun, K.; Jeon, B.; Oh, K. High-fidelity multiphysics model of a permanent magnet synchronous motor for fault data generation. *J. Sound Vib.* **2024**, *589*, 118573. [CrossRef]
63. Zhu, C.; Bao, L.; Zheng, B.; Qian, J.; Cai, Y.; Wang, B. Motor Dynamic Loading and Comprehensive Test System Based on FPGA and MCU. *Electronics* **2022**, *11*, 1317. [CrossRef]
64. Hidalgo-Mompeán, F.; Fernández, J.F.G.; Cerruela-García, G.; Márquez, A.C. Dimensionality analysis in machine learning failure detection models. A case study with LNG compressors. *Comput. Ind.* **2021**, *128*, 103434. [CrossRef]
65. Garpelli, L.N.; Alves, D.S.; Cavalca, K.L.; de Castro, H.F. Physics-guided neural networks applied in rotor unbalance problem. *Struct. Health Monit.* **2023**, *22*, 4117–4130. [CrossRef]
66. Shen, S.; Lu, H.; Sadoughi, M.; Hu, C.; Nemani, V.; Thelen, A.; Webster, K.; Darr, M.; Sidon, J.; Kenny, S. A physics-informed deep learning approach for bearing fault detection. *Eng. Appl. Artif. Intell.* **2021**, *103*, 104295. [CrossRef]

67. De Vitis, G.; Di Tecco, A.; Foglia, P.; Prete, C. Fast Blob and Air Line Defects Detection for High Speed Glass Tube Production Lines. *J. Imaging* **2021**, *7*, 223. [CrossRef] [PubMed]
68. Nunes, P.; Santos, J.; Rocha, E. Challenges in predictive maintenance—A review. *CIRP J. Manuf. Sci. Technol.* **2023**, *40*, 53–67. [CrossRef]
69. Yan, P.; Abdulkadir, A.; Luley, P.; Rosenthal, M.; Schatte, G.; Grewe, B.; Stadelmann, T. A Comprehensive Survey of Deep Transfer Learning for Anomaly Detection in Industrial Time Series: Methods, Applications, and Directions. *IEEE Access* **2023**, *12*, 3768–3789. [CrossRef]
70. Soytürk, M.; Coşkun, K.; İzmitlioğlu, O.; Tümer, B.; Güneş, D.; Saraçoğlu, S.; Bulut, B.; Ketmen, H.; Hanedar, İ.; Aşan, T.; et al. An AI-based Architecture Framework for Improving End-of-line Reliability Tests of Electric Motor. In Proceedings of the IECON 2022—48th Annual Conference of the IEEE Industrial Electronics Society, Brussels, Belgium, 17–20 October 2022; pp. 1–6.
71. Montejano Leija, A.B.; Ruiz Beltrán, E.; Orozco Mora, J.L.; Valdés Valadez, J.O. Performance of Machine Learning Algorithms in Fault Diagnosis for Manufacturing Systems: A Comparative Analysis. *Processes* **2025**, *13*, 1624. [CrossRef]
72. Brusa, E.; Cibrario, L.; Delprete, C.; Di Maggio, L. Explainable AI for Machine Fault Diagnosis: Understanding Features' Contribution in Machine Learning Models for Industrial Condition Monitoring. *Appl. Sci.* **2023**, *13*, 2038. [CrossRef]
73. Wang, H.; Liang, Q.; Hancock, J.; Khoshgoftaar, T. Feature selection strategies: A comparative analysis of SHAP-value and importance-based methods. *J. Big Data* **2024**, *11*, 44. [CrossRef]
74. Eltouny, K.; Gomaa, M.; Liang, X. Unsupervised Learning Methods for Data-Driven Vibration-Based Structural Health Monitoring: A Review. *Sensors* **2023**, *23*, 3290. [CrossRef]
75. Li, C.; Li, S.; Wang, H.; Gu, F.; Ball, A. Attention-based deep meta-transfer learning for few-shot fine-grained fault diagnosis. *Knowl.-Based Syst.* **2023**, *264*, 110345. [CrossRef]
76. Zhang, W.; Peng, G.; Li, C.; Chen, Y.; Zhang, Z. A New Deep Learning Model for Fault Diagnosis with Good Anti-Noise and Domain Adaptation Ability on Raw Vibration Signals. *Sensors* **2017**, *17*, 425. [CrossRef]
77. Ye, L.; Ma, X.; Wen, C. Rotating Machinery Fault Diagnosis Method by Combining Time-Frequency Domain Features and CNN Knowledge Transfer. *Sensors* **2021**, *21*, 8168. [CrossRef] [PubMed]
78. Hyvärinen, A.; Karhunen, J.; Oja, E. *Independent Component Analysis*; Wiley-Interscience: New York, NY, USA, 2001.
79. Guo, S.; Yang, T.; Gao, W.; Zhang, C. A Novel Fault Diagnosis Method for Rotating Machinery Based on a Convolutional Neural Network. *Sensors* **2018**, *18*, 1429. [CrossRef] [PubMed]
80. Li, C.; Dong, C.; Fang, T. Bearing Fault Diagnosis Based on FFT-CNN-BiGRU-Attention. In Proceedings of the 4th International Conference on Computer, Artificial Intelligence and Control Engineering (CAICE '25), Hefei, China, 10–12 January 2025; Association for Computing Machinery: New York, NY, USA, 2025.
81. Verstraete, D.; Ferrada, A.; Droguett, E.L.; Meruane, V.; Modarres, M. Deep Learning Enabled Fault Diagnosis Using Time-Frequency Image Analysis of Rolling Element Bearings. *Shock. Vib.* **2017**, *2017*, 5067651. [CrossRef]
82. Islam, M.; Zamil, M.; Rayed, M.; Kabir, M.; Mridha, M.; Nishimura, S.; Shin, J. Deep Learning and Computer Vision Techniques for Enhanced Quality Control in Manufacturing Processes. *IEEE Access* **2024**, *12*, 121449–121479. [CrossRef]
83. McFee, B.; Raffel, C.; Liang, D.; Ellis, D.P.; McVicar, M.; Battenberg, E.; Nieto, O. librosa: Audio and Music Signal Analysis in Python. In Proceedings of the 14th Python in Science Conference, Austin, TX, USA, 6–12 July 2015.
84. Yan, J.; Cheng, Y.; Zhang, F.; Zhou, N.; Wang, H.; Jin, B.; Wang, M.; Zhang, W. Multimodal Imitation Learning for Arc Detection in Complex Railway Environments. *IEEE Trans. Instrum. Meas.* **2025**, *74*, 1–13. [CrossRef]
85. Zhao, Z.; Chen, W.; Wu, X.; Chen, P.C.Y.; Liu, J. LSTM network: A deep learning approach for short-term traffic forecast. *IET Intell. Transp. Syst.* **2017**, *108*, 68–75. [CrossRef]
86. Yasenjiang, J.; Zhao, Y.; Xiao, Y.; Hao, H.; Gong, Z.; Han, S. Bearing Fault Diagnosis Based on Time–Frequency Dual Domains and Feature Fusion of ResNet-CACNN-BiGRU-SDPA. *Sensors* **2025**, *25*, 3871. [CrossRef]
87. Bhuiyan, M.; Uddin, J. Deep Transfer Learning Models for Industrial Fault Diagnosis Using Vibration and Acoustic Sensors Data: A Review. *Vibration* **2023**, *6*, 218–238. [CrossRef]
88. Perez-Sanjines, F.P.C.; Verstraeten, T.; Antoni, J.; Nowé, A.; Helsen, J. Fleet-based early fault detection of wind turbine gearboxes using physics-informed deep learning based on cyclic spectral coherence. *Mech. Syst. Signal Process.* **2022**, *185*, 109760. [CrossRef]
89. Gao, Y.; Chen, M.; Yu, D. Semi-supervised graph convolutional network and its application in intelligent fault diagnosis of rotating machinery. *Measurement* **2021**, *186*, 110084. [CrossRef]
90. Cui, L.; Tian, X.; Wei, Q.; Liu, Y. A self-attention based contrastive learning method for bearing fault diagnosis. *Expert Syst. Appl.* **2024**, *238*, 121645. [CrossRef]
91. De Fabritiis, F.; Gryllias, K. A Self-supervised Learning Approach for Anomaly Detection in Rotating Machinery. In Proceedings of the Annual Conference of the PHM Society, Nashville, TN, USA, 9–10 November 2024; Volume 16.
92. Huang, C.; Xu, Q.; Wang, Y.; Wang, Y.; Zhang, Y. Self-Supervised Masking for Unsupervised Anomaly Detection and Localization. *IEEE Trans. Multimed.* **2022**, *25*, 4426–4438. [CrossRef]

93. Li, C.; Sohn, K.; Yoon, J.; Pfister, T. CutPaste: Self-Supervised Learning for Anomaly Detection and Localization. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), Virtual, 19–25 June 2021.
94. Holly, S.; Heel, R.; Katic, D.; Schoeffl, L.; Stiftinger, A.; Holzner, P.; Kaufmann, T.; Haslhofer, B.; Schall, D.; Heitzinger, C.; et al. Autoencoder Based Anomaly Detection and Explained Fault Localization in Industrial Cooling Systems. In Proceedings of the PHM Society European Conference, Turin, Italy, 6–8 July 2022.
95. Defard, T.; Setkov, A.; Loesch, A.; Audigier, R. PaDiM: A Patch Distribution Modeling Framework for Anomaly Detection and Localization. In Proceedings of the Pattern Recognition. ICPR International Workshops and Challenges, Virtual, 10–15 January 2021.
96. Thill, M.; Konen, W.; Wang, H.; Bäck, T. Temporal convolutional autoencoder for unsupervised anomaly detection in time series. *Appl. Soft Comput.* **2021**, *112*, 107751. [CrossRef]
97. Lee, H.; Yu, J. Fault Detection Framework for Rotating Machinery with a Spectrogram and Convolutional Autoencoder. *Appl. Sci.* **2025**, *15*, 7698. [CrossRef]
98. Neto, F.; Alves, W.; Cavalcante, V.; Alexandre, C.; Phuc, D. Deep reinforcement learning for maintenance optimization of a scrap-based steel production line. *Reliab. Eng. Syst. Saf.* **2024**, *249*, 110199. [CrossRef]
99. Matamoros, O.; Nava, J.; Escobar, J.; Chávez, B. Artificial Intelligence for Quality Defects in the Automotive Industry: A Systemic Review. *Sensors* **2025**, *25*, 1288. [CrossRef]
100. Khanam, R.; Hussain, M.; Hill, R.; Allen, P. A Comprehensive Review of Convolutional Neural Networks for Defect Detection in Industrial Applications. *IEEE Access* **2024**, *12*, 94250–94295. [CrossRef]
101. Chen, Z.-Y.; Lin, W.-C.; Ke, S.-W.; Tsai, C.-F. Evolutionary feature and instance selection for traffic sign recognition. *Comput. Ind.* **2015**, *74*, 201–211. [CrossRef]
102. Liu, Y.; Pan, S.; Gong, C.; Zhou, C.; Karypis, G. Anomaly Detection on Attributed Networks via Contrastive Self-Supervised Learning. *IEEE Trans. Neural Netw. Learn. Syst.* **2021**, *33*, 2378–2392. [CrossRef]
103. Tang, M.; Liang, L.; Zheng, H.; Chen, J.; Chen, D. Anomaly Detection of Permanent Magnet Synchronous Motor Based on Improved DWT-CNN Multi-Current Fusion. *Sensors* **2024**, *24*, 2553. [CrossRef]
104. Finn, C.; Abbeel, P.; Levine, S. Model-Agnostic Meta-Learning for Fast Adaptation of Deep Networks. In Proceedings of the 34th International Conference on Machine Learning, Sydney, Australia, 6–11 August 2017.
105. Wang, Y.; Li, J.; Yang, B.; Li, H. Stream-data-clustering based adaptive alarm threshold setting approaches for industrial processes with multiple operating conditions. *ISA Trans.* **2022**, *129*, 594–608. [CrossRef]
106. Choi, W.; Kim, J. Unsupervised Learning Approach for Anomaly Detection in Industrial Control Systems. *Appl. Syst. Innov.* **2024**, *7*, 18. [CrossRef]
107. Tricco, A.C.; Lillie, E.; Zarin, W.; O'Brien, K.K.; Colquhoun, H.; Levac, D.; Moher, D.; Peters, M.D.J.; Horsley, T.; Weeks, L.; et al. PRISMA Extension for Scoping Reviews (PRISMAScR): Checklist and Explanation. *Ann. Intern. Med.* **2018**, *169*, 467–473. [CrossRef]