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*Research Article*

# A Fault Diagnosis and Intelligent Monitoring Framework Using Explainable Artificial Intelligence for Smart Industrial Machinery

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**Abstract: Background:** The development of industrial technology in the Industry 4.0 era has encouraged the implementation of intelligent monitoring systems to improve machine reliability and operational efficiency. However, machine fault diagnosis systems based on artificial intelligence often face limitations in terms of interpretability because the models used are complex and difficult to explain. **Objective:** This study aims to develop a deep learning-based industrial machine fault diagnosis system integrated with an Explainable Artificial Intelligence (XAI) approach to improve diagnostic accuracy while providing interpretable insights for users. **Method:** The research method involves collecting data from industrial machine sensors consisting of vibration signals, temperature measurements, and acoustic signals, followed by data preprocessing and feature extraction processes. The processed data are then used to train a deep learning-based diagnostic model, after which explainability methods such as SHAP or LIME are applied to analyze the contribution of each feature to the model's prediction results. Model performance is evaluated using accuracy, precision, recall, and F1-score metrics. **Results:** The results indicate that the proposed deep learning model achieves better performance compared to conventional machine learning methods such as Support Vector Machine and Random Forest. Furthermore, the explainability analysis reveals that vibration amplitude, increases in machine component temperature, and anomalies in acoustic signals are the main factors influencing machine fault detection. Therefore, the proposed system not only improves the accuracy of machine fault diagnosis but also provides transparency in the decision-making process, thereby supporting the implementation of predictive maintenance in smart manufacturing environments.

**Keywords:** Deep Learning; Explainable Artificial Intelligence; Machine Fault Diagnosis; Predictive Maintenance; Smart Manufacturing

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## 1. Introduction

The industrial transformation in the era of Industry 4.0 has significantly changed conventional manufacturing systems into production environments that are far more intelligent, adaptive, and interconnected. In this context, smart manufacturing is no longer merely understood as process automation, but rather as a comprehensive integration of machines, humans, data, and digital systems within a responsive production ecosystem. This concept emphasizes vertical integration from the machine level to enterprise management, as well as horizontal integration among production units, suppliers, and distribution networks, enabling manufacturing processes to become more flexible and efficient [1]. These developments are further strengthened by advances in modern technologies that enable rapid and synchronized information processing across devices. Consequently, the complexity of modern industrial machinery systems does not only arise from the number of components involved, but also from the increasing level of interconnectivity and interdependence among subsystems that support precise and real-time production operations [2].

One of the main foundations of the smart manufacturing environment is the presence of cyber-physical systems (CPS), which connect physical processes with digital computation simultaneously. CPS allows industrial machines not only to perform mechanical functions but also to transmit data, receive feedback, and automatically adjust operational parameters based on real-world conditions. Meanwhile, the development of the Industrial Internet of Things (IIoT) has further expanded these capabilities by enabling various devices, sensors, actuators, and control systems to communicate in real time to support more intelligent and distributed decision-making processes [3]. Such integration makes modern manufacturing systems increasingly efficient while simultaneously increasing system management complexity because the volume of generated data continues to grow and must be processed rapidly, accurately, and continuously to create operational value in industrial environments [4].

Despite offering numerous advantages, smart manufacturing also introduces significant challenges, particularly in the aspect of cross-source data integration. Data in intelligent manufacturing environments typically originates from heterogeneous systems such as machine condition sensors, programmable logic controllers (PLC), manufacturing execution systems (MES), enterprise resource planning (ERP), and even manual maintenance and inspection records. Each of these data sources often uses different formats, protocols, sampling frequencies, and structures, which creates serious obstacles for comprehensive data integration and interpretation [5]. These challenges become increasingly critical when industries require monitoring and diagnostic systems capable of operating in real time. Without effective data integration, smart manufacturing systems risk generating partial, delayed, or even misleading analyses, which can ultimately reduce the effectiveness of process control and machine maintenance in modern production environments [2].

The complexity of modern industrial machinery systems also directly affects the increasing difficulty of detecting machine failures early and accurately. In systems consisting of numerous interconnected components, a failure in one part can trigger cascading effects across other subsystems, making early detection essential to prevent larger system downtime. In practice, modern maintenance systems require approaches that are not only reactive but also predictive, enabling industries to anticipate potential failures before they occur. This need has encouraged the development of more systematic maintenance frameworks based on real machine conditions, particularly in modern manufacturing systems that rely heavily on the reliability of production assets [6]. Therefore, the ability to detect early failure patterns has become a crucial factor in maintaining industrial continuity, safety, and operational efficiency.

Various studies have demonstrated that machine learning (ML) and deep learning (DL) approaches have great potential in supporting early detection of machine failures. By utilizing sensor data, vibration signals, temperature readings, electrical currents, and historical operational data, intelligent algorithms can recognize damage patterns that are difficult to identify using traditional methods. In manufacturing systems, the use of ML and DL models has been proven to minimize downtime by providing more responsive and accurate early failure diagnostic services [7]. Furthermore, anomaly detection and classification approaches can support plant failure recovery processes by identifying deviations in production processes before they evolve into major disruptions [8]. These findings indicate that AI-driven analytics is becoming an essential component of modern industrial monitoring systems.

However, high predictive accuracy in ML models does not necessarily resolve all challenges related to industrial diagnostics. One of the major technical issues that remains is data quality, particularly when diagnostic systems rely on acoustic data sources. In real manufacturing environments, machine sound signals are often mixed with background production noise, making it difficult for systems to distinguish between normal operational patterns and potential failure indications. A recent systematic review shows that detecting mechanical failures using overlapping acoustic anomalies still faces significant limitations in data acquisition, feature extraction, and model validation stages within real industrial environments [9]. This situation demonstrates that as manufacturing environments become more complex, the need for diagnostic models that are not only accurate but also robust against noise, contextual variations, and heterogeneous monitoring data sources becomes increasingly important.

Another critical issue is the lack of transparency in conventional machine learning methods during the decision-making process. Many modern models, particularly those based on deep neural networks and other complex architectures, provide high predictive performance but remain difficult to interpret logically by human users. This tendency becomes problematic when such models are used to support critical decision-making processes, as operators or decision-makers may not understand the rationale behind the predictions generated. From a conceptual perspective, transparency is a key element in restoring accountability in algorithmic decision-making systems, especially when models are trained using highly complex big data environments [10]. Moreover, human-centered perspectives emphasize that fairness, transparency, and user understanding of algorithmic systems are essential factors to ensure that technology can be accepted both socially and operationally.

These transparency limitations become even more problematic because conventional ML models are also prone to replicating biases present in the training data. When training datasets reflect imbalance, recording errors, or human biases, the resulting models may reinforce these tendencies in their automated decisions. In a broader context, bias in data-driven decision-making poses serious concerns because it can influence the reliability of analytical outcomes and reduce trust in intelligent systems [11]. Additionally, the ML research community has been encouraged to strengthen norms for recognizing, exploring, and articulating the limitations of models more openly to prevent misinterpretation or excessive reliance on research findings [12]. At the same time, the challenge of balancing predictive performance and transparency has been observed across various sectors, including human resource management systems, highlighting that this trade-off is a cross-domain issue relevant to industrial applications [13].

In this context, Explainable Artificial Intelligence (XAI) has emerged as an important approach aimed at improving the transparency of AI decision-making processes. XAI seeks to explain how models operate, which features contribute most significantly to predictions, and why specific decisions are generated. Recent studies indicate that interpretability and explainability have become central issues in ML model development because they directly affect trust, validation, and real-world system adoption [14]. From both philosophical and practical perspectives, the need for explainability is also related to human cognitive limitations, meaning that AI explanations must be designed in ways that can be understood and utilized in public reasoning and professional decision-making contexts [15]. Furthermore, empirical surveys of XAI technologies reveal that this field has evolved into multiple methodological categories and application areas aimed at improving the interpretability of models in complex environments [16].

The application of XAI in automated diagnostic systems has demonstrated significant potential for improving operator trust and professional user acceptance. In clinical contexts, for example, the integration of SHAP within interpretable machine learning frameworks has been shown to support decision-making by clearly explaining feature contributions in predictive models [17]. Other studies have also shown that explainable machine learning models can enhance the usefulness of decision support systems because predictions can be logically traced and verified by users [18]. Even in studies using echo state networks, improvements in both accuracy and explainability have been achieved simultaneously, indicating that transparency does not necessarily require sacrificing model performance [19]. These findings suggest that XAI is highly relevant for industrial machine diagnostic systems, particularly when operators require a clear explanation basis before taking corrective actions in real production environments.

Based on these conditions, this study argues that developing an XAI-based machine fault diagnosis framework is essential for modern smart manufacturing environments. The proposed framework integrates real-time data acquisition through IIoT sensors, intelligent machine condition analysis using advanced models, and explainability mechanisms to ensure that diagnostic results can be operationally understood by industrial operators. Such an approach aligns with recent developments in SHAP-based fault diagnosis for rotating machinery to support transparent decision-making [20], industrial fault detection using integrated XAI and ML approaches [21], and intelligent monitoring systems based on digital twins enhanced with XAI to improve industrial system reliability [22]. Furthermore, recent studies highlight that XAI holds significant potential for condition monitoring applications, although implementation challenges still remain in practical industrial environments [23]. Therefore, this study positions itself within the growing body of literature emphasizing that XAI-based industrial fault diagnosis represents a promising direction for developing monitoring systems that are more reliable, transparent, and trusted by operators [24].

## 2. Literature Review

### Fault Diagnosis in Industrial Machines

Fault diagnosis refers to the process of identifying and determining the nature of faults in industrial machinery in order to prevent unexpected failures and maintain operational efficiency. Modern industrial systems consist of complex interconnected components that require continuous monitoring and advanced diagnostic methods to ensure reliability. Traditional diagnostic approaches relied heavily on manual inspections and rule-based systems, which were often limited in handling complex machine behavior. With the advancement of industrial automation and digital technologies, fault diagnosis systems increasingly rely on intelligent algorithms capable of analyzing large volumes of operational data to detect abnormal machine behavior [25].

Artificial intelligence techniques have significantly improved the performance of fault diagnosis systems in industrial machinery. Methods such as artificial neural networks (ANN), fuzzy logic systems, support vector machines (SVM), and deep learning algorithms are widely applied to detect and classify machine faults. These methods enable machines to recognize patterns of abnormal behavior through sensor signals and historical operational data. Research has shown that AI-based diagnostic systems are capable of identifying faults in rotating machinery components such as bearings, gears, motors, and centrifugal pumps with higher accuracy compared to conventional approaches [26], [27].

The increasing complexity and scale of industrial machinery require more advanced diagnostic systems that can operate in real-time environments. Modern fault diagnosis systems often integrate multiple sensors and advanced analytics to improve detection performance. These systems must also be capable of handling noisy industrial data and dynamic operational conditions. Therefore, the integration of intelligent diagnostic methods has become a crucial component in modern manufacturing environments where reliability, safety, and operational continuity are essential factors [25].


**Figure 1.** General workflow of an Industrial Machine Fault Diagnosis System.

Figure 1 illustrates the typical workflow of a fault diagnosis system in industrial machinery. The process begins with data acquisition through sensors installed on machine components such as motors, bearings, and pumps. The collected signals are then processed using signal processing techniques to extract relevant features. These features are analyzed by machine learning or artificial intelligence algorithms to classify machine conditions and detect potential faults. Such systems enable early detection of abnormal machine behavior and support preventive maintenance strategies.

### Condition Monitoring in Industrial Systems

Condition monitoring is a process of continuously evaluating the operational health of industrial machines in order to detect early signs of component degradation or malfunction. Unlike traditional maintenance strategies that rely on scheduled inspections, condition monitoring focuses on real-time monitoring of machine performance using sensor-based technologies. This approach allows maintenance teams to detect abnormal conditions early and take corrective actions before severe failures occur. As industrial systems become more complex, condition monitoring has become an essential component of modern maintenance strategies [28].

Several techniques are commonly used in condition monitoring systems, including vibration analysis, temperature monitoring, acoustic emission analysis, and signal processing methods. These techniques allow engineers to detect small changes in machine behavior that may indicate potential faults. Infrared thermography, for instance, is widely used to monitor abnormal temperature variations in machine components without physical contact. Such monitoring techniques provide valuable information about equipment health and help reduce unexpected machine breakdowns [28].

Recent developments in condition monitoring have incorporated artificial intelligence technologies to enhance diagnostic capabilities. Machine learning and data analytics can process large volumes of sensor data to identify patterns that indicate early-stage faults. These intelligent monitoring systems not only improve fault detection accuracy but also support predictive maintenance strategies by providing continuous insights into machine health conditions. Consequently, condition monitoring systems play a critical role in improving system reliability and reducing maintenance costs in modern manufacturing environments [25].

**Predictive Maintenance in Industrial Machines**

Predictive maintenance (PdM) is a maintenance strategy that focuses on predicting equipment failures before they occur so that maintenance actions can be performed proactively. Unlike reactive maintenance, which only responds after a failure occurs, predictive maintenance uses operational data and advanced analytics to estimate the future condition of machinery. This strategy enables industries to optimize maintenance schedules, reduce downtime, and improve equipment reliability [29].

The implementation of predictive maintenance relies heavily on sensor technologies and data analytics. Machines equipped with sensors continuously generate operational data such as vibration, temperature, pressure, and acoustic signals. These data are analyzed to identify patterns of degradation or abnormal machine behavior. Predictive models can then estimate the remaining useful life of machine components, allowing maintenance teams to plan interventions more efficiently and prevent unexpected equipment failures [30].

Predictive maintenance has become a key component of smart manufacturing systems because it enables data-driven decision-making in maintenance management. By leveraging artificial intelligence and machine learning technologies, predictive maintenance systems can analyze large-scale operational data and identify complex relationships between machine parameters and failure patterns. As a result, organizations can significantly improve production efficiency while reducing operational costs associated with unplanned downtime [29].

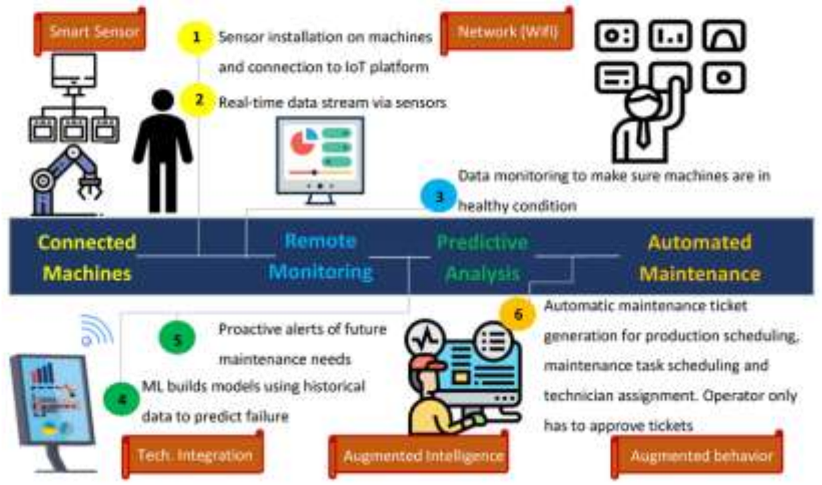


**Figure 2.** Predictive Maintenance Framework in Smart Manufacturing Systems.

Figure 2 illustrates the predictive maintenance framework used in modern industrial environments. The framework integrates sensor-based data acquisition, data storage systems, analytical models, and predictive algorithms. Machine learning models analyze historical and real-time data to estimate equipment health and predict possible failures. Based on these predictions, maintenance activities can be scheduled proactively to reduce system downtime and improve operational reliability.

**Machine Learning for Predictive Maintenance**

Machine learning (ML) techniques have become one of the most widely used approaches in predictive maintenance systems due to their ability to analyze large volumes of sensor data. ML algorithms can identify patterns and relationships within operational data that indicate potential equipment failures. Several algorithms commonly used in predictive maintenance include Support Vector Machines (SVM), Random Forest, Gradient Boosting, and K-Nearest Neighbors (KNN). These methods provide effective tools for anomaly detection and machine health prediction [31].

The application of machine learning in predictive maintenance has demonstrated significant improvements in maintenance accuracy and operational efficiency. ML models are capable of analyzing complex datasets obtained from industrial sensors and identifying early-stage anomalies that may indicate machine degradation. In many cases, ML algorithms such as Random Forest have shown strong performance in predicting equipment failures due to their ability to handle high-dimensional data and nonlinear relationships between variables [32].

Another advantage of machine learning models is their relatively lower computational requirements compared to deep learning models. This makes ML techniques suitable for industrial environments where computational resources may be limited. Additionally, ML models often provide better interpretability, allowing engineers and maintenance teams to understand the reasoning behind predictive results. Consequently, machine learning remains a practical and effective approach for predictive maintenance applications across various industrial sectors [31].

**Deep Learning for Predictive Maintenance**

Deep learning (DL) represents an advanced branch of machine learning that uses deep neural network architectures to analyze complex datasets. In predictive maintenance applications, deep learning models are particularly effective in handling time-series sensor data generated by industrial machines. Common architectures used in predictive maintenance include Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), and Gated Recurrent Units (GRU). These models are capable of automatically extracting features from raw data, eliminating the need for extensive manual feature engineering [33].

One of the major advantages of deep learning is its ability to detect complex patterns within large datasets. In industrial environments where machines generate massive volumes of operational data, deep learning models can analyze these datasets to identify subtle changes that may indicate early-stage equipment degradation. This capability makes DL models highly suitable for predictive maintenance tasks involving complex machinery and dynamic operational conditions [34].

However, deep learning models also present certain challenges, particularly in terms of data requirements and computational complexity. Training deep neural networks typically requires large datasets and high-performance computing resources. Despite these challenges, comparative studies have shown that deep learning models often outperform traditional machine learning models when applied to large-scale industrial datasets with complex patterns and temporal dependencies [35].

**Explainable Artificial Intelligence (XAI) in Industrial Systems**

Explainable Artificial Intelligence (XAI) has emerged as an important research field aimed at improving the transparency and interpretability of artificial intelligence systems. Traditional AI models, particularly deep learning algorithms, often function as black-box systems where the internal decision-making process is difficult for users to understand. In industrial environments, this lack of transparency can reduce user trust and hinder the adoption of AI-based decision-making systems. Therefore, XAI focuses on developing techniques that allow users to understand how models generate predictions and which input factors influence decision outcomes [36], [37].

The increasing use of artificial intelligence in Industry 4.0 applications has further emphasized the need for explainability in industrial systems. AI technologies are widely applied in tasks such as predictive maintenance, fault detection, process optimization, and quality monitoring. However, if the reasoning behind AI decisions cannot be interpreted, operators may be reluctant to rely on automated systems for critical operational decisions. XAI addresses this issue by providing interpretable explanations that allow users to validate model predictions and understand system behavior in complex industrial environments [38].

Various techniques have been developed to support explainability in AI models. Some of the most widely used methods include SHapley Additive exPlanations (SHAP), Local Interpretable Model-Agnostic Explanations (LIME), Grad-CAM, Integrated Gradients, and saliency maps. These techniques analyze model behavior and identify the most influential features affecting predictions. By providing insights into how models interpret input data, these methods help engineers understand model reasoning and improve transparency in industrial AI applications [39].

### Challenges and Opportunities of XAI in Industrial Applications

Despite the growing interest in explainable artificial intelligence, several challenges remain in its implementation within industrial environments. One major challenge is the absence of standardized frameworks for integrating explainability into complex machine learning models. Many industrial AI systems are designed primarily to maximize predictive accuracy, which often results in highly complex models that are difficult to interpret. As a result, balancing model performance with interpretability remains a key issue in the development of explainable industrial AI systems [37].

Another important challenge is related to the usability of explanations generated by XAI methods. Industrial environments involve multiple stakeholders, including engineers, operators, and managers, each with different levels of technical expertise. Therefore, explanations produced by AI systems must be understandable to non-expert users while still providing sufficient technical insight for domain experts. Research investigating how machine learning practitioners perceive explainability highlights the need for user-centered explanation design to ensure that XAI systems provide meaningful and actionable insights for industrial users [40].

Although these challenges exist, XAI also presents significant opportunities for improving the reliability and trustworthiness of industrial AI systems. By providing interpretable explanations, organizations can increase user confidence in automated decision-making systems and support better human–AI collaboration. Furthermore, explainability mechanisms can assist engineers in diagnosing model errors, improving model performance, and ensuring compliance with industrial safety and regulatory requirements. Consequently, the integration of XAI into industrial applications is expected to become increasingly important in the future development of intelligent manufacturing systems [36], [41].

### Smart Manufacturing in Industry 4.0

Smart manufacturing is one of the key concepts in Industry 4.0 that integrates advanced digital technologies into manufacturing processes to enhance productivity, flexibility, and product quality. This paradigm combines technologies such as Internet of Things (IoT), artificial intelligence, cloud computing, and cyber-physical systems to create intelligent production environments capable of autonomous monitoring and decision-making. Through real-time data acquisition and advanced analytics, smart manufacturing systems allow manufacturers to optimize production processes and improve operational efficiency [42].

In smart manufacturing environments, IoT devices and industrial sensors play an essential role in collecting operational data from machines and production lines. These devices continuously capture data related to machine performance, environmental conditions, and production parameters. The collected data are then processed using analytical algorithms to identify patterns, detect anomalies, and support decision-making processes. This data-driven approach allows organizations to gain valuable insights into production performance and improve the overall efficiency of manufacturing operations [43].

Another important component of smart manufacturing is the integration of cyber-physical systems and cloud computing technologies. Cyber-physical systems enable communication between physical machines and digital platforms, while cloud computing provides scalable infrastructure for storing and processing large volumes of industrial data. Together, these technologies enable real-time monitoring, automated process control, and intelligent decision-making across the manufacturing system. As a result, smart manufacturing environments are able to adapt quickly to changes in production requirements while maintaining high levels of efficiency and product quality [36], [42].

### Intelligent Monitoring Systems in Smart Manufacturing

Intelligent monitoring systems play a critical role in supporting automation and optimization within smart manufacturing environments. These systems utilize sensor technologies and data analytics to monitor machine conditions and production processes continuously. By collecting real-time data from machines and manufacturing equipment, intelligent monitoring systems are able to detect anomalies and identify potential performance issues before they develop into critical failures. Such capabilities enable industries to maintain reliable production systems and reduce the risk of unexpected downtime [44].

One implementation of intelligent monitoring systems involves the use of IoT-based product monitoring technologies in manufacturing environments. These systems enable manufacturers to track product conditions and production parameters throughout the manufacturing process. Sensor data are transmitted to monitoring platforms where they are analyzed to ensure that products meet required quality standards. Research has shown that IoT-based monitoring systems can significantly improve the ability of manufacturers to control production processes and maintain consistent product quality [45].

Another example of intelligent monitoring technology involves automated recognition systems used in industrial robotics and manufacturing equipment. For example, color recognition systems combined with robotic control mechanisms allow machines to automatically identify and classify objects during manufacturing operations. These systems enhance process automation and enable real-time adjustments during production. The integration of intelligent monitoring technologies with automated control systems represents an important step toward the realization of fully autonomous manufacturing environments in Industry 4.0 [46], [47].

## 3. Research Methods

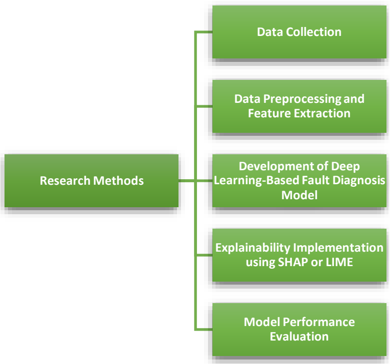


**Figure 3**. Research Methodology Flowchart.

### Data Collection

The first stage of this research involves collecting operational data from industrial machines using multiple types of sensors. The sensor system is designed to capture key machine condition indicators such as vibration signals, temperature measurements, and acoustic emissions. Vibration sensors are used to detect abnormal mechanical movements in rotating components such as bearings and motors, while temperature sensors monitor thermal variations that may indicate excessive friction or mechanical degradation. Acoustic sensors are also utilized to capture sound patterns generated during machine operation, which may reveal early signs of mechanical faults.

These sensors are installed at critical points of industrial machines to continuously monitor machine performance during operation. The collected data are recorded in real time and stored in a centralized data acquisition system. The dataset generated from this process contains time-series signals representing normal operating conditions as well as potential fault conditions. This multi-sensor approach allows the system to capture comprehensive information about machine behavior and provides a reliable foundation for machine fault diagnosis analysis.

### Data Preprocessing and Feature Extraction

After data collection, the next stage involves preprocessing the raw sensor data to improve data quality and ensure reliable model training. Industrial sensor data often contain noise, missing values, and inconsistencies that may negatively affect model performance. Therefore, preprocessing techniques such as noise filtering, normalization, and data cleaning are applied to remove irrelevant information and standardize the data format.

Following preprocessing, feature extraction is performed to identify meaningful characteristics from the sensor signals. For vibration and acoustic signals, statistical features such as mean, variance, skewness, kurtosis, and frequency-domain features are extracted using signal processing techniques. In the case of temperature signals, temporal features and trend patterns are analyzed to capture machine operating behavior. These extracted features represent important indicators of machine condition and serve as input variables for the deep learning model used in the next stage.

### Development of Deep Learning-Based Fault Diagnosis Model

The core component of this research is the development of a deep learning model for machine fault diagnosis. Deep learning techniques are selected because they have strong capabilities in identifying complex patterns within large-scale industrial datasets. In this study, deep neural network architectures are used to analyze sensor data and classify machine conditions into normal and fault categories.

The model training process involves dividing the dataset into training, validation, and testing subsets. The training dataset is used to train the deep learning model, while the validation dataset is used to tune hyperparameters and prevent overfitting. The testing dataset is used to evaluate the final performance of the model. During training, the model learns to identify relationships between sensor signals and machine health conditions, enabling the system to detect abnormal patterns that may indicate machine faults.

### Explainability Implementation using SHAP or LIME

Although deep learning models can achieve high predictive accuracy, they often lack interpretability because their internal decision processes are difficult to understand. To address this limitation, explainable artificial intelligence techniques are incorporated into the proposed diagnostic system. In this research, explainability methods such as SHapley Additive exPlanations (SHAP) or Local Interpretable Model-Agnostic Explanations (LIME) are applied to interpret model predictions.

These explainability methods analyze the contribution of each input feature to the model's prediction results. By identifying which features most strongly influence the model's decision, the system provides interpretable insights into the reasoning behind fault detection results. This approach allows engineers and machine operators to understand the factors that contribute to machine failures and validate the predictions generated by the deep learning model.

### Model Performance Evaluation

The final stage of the research involves evaluating the performance of the proposed fault diagnosis model. Several evaluation metrics are used to measure the effectiveness of the model in detecting machine faults. These metrics include accuracy, precision, recall, and F1-score. Accuracy measures the overall correctness of the model in classifying machine conditions, while precision evaluates the proportion of correctly identified fault cases among all predicted fault cases.

Recall is used to measure the ability of the model to correctly detect actual fault conditions, which is particularly important in industrial monitoring systems where missed fault detection can lead to severe operational consequences. In addition to predictive performance metrics, interpretability evaluation is also considered to assess the effectiveness of the explainability methods. This evaluation examines whether the explanations generated by SHAP or LIME provide meaningful insights into model behavior and assist engineers in understanding the reasoning behind diagnostic decisions.

## 4. Results and Discussion

### Results

This study aims to develop a deep learning-based industrial machine fault diagnosis system integrated with Explainable Artificial Intelligence (XAI) methods to improve model interpretability. The dataset used in this study was obtained from industrial machine sensor data, including vibration signals, temperature measurements, and acoustic signals. After undergoing preprocessing and feature extraction processes, the data were used to train a deep learning-based diagnostic model. Furthermore, explainability methods such as SHAP or LIME were applied to interpret the decisions generated by the model. The evaluation was conducted using accuracy, precision, recall, and F1-score metrics to measure the model's performance in detecting machine faults.

#### ***Model Performance Evaluation Results***

The evaluation results of the machine fault diagnosis model are presented in Table 1. The evaluation was conducted by comparing the proposed deep learning model with conventional machine learning methods such as Support Vector Machine (SVM) and Random Forest.

**Table 1.** Comparison of Machine Fault Diagnosis Model Performance.

| Model | Accuracy | Precision | Recall | F1-Score |
|---|---|---|---|---|
| Support Vector Machine | 0.86 | 0.84 | 0.82 | 0.83 |
| Random Forest | 0.89 | 0.88 | 0.86 | 0.87 |
| Deep Learning + XAI | 0.94 | 0.93 | 0.92 | 0.92 |

Based on Table 1, it can be observed that the deep learning-based machine fault diagnosis model integrated with explainability methods demonstrates better performance compared to conventional machine learning approaches. The proposed model achieved an accuracy of 94%, which is higher than the Support Vector Machine model with an accuracy of 86% and the Random Forest model with an accuracy of 89%. In addition, the precision, recall, and F1-score values also show significant improvements. These results indicate that the deep learning model has a stronger capability to identify machine fault patterns from complex industrial sensor data.

***Visualization of Diagnosis Model Performance***

To provide a clearer visualization of the comparison of machine fault diagnosis model performance, the evaluation results are presented in the form of a graphical diagram. This graph illustrates the comparison of accuracy, precision, and recall values between conventional machine learning methods and the proposed deep learning model.

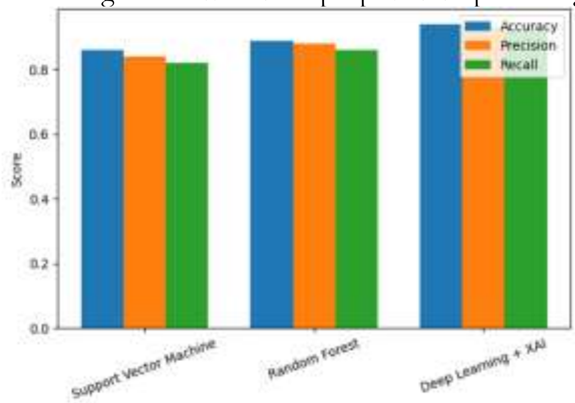


**Figure 4.** Comparison of Machine Fault Diagnosis Model Performance.

Based on Figure 4, it can be observed that the Deep Learning + XAI model achieves the best performance across all evaluation metrics compared to the Support Vector Machine and Random Forest models. The deep learning model achieves an accuracy of 0.94, a precision of 0.93, and a recall of 0.92. Meanwhile, the Random Forest model shows better performance than the Support Vector Machine model but still remains below the deep learning model. These results indicate that the deep learning approach is more effective in recognizing complex patterns in industrial machine sensor data, thereby improving the accuracy of machine fault diagnosis.

***Diagnosis Explanatory Model Analysis***

In addition to evaluating the predictive performance of the model, this study also analyzes the factors that most significantly influence machine fault diagnosis decisions using an Explainable Artificial Intelligence (XAI) approach. The explainability analysis was conducted using the SHAP method to identify the contribution of each sensor feature to the model's prediction results. The results of this analysis are presented in the form of a feature importance graph that illustrates the level of influence of each sensor parameter on machine fault detection.

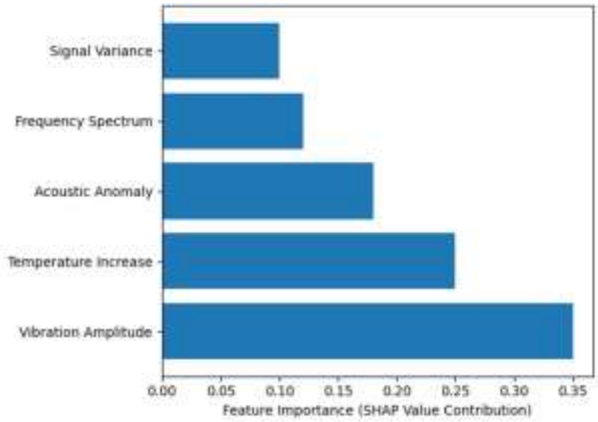


**Figure 5.** Feature Importance Analysis for Machine Fault Diagnosis using Explainable Artificial Intelligence.

Based on Figure 5, it can be observed that the feature with the greatest influence on machine fault prediction is vibration amplitude, which has the largest contribution in determining the machine condition. This indicates that changes in vibration patterns are a primary indicator in detecting potential mechanical failures in industrial machines. The next factor with significant influence is the increase in machine component temperature, which often indicates excessive friction or component degradation. In addition, anomalies in acoustic signals also play an important role in detecting machine faults at an early stage. Meanwhile, other features such as signal frequency spectrum and signal variance have relatively smaller contributions but still provide additional information that helps the model identify machine conditions. These findings demonstrate that explainable AI methods are capable of providing clearer insights into the main factors contributing to machine failures.

## Discussion

### *Improvement in Machine Fault Diagnosis Accuracy*

The results of this study indicate that the deep learning-based machine fault diagnosis model achieves a higher level of accuracy compared to conventional machine learning methods. This improvement is mainly attributed to the capability of deep learning models to extract complex features from nonlinear and high-dimensional machine sensor data. Unlike conventional models that require manual feature engineering processes, deep learning models are able to automatically learn feature representations directly from raw data. This capability allows the model to recognize machine fault patterns more accurately and consistently.

Furthermore, the integration of multi-sensor data such as vibration, temperature, and acoustic signals provides more comprehensive information regarding machine conditions. The combination of these different types of sensor data enables the model to detect subtle changes in machine behavior that may indicate early signs of machine failure. As a result, the proposed diagnostic system demonstrates a better ability to detect potential machine faults at an early stage compared to conventional diagnostic systems.

### *System Capability in Explaining Failure Causes*

One of the main advantages of the system developed in this study is its explainability capability, which is achieved through the implementation of SHAP or LIME methods. These methods enable the system to explain the contribution of each input feature to the model's prediction results. Consequently, machine operators and engineers can identify the key factors that contribute to machine failures.

The explainability analysis results indicate that the most influential features in predicting machine faults include changes in vibration amplitude, increases in machine component temperature, and anomaly patterns in acoustic signals. This information is highly valuable for maintenance technicians because it allows them to identify the root causes of machine faults more quickly and implement appropriate corrective actions.

### *Performance Comparison with Conventional Machine Learning Methods*

The performance comparison between the deep learning model and conventional machine learning methods demonstrates that the deep learning approach has advantages in handling complex industrial data. Models such as Support Vector Machine (SVM) and Random Forest have limitations in processing temporal patterns present in machine sensor data. In contrast, deep learning models are capable of utilizing time-series data structures to capture patterns of machine condition changes more effectively.

In addition, deep learning models also exhibit better generalization capabilities when applied to datasets with high variations in operational conditions. This characteristic makes deep learning models more suitable for industrial monitoring systems that operate in highly dynamic environments where machine conditions continuously change.

***Impact on Reliability and Maintenance Efficiency***

The implementation of a deep learning-based machine fault diagnosis system integrated with explainable AI has a positive impact on improving the reliability of industrial systems. By enabling early detection of machine faults, the system can help organizations reduce the risk of unexpected machine failures. This capability directly contributes to increased machine availability and improved stability in production processes.

In addition to improving system reliability, the proposed approach also has the potential to enhance maintenance efficiency. More accurate and interpretable diagnostic information allows maintenance technicians to determine appropriate maintenance actions more effectively, thereby reducing repair time and maintenance costs. Therefore, the integration of deep learning and explainable AI provides an effective solution for supporting predictive maintenance implementation in smart manufacturing environments.

## 5. Comparison

The proposed deep learning-based machine fault diagnosis system integrated with Explainable Artificial Intelligence demonstrates superior performance compared to conventional machine learning methods. Based on the experimental results, the developed deep learning model achieved higher evaluation scores across all performance metrics, including accuracy, precision, recall, and F1-score. In particular, the proposed model achieved an accuracy of 0.94, which is significantly higher than the Support Vector Machine and Random Forest models. These results indicate that the deep learning model has a stronger capability to capture complex patterns present in industrial machine sensor data.

One of the main factors contributing to this performance improvement is the ability of deep learning models to learn hierarchical feature representations directly from raw sensor data. Conventional machine learning methods typically require manual feature engineering and often face limitations in capturing nonlinear relationships within large-scale industrial datasets. In contrast, deep learning models are designed to handle high-dimensional data and are capable of extracting meaningful feature representations from multiple sensor sources such as vibration, temperature, and acoustic signals. This capability enables the model to detect machine degradation patterns and early fault conditions more effectively.

In addition to improving predictive performance, the integration of Explainable Artificial Intelligence provides an additional advantage that is generally not available in conventional machine learning systems. Techniques such as SHAP or LIME enable the model to provide interpretable explanations for its predictions by identifying the most influential features involved in the machine fault detection process. This interpretability capability increases user trust and helps engineers better understand the root causes of machine failures. Therefore, the combination of deep learning and explainable AI not only improves predictive accuracy but also enhances transparency in industrial diagnostic systems.

## 6. Conclusion

This study proposes a deep learning-based industrial machine fault diagnosis system integrated with Explainable Artificial Intelligence to improve both predictive performance and model interpretability in industrial environments. The developed system utilizes multi-sensor data consisting of vibration signals, temperature measurements, and acoustic signals to detect machine fault conditions. The evaluation results show that the proposed deep learning model outperforms conventional machine learning methods such as Support Vector Machine and Random Forest, achieving higher accuracy, precision, recall, and F1-score values. These findings indicate that the deep learning approach is more effective in recognizing complex patterns in industrial machine sensor data.

In addition to improving predictive performance, the integration of Explainable Artificial Intelligence methods such as SHAP or LIME enables the system to provide clearer explanations of the factors influencing diagnostic results. The explainability analysis reveals that changes in vibration amplitude, increases in machine component temperature, and anomalies in acoustic signals are the primary indicators for detecting potential machine faults. Therefore, the proposed diagnostic system not only improves the accuracy of machine fault detection but also provides interpretable insights that can be understood by machine operators and maintenance technicians. This approach has the potential to support predictive maintenance implementation and improve reliability and operational efficiency in smart manufacturing environments.

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