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Comparative Analysis of Intelligent Algorithms for the Failure Prediction in Industrial Systems

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Abstract

Failure prediction in industrial systems constitutes a fundamental component for optimizing maintenance strategies, reducing operational costs, and ensuring safety within increasingly complex production environments. Conventional monitoring approaches, typically based on fixed thresholds or simplified statistical analyses, are often inadequate to capture the nonlinear, dynamic, and multi-scale behaviors that characterize modern industrial processes. This study presents a comprehensive and critical comparative analysis of the principal intelligent algorithms, including machine learning, deep learning, and hybrid approaches, applied to industrial failure prediction. By systematically evaluating their respective strengths, limitations, and domains of applicability, the study highlights persistent challenges, particularly regarding model interpretability and robustness under real-world operating conditions. Building upon these observations, a novel hybrid architecture is proposed, integrating wavelet-based signal decomposition, convolutional neural networks for feature extraction, long short-term memory networks for temporal modeling, and evolutionary optimization techniques. This approach is designed to enhance predictive accuracy, improve resilience to noisy sensor data, and provide more interpretable outputs. Overall, the proposed framework contributes to the development of a new generation of predictive maintenance tools better suited to the complexity and variability of modern industrial systems.

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1. Introduction

Predictive maintenance has become a critical component of modern industrial systems, as it enables the reduction of operational costs, the optimization of equipment availability, and the enhancement of operational safety (El

Hammoumi et al., 2025). In contrast to corrective and preventive maintenance strategies, predictive maintenance relies on the continuous monitoring and advanced analysis of data collected from sensors and control systems to anticipate potential failures before their occurrence (Lee et al., 2014).

The rapid proliferation of industrial data, coupled with significant advancements in digital technologies, has accelerated the development of intelligent algorithms, which have become indispensable for accurate and reliable failure prediction (Zhao et al., 2019). These approaches enable the automatic extraction of relevant features from complex datasets and facilitate the modeling of nonlinear and dynamic system behaviors, thereby often outperforming traditional rule-based or statistical methods (Wang et al., 2019).

Despite these considerable advancements, several critical challenges persist. These include ensuring the quality, availability, and representativeness of industrial data, improving the interpretability of increasingly complex models, and facilitating the effective integration of predictive solutions within real-world industrial environments (Susto et al., 2015). These limitations highlight the need for more robust, transparent, and adaptable predictive frameworks.

This review aims to provide a comprehensive and structured overview of intelligent algorithms for industrial failure prediction, with a particular focus on supervised and unsupervised learning techniques, ensemble methods, and hybrid architectures. For each category, the methodological foundations, implementation strategies, and practical applications across diverse industrial sectors are examined. In addition, key limitations—such as data dependency, computational complexity, and lack of interpretability—are critically analyzed. Emerging trends, including transfer learning, edge computing, and explainable artificial intelligence, are also discussed in light of the new challenges they introduce in terms of system integration and robustness.

Within this context, a rigorous comparative analysis is essential to support the selection of appropriate methods, identify existing research gaps, and guide the development of more efficient and scalable predictive solutions. This study addresses these needs by providing a critical comparative evaluation of intelligent algorithms applied to industrial failure prediction, while also proposing a hybrid architecture that integrates wavelet-based preprocessing, convolutional neural networks (CNN), long short-term memory (LSTM) networks, and evolutionary optimization techniques. This dual contribution aims to establish a set of design principles for the development of more reliable, robust, and interpretable predictive models adapted to the constraints of real-world industrial environments.

2. Methodology of the Review

This study adopts a structured analytical approach to provide a critical comparison of intelligent algorithms used for industrial failure prediction. The review focuses on representative methods from machine learning (ML), deep learning (DL), and hybrid approaches applied in predictive maintenance contexts. The comparison is based on key evaluation criteria, including predictive performance, robustness to noise, computational complexity, interpretability, and adaptability to industrial environments. Particular attention is given to the influence of data characteristics, such as dimensionality, temporal structure, and data quality.

A qualitative synthesis of existing studies is conducted to identify common trends, strengths, limitations, and research gaps. These insights are subsequently used to support the design of hybrid predictive architecture addressing the main limitations identified in current approaches

3. Overview of Key Intelligent Algorithms

The Failure prediction in industrial systems primarily relies on intelligent algorithms derived from machine learning and deep learning. These approaches enable the efficient exploitation of sensor data to detect anomalies and predict the future condition of equipment. This section provides a structured overview of the main families of algorithms employed in this domain.

3.1 Supervised Machine Learning

Associated with a predefined class (e.g., healthy or faulty state). These methods are widely used in prediction of industrial failure due to their relative simplicity, interpretability, and effectiveness on structured data.

Among the most used algorithms are:

- Support Vector Machines (SVM): SVMs construct optimal separating hyper planes in feature space and are particularly effective in handling complex classification tasks, especially in scenarios with limited or structured data (Lefrouni & Taibi, 2025).
- Decision Trees and Random Forests: are widely used in predictive maintenance due to their interpretability, robustness to noise, and ability to handle both categorical and continuous variables. Random Forests further enhance predictive performance through ensemble learning techniques (Zonta et al., 2021).
- K-Nearest Neighbors (KNN): This intuitive method relies on distance-based similarity between observations. While effective for simple datasets, its performance is highly sensitive to dimensionality and data scaling.
- Logistic Regression: Commonly used for binary classification tasks, this method models the probability of system failure and provides a high level of interpretability, although it is limited in capturing complex nonlinear relationships.

Overall, supervised machine learning methods are particularly suitable for structured datasets and industrial contexts where interpretability and computational efficiency are essential.

Table 1 summarizes the main approaches reported in the literature, highlighting their datasets, predictive performance, and key limitations.

Table 1. Overview of Machine Learning Algorithms: Performance Conditions and Limitations

Algorithm	Strengths	Limitations	Optimal Conditions	Industrial Relevance
SVM	High classification accuracy in low-dimensional spaces	Poor scalability on large datasets	Well-separated classes, limited data size	Fault classification in controlled environments
Random Forest	Robust to noise, handles mixed data types, good interpretability	Moderate computational cost	Structured datasets with heterogeneous variables	Predictive maintenance with sensor fusion
KNN	Simple implementation, no training phase	Sensitive to dimensionality and noise	Low-dimensional datasets, small sample size	Basic anomaly detection tasks
Logistic Regression	High interpretability, probabilistic output	Limited to linear relationships	Binary classification with simple relationships	Failure probability estimation

3.2 Deep Learning

Deep learning relies on multi-layer neural network architectures capable of automatically extracting high-level and complex features from raw data. Unlike traditional machine learning approaches, which often require manual feature engineering, deep learning models learn hierarchical representations directly from input signals. This makes them particularly suitable for handling complex and high-dimensional industrial datasets.

Among the most used deep learning models in failure prediction are:

- Multilayer Perceptron (MLP): MLPs are fully connected neural networks that are well suited for tabular and structured data. They enable the modeling of nonlinear relationships between input variables and system states. However, their performance may be limited when dealing with spatial or temporal dependencies inherent in industrial signals.

- Convolutional Neural Networks (CNN): CNNs are particularly effective for processing data with spatial structure, such as images or time–frequency representations of signals (e.g., vibration spectrograms). They automatically extract relevant spatial features through convolutional layers, reducing the need for manual feature design and improving fault detection accuracy (Zhao et al., 2019).
- Recurrent Neural Networks (RNN), including Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU): These architectures are specifically designed to process sequential and temporal data. They are widely used for analyzing sensor time series and capturing long-term dependencies in system behavior, making them highly suitable for degradation modeling and failure prediction (Malhotra et al., 2015).

Deep learning approaches demonstrate strong performance in complex industrial environments, particularly when large volumes of data are available. However, their effectiveness is often constrained by high computational requirements, the need for extensive labeled datasets, and limited interpretability in practical applications. These characteristics are synthesized in Table 2, which summarizes the strengths, optimal conditions, and limitations of the main deep learning models used for failure prediction.

Table 2. Performance Conditions and Limitations of Deep Learning Models in Industrial Failure Prediction

Model	Strengths	Optimal Conditions	Limitations	Failure Scenarios
CNN	Automatic extraction of spatial features; high accuracy on structured signal representations	Data represented as spectrograms or images (e.g., transformed vibration signals); large training datasets; availability of GPU resources	Requires large, labeled datasets; computationally intensive	Low efficiency when signals lack clear spatial structure; risk of overfitting on small datasets
LSTM / GRU	Effective modeling of temporal dependencies; suitable for sequential data	Long time-series data with strong temporal continuity (e.g., IoT sensor streams)	High training time; significant memory requirements	Sensitive to noisy or short sequences; performance degradation with irregular sampling
MLP	Simple architecture; effective for tabular data; models nonlinear relationships	Large, structured datasets with moderate nonlinear interactions	Limited ability to capture spatial and temporal dependencies	Outperformed by CNN or LSTM when spatial or temporal structure dominates

3.3 Hybrid Methods and Expert Systems

In many industrial applications, a single algorithm may not be sufficient to achieve reliable failure prediction. To overcome the limitations of individual methods, hybrid approaches combine complementary techniques to improve predictive performance, robustness, and generalization capability. These approaches leverage the strengths of different models while mitigating their respective weaknesses.

In industrial failure prediction, hybrid methods often integrate statistical modeling, machine learning, and domain-specific knowledge. Typically, a model is formulated using key system parameters, and operational data are subsequently collected and analyzed to estimate indicators such as the Remaining Useful Life (RUL) of equipment. This framework can be extended to develop hybrid fault detection systems that combine data-driven and model-based approaches. Such methods are particularly valuable when dealing with noisy or incomplete data, complex nonlinear system dynamics, or situations where both statistical learning and expert knowledge are required. However, the integration of multiple components may increase system complexity and require careful calibration, making implementation more demanding.

3.3.1 Neural Network and Signal Processing Hybrids

A common hybrid strategy consists of combining signal processing techniques with neural networks. In this approach, preprocessing methods such as wavelet transforms or Short-Time Fourier Transform (STFT) are applied to raw sensor data to reduce noise and extract discriminative time–frequency features. These processed representations are then used as inputs to deep learning models such as CNN or LSTM. This combination significantly improves sensitivity to weak fault signatures and enhances robustness to noisy environments. Nevertheless, the overall performance remains highly dependent on the quality of preprocessing, and inappropriate parameter selection may propagate errors throughout the prediction pipeline.

Several studies illustrate the effectiveness of this approach. Recent studies have leveraged vibration signal analysis combined with advanced machine learning and deep learning techniques for early fault detection in industrial systems (Zhang et al., 2022). Time–frequency representations, such as wavelet transforms and spectrograms, are widely used to extract meaningful features from non-stationary signals (Zhang et al., 2022; Wen et al., 2022; Nguyen et al., 2023). These features are then analyzed using neural networks, including convolutional and recurrent architectures, to improve fault classification and diagnostic accuracy under varying operating conditions (Li & Li, 2025; Carvalho et al., 2021; Achouch et al., 2022). Such hybrid approaches have demonstrated strong performance in handling complex industrial environments and ensuring reliable diagnostics.

Vibration analysis remains a widely used technique for monitoring industrial machinery due to its effectiveness in capturing early signs of degradation. Recent studies have combined vibration signal processing with advanced machine learning and deep learning techniques to improve fault detection accuracy, even in noisy industrial environments (Zhang et al., 2022; Zhao et al., 2021; Pandya et al., 2022; Nguyen et al., 2023). In particular, neural network-based models, including convolutional architectures, have demonstrated strong robustness in classifying vibration patterns and detecting anomalies under varying operating conditions (Li & Li, 2025). However, the performance of these approaches strongly depends on effective signal preprocessing and feature extraction, as improper configuration can significantly reduce model reliability.

3.3.2 Statistical–Physical Hybrid Methods

Another important category of hybrid approaches involves the integration of statistical models with physical system knowledge. In these methods, physics-based parameters—such as wear mechanisms or stress measurements—are combined with machine learning or deep learning models to improve prediction accuracy and interpretability. This integration enhances the ability of models to generalize across different operating conditions, particularly when reliable physical insights are available. However, the development of such models requires detailed understanding of the system and may involve complex multi-physics modeling, which can limit their practical implementation.

Several studies have explored this approach. Recent studies have explored data-driven and hybrid approaches to improve failure prediction accuracy in industrial systems (Carvalho et al., 2021; Zhang et al., 2022). Machine learning and deep learning models have been widely applied to capture complex degradation patterns and enhance predictive performance (Carvalho et al., 2021; Zhang et al., 2022; Li & Li, 2025). In addition, hybrid frameworks combining data-driven techniques with domain knowledge have been proposed to improve fault detection and system monitoring (Jardine et al., 2021; Wen et al., 2022; Achouch et al., 2022). Although these approaches can achieve high predictive accuracy, they often remain dependent on data quality, model interpretability, and the availability of domain expertise.

3.4 Optimization-Enhanced Learning

Evolutionary algorithms, such as Genetic Algorithms (GA) and Particle Swarm Optimization (PSO), are increasingly employed to enhance the performance of predictive models in industrial failure prediction. These techniques are typically used to optimize feature selection, neural network architecture, and hyperparameter configurations, thereby improving model accuracy and convergence efficiency.

By exploring large and complex search spaces, optimization-enhanced learning methods can significantly improve predictive performance and enable more efficient model tuning. They facilitate the identification of optimal parameter combinations that would be difficult to obtain through manual calibration. However, these advantages come at the cost of increased computational complexity, and the effectiveness of such approaches strongly depends on the proper definition of the search space. Poorly configured optimization processes may lead to overfitting or suboptimal solutions, especially in data-limited environments.

A comparative synthesis of hybrid and optimization-enhanced approaches is presented in Table 3, highlighting their performance characteristics and operational constraints.

Table 3. Comparative Analysis of Hybrid and Optimization-Enhanced Approaches

Approach	Key Components	Strengths	Limitations	Optimal Conditions	Deployment Constraints
Signal Processing + DL (CNN/LSTM)	Wavelet / STFT + CNN / LSTM	High sensitivity to weak faults; robust feature extraction in noisy environments	Strong dependence on preprocessing quality; parameter tuning complexity	Noisy signals; faults localized in specific frequency bands	High computational cost; requires careful preprocessing design
Statistical–Physical Hybrid	Physical models + statistical / ML models	Improved interpretability; good generalization with limited data	Requires accurate physical modeling; complex implementation	Systems with well-understood physical behavior; limited datasets	High expertise required; multi-physics modeling complexity
Optimization-Enhanced Learning (GA, PSO)	Evolutionary algorithms + ML/DL models	Improved accuracy; efficient hyperparameter tuning; better convergence	High computational cost; risk of overfitting if search space is poorly defined	Complex models requiring parameter optimization; large search spaces	Limited real-time applicability; resource-intensive training
Fully Hybrid Systems	Signal processing + DL + optimization	Highest predictive performance; strong robustness to noise and variability	Very high complexity; difficult calibration and integration	Complex industrial environments; heterogeneous data sources	Challenging deployment on edge systems; high hardware requirements

3.4.1 Performance Insights

The analysis of existing studies reveals that the performance of hybrid and optimization-based methods is highly dependent on the nature of the data and the configuration of the modeling pipeline. Approaches combining signal processing techniques with deep learning models, such as CNN or LSTM, demonstrate superior performance in environments characterized by high levels of noise or when fault signatures are subtle and localized within specific frequency bands. These methods benefit from enhanced feature extraction capabilities, which improve the detection of early-stage faults.

In contrast, statistical–physical hybrid models are more suitable when reliable physical representations of the system are available, but data remain limited. In such cases, the integration of domain knowledge compensates for the lack of extensive datasets and improves model interpretability.

Despite their strong predictive capabilities, these approaches exhibit several failure modes. Model performance may degrade significantly when preprocessing steps are improperly configured, particularly in techniques involving STFT or wavelet transformations, where parameter selection is critical. In addition, the high computational requirements associated with hybrid and optimization-enhanced models can limit their deployment in real-time applications, especially in edge or embedded systems with constrained resources.

4. Advantages of Intelligent Algorithms

Intelligent algorithms, including machine learning (ML), deep learning (DL), and hybrid approaches, constitute powerful tools for predictive maintenance (PdM) in modern industrial systems. Their effectiveness lies in their ability to process large volumes of data, extract meaningful patterns, and provide accurate predictions in complex and dynamic environments. The following subsections highlight their main advantages, supported by representative industrial and research applications.

4.1 Ability to Handle Large-Scale and Multivariate Data

Modern industrial systems generate massive streams of multivariate sensor data, including vibration, temperature, pressure, and voltage measurements. Intelligent algorithms are particularly well suited to process such high-dimensional datasets and extract relevant information for failure prediction.

Wahid et al. (2022) developed a hybrid CNN–LSTM framework for predictive maintenance in an Industry 4.0 environment, demonstrating improved accuracy and robustness compared with standalone CNN or LSTM models when handling high-dimensional sensor data. Similarly, (Molano et al., 2022) applied Random Forest models to vibration and temperature data from a tube-filling machine, achieving a significant improvement in Overall Equipment Effectiveness (OEE) compared with traditional rule-based maintenance strategies. These results illustrate the capacity of intelligent algorithms to efficiently manage complex and heterogeneous data sources.

4.2 Automatic Feature Extraction

A major advantage of deep learning approaches lies in their ability to automatically extract hierarchical and discriminative features directly from raw sensor signals, thereby reducing the need for manual feature engineering.

Wahid et al., (2022) demonstrated that convolutional layers can automatically identify relevant time–frequency patterns prior to LSTM-based temporal modeling, significantly reducing engineering effort. Similarly, (Zhao et al., 2019) achieved high accuracy in bearing fault detection by allowing CNN models to learn features directly from vibration spectrograms, leading to a substantial reduction in model development time compared with traditional feature engineering approaches.

4.3 Flexibility and Adaptability across Equipment Types

Intelligent algorithms exhibit a high degree of flexibility and can be adapted or fine-tuned to different industrial assets and operating conditions. This adaptability makes them suitable for a wide range of applications across diverse industrial sectors.

Xu et al. 2022 proposed a deep learning framework combined with augmented reality for predictive maintenance in IoT-enabled machine tools, showing that a common CNN–LSTM architecture could be adapted to multiple machining operations. In addition, Molano et al., 2022 demonstrated that machine learning models can be effectively transferred across different rotating machinery datasets with minimal redesign, highlighting their scalability and adaptability.

4.4 Superior Predictive Performance

By capturing complex nonlinear relationships and temporal dependencies, intelligent algorithms often outperform traditional statistical methods in failure prediction tasks.

(Hasib et al. 2023) reported that GRU and LSTM models achieved accuracy approaching 97% on the NASA CMAPSS dataset for engine predictive maintenance. Similarly, (Peng et al. 2019) achieved an accuracy of 96.1%

using deep CNN models for bearing fault diagnosis under noisy conditions, outperforming classical methods such as Support Vector Machines. These results confirm the superior predictive capabilities of deep learning and hybrid approaches in complex industrial environments.

4.5 Integration into Modern Industrial Systems

Recent advancements in cloud computing and edge computing have facilitated the integration of intelligent algorithms into real-time industrial systems. These technologies enable the deployment of computationally intensive models without disrupting production processes.

(Susto et al. 2015) implemented a multi-classifier predictive maintenance system in an electronics manufacturing environment, achieving real-time fault prediction while maintaining operational continuity. This demonstrates the growing feasibility of integrating advanced predictive models into industrial infrastructures.

5. Limitations and Challenges

Despite their significant advantages, intelligent algorithms for failure prediction present several limitations that must be addressed to ensure effective and sustainable industrial deployment.

5.1 Computational Complexity and Hardware Requirements

Deep learning models, particularly CNNs, LSTMs, and hybrid architectures, require substantial computational resources and memory capacity. This constraint can limit their applicability in environments with restricted hardware capabilities.

Wahid et al. (2022) reported that their CNN–LSTM hybrid model, although highly accurate, required significant training time and GPU resources, thereby limiting its deployment on edge devices.

5.2 Limited Interpretability

Many intelligent models, especially deep learning approaches, operate as black-box systems, making it difficult for engineers to interpret and validate their predictions. This lack of transparency can reduce user trust and hinder adoption in safety-critical applications.

Hrnjica et al. 2020 demonstrated the use of explainable artificial intelligence (XAI) techniques in predictive maintenance, highlighting the importance of post hoc interpretability methods to improve understanding and acceptance of model outputs.

5.3 Sensitivity to Data Quality and Representativeness

The performance of intelligent algorithms is highly dependent on data quality. Noisy, incomplete, or non-representative datasets can significantly degrade model accuracy and reliability.

Peng et al. 2019 reported a noticeable decrease in prediction accuracy when vibration signals contained noise not represented in the training data, illustrating the importance of robust data preprocessing and dataset representativeness.

5.4 Integration and Organizational Constraints

Beyond technical challenges, the successful deployment of predictive maintenance systems also depends on organizational and infrastructural factors. The integration of intelligent algorithms requires compatible IT/OT systems, reliable data pipelines, and adequately trained personnel.
Molano et al., 2022 observed that hardware limitations could constrain predictive performance despite strong algorithmic capabilities. Furthermore, Olokede et al. (2025) emphasized that the success of predictive maintenance initiatives depends not only on algorithm performance but also on organizational readiness and the stability of data management systems.

6. Comparative Summary

The central objective of this review is to provide a systematic comparison of the main intelligent algorithms applied to industrial failure prediction. While previous sections detailed the methodological principles, strengths, and limitations of each approach, this section synthesizes quantitative evidence from multiple studies in order to highlight their relative performance and contextual suitability.

6.1 Cross-Study Insights

Numerous benchmark studies have evaluated predictive algorithms using widely recognized datasets, such as the Case Western Reserve University (CWRU) bearing dataset, the NASA CMAPSS turbofan engine dataset, and various proprietary industrial sensor datasets. These evaluations provide valuable insights into the comparative performance of different algorithmic approaches under diverse conditions.

The analysis of these studies reveals consistent performance trends across algorithm families. Random Forest models demonstrate high accuracy, typically around 95%, while maintaining moderate computational cost, making them particularly suitable for structured sensor data and real-time monitoring in manufacturing environments (Molano et al., 2022). Similarly, Support Vector Machines achieve competitive performance, with accuracy levels around 93% when class boundaries are well defined and datasets are of moderate size (Peng et al., 2019).

Deep learning models exhibit superior performance in more complex data scenarios. Convolutional Neural Networks consistently outperform classical machine learning approaches when applied to high-dimensional vibration or acoustic signals, achieving accuracy levels between 95% and 97% on noisy bearing datasets (Zhao et al., 2021). Recurrent architectures, including LSTM and GRU networks, are particularly effective for sequential data analysis, reaching accuracies of 96–97% on the NASA CMAPSS dataset when sufficient labeled temporal data are available (Hasib et al., 2023).

Hybrid approaches generally provide the highest predictive performance. Models combining signal processing techniques with deep learning architectures—such as wavelet-CNN, CNN-LSTM, or CNN integrated with evolutionary optimization—frequently exceed 97% accuracy, particularly in environments characterized by high noise levels or incomplete data (Wahid et al., 2022). This superior performance highlights the advantage of combining complementary techniques to address complex industrial conditions.

These comparative results are summarized in Table 4, which provides a structured overview of algorithm performance across different datasets and operational contexts.

Table 4. Comparative Performance of Intelligent Algorithms for Industrial Failure Prediction

Algorithm	Typical Accuracy	Data Type	Strengths	Limitations	Optimal Use Cases
Random Forest (RF)	~95%	Structured sensor data (tabular, multivariate)	Robust to noise; good interpretability; moderate computational cost	Limited performance on highly complex nonlinear patterns	Real-time monitoring; industrial systems with structured data
Support Vector Machine (SVM)	~93%	Medium-sized structured datasets	Effective in well-defined class boundaries; good generalization	Poor scalability with large datasets; sensitive to parameter tuning	Fault classification with moderate dataset size
Convolutional Neural Networks (CNN)	95–97%	High-dimensional signals (vibration, acoustic, images)	Automatic feature extraction; high accuracy on complex data	High computational cost; requires large labeled datasets	Signal-based fault diagnosis; noisy industrial environments

LSTM / GRU	96–97%	Time-series data (sensor sequences)	Captures temporal dependencies; effective for degradation modeling	High training time; sensitive to data quality	Sequential data (e.g., engine cycles, IoT monitoring)
Hybrid Models (CNN + LSTM, Wavelet + CNN, etc.)	>97%	Complex, noisy, or incomplete datasets	Highest accuracy; strong robustness; combines multiple strengths	High complexity; difficult tuning; high computational requirements	Complex industrial environments; multi-source data systems

7. Proposed Hybrid Algorithm

Building on the comparative analysis of existing approaches and their identified limitations—particularly the lack of interpretability, sensitivity to noise, and difficulty in capturing long-term temporal dependencies—this study proposes a novel hybrid architecture for industrial failure prediction. The proposed framework integrates wavelet-based signal preprocessing, Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM) networks, Genetic Algorithm (GA) optimization, and an embedded explainability module.

The objective of this architecture is to simultaneously achieve high predictive accuracy, robustness to noisy sensor data, and enhanced interpretability, thereby addressing key challenges associated with real-world industrial deployment.

7.1 Motivation

The comparative analysis presented in Section 5 highlights several limitations in existing approaches. Convolutional Neural Networks are highly effective for extracting features from high-dimensional signals but remain limited in modeling long-term temporal dependencies. Conversely, LSTM-based models are well suited for capturing sequential dynamics, yet their performance strongly depends on the quality of input preprocessing.

Furthermore, most existing hybrid approaches focus primarily on combining feature extraction and temporal modeling, while often neglecting adaptive hyperparameter optimization and integrated interpretability mechanisms. This results in models that, although accurate, remain difficult to calibrate and interpret in industrial contexts.

The proposed architecture addresses these limitations by combining complementary techniques within a unified and optimized pipeline, enabling both improved predictive performance and greater transparency.

7.2 Methodological Framework

The proposed hybrid model follows a multi-stage processing pipeline designed to progressively transform raw sensor data into reliable and interpretable predictions.

First, wavelet-based preprocessing is applied using multi-resolution wavelet packet decomposition to isolate the most informative time–frequency components while reducing noise. This step enhances signal quality and facilitates subsequent feature extraction.

Next, the processed signals are transformed into time–frequency representations and provided as input to a Convolutional Neural Network. The CNN automatically learns discriminative spatial features, capturing localized fault patterns within the signal.

The extracted features are then passed to a Long Short-Term Memory network, which models temporal dependencies and captures degradation trends over time. This combination allows the model to account for both spatial and temporal characteristics of industrial data.

To further improve model performance, a Genetic Algorithm is employed to optimize key hyperparameters, including network architecture and training configurations. This adaptive optimization process enables efficient exploration of the parameter space while balancing accuracy and computational cost.

Finally, an explainability module based on techniques such as SHAP or LIME is integrated into the pipeline. This component provides insights into the contribution of input features to model predictions, thereby enhancing transparency and facilitating decision-making for industrial operators.

A schematic representation of the proposed architecture is provided in Figure 1.

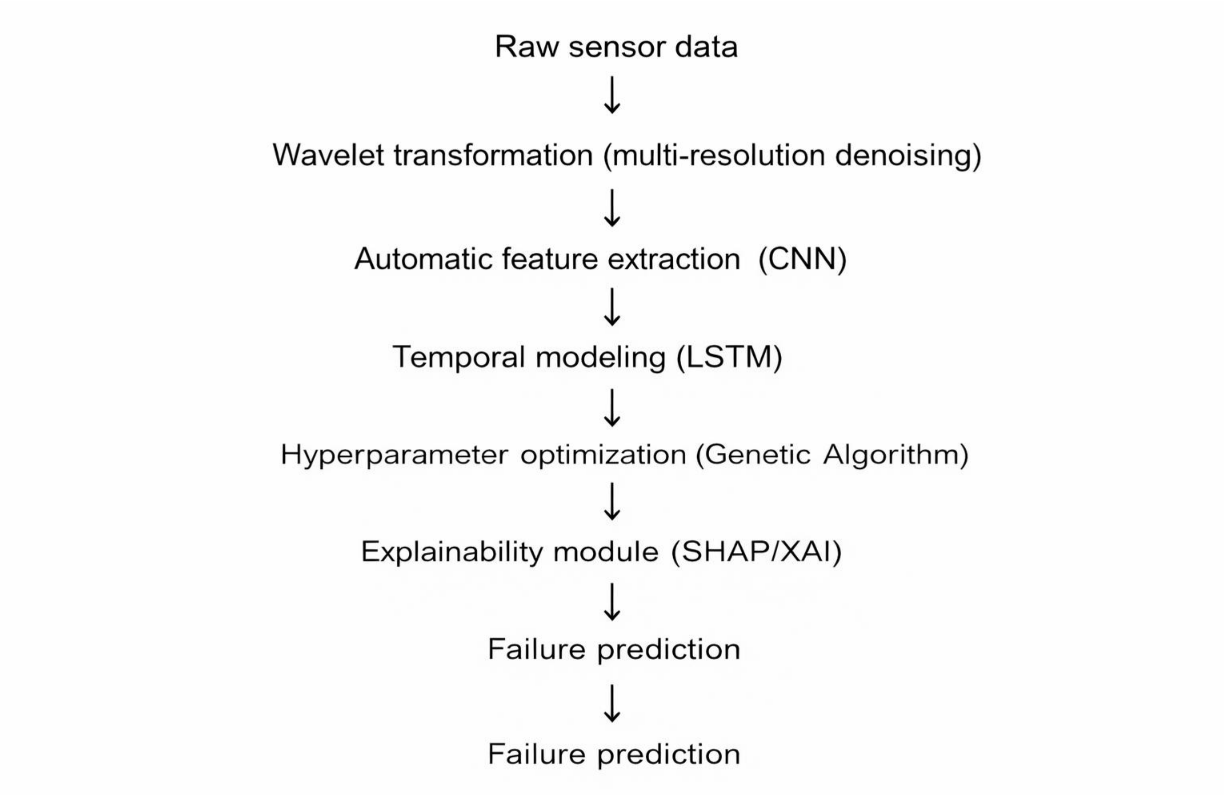

Figure 1. Proposed Hybrid Algorithm: Multi-Stage Processing for Industrial Failure Prediction.

7.3 Differentiation from Existing Hybrid Models

Compared to existing hybrid approaches, such as Wavelet-CNN or CNN-LSTM models, the proposed architecture introduces several key innovations.

First, it integrates multiple processing stages—signal preprocessing, spatial feature extraction, temporal modeling, and optimization—within a unified framework, enabling end-to-end learning and improved overall performance. Second, it incorporates a native explainability module, reducing reliance on purely post hoc interpretation methods and improving model transparency. Third, architecture is specifically designed for high-noise industrial environments, such as agro-industrial production systems, where signal variability is significant and robust feature extraction is essential.

7.4 Development Status

At this stage, the proposed hybrid model remains a methodological framework supported by preliminary simulations. Experimental validation on real-world industrial datasets is planned as the next phase of the study. Future work will focus on large-scale empirical evaluation, comparative benchmarking, and validation under diverse operational conditions.

7.5 Industrial Prospects

The proposed architecture presents several advantages for industrial deployment. Its modular design ensures flexibility, allowing adaptation to various types of equipment, including rotating machinery, electric motors, and agro-industrial production systems.

Moreover, the integration of Genetic Algorithm optimization enables a balance between predictive performance and computational constraints, facilitating potential deployment in edge computing environments. The inclusion of an explainability module further enhances user trust and supports informed maintenance decision-making, thereby improving the practical applicability of the model in industrial contexts.

8. Conclusion

This study provided a critical and comparative review of intelligent algorithms for prediction of industrial failure, emphasizing both their strengths and inherent limitations. Through the analysis of machine learning, deep learning, and hybrid approaches, it was demonstrated that no single method ensures universal superiority. Classical machine learning models remain highly effective when dealing with structured data and when interpretability is required, whereas deep learning approaches achieve superior performance on complex and high-dimensional signals, albeit at the cost of increased computational demands and stricter data requirements. Hybrid methods, by combining multiple techniques, generally offer improved robustness and predictive performance in noisy industrial environments, although they often involve higher implementation complexity and require careful configuration.

Beyond this comparative perspective, the study proposed an innovative hybrid architecture integrating wavelet-based preprocessing, CNN-driven feature extraction, LSTM-based temporal modeling, Genetic Algorithm optimization, and an embedded explainability module. This integrated framework addresses critical industrial challenges by simultaneously enhancing prediction accuracy, robustness to noise, and interpretability, three key requirements that are rarely satisfied together in existing solutions.

However, this work remains primarily methodological. While preliminary validations have been conducted on benchmark datasets, real-world implementation, particularly within agro-industrial production systems, constitutes the next stage of development. Future research will therefore focus on the acquisition and annotation of industrial operational data, large-scale experimental validation, and the optimization of deployment strategies, including integration into edge computing environments and explainable AI frameworks.

By combining a rigorous comparative analysis with the design of a novel hybrid approach, this study contributes both to the theoretical advancement of predictive maintenance methodologies and to their practical applicability in modern industrial contexts.

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Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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