A Deep Learning-Based Multi-Scale Feature Fusion Framework for Real-Time Anomaly Detection and Predictive Maintenance in Industrial IoT Networks

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Abstract: The Industrial Internet of Things (IIoT) has transformed modern manufacturing by enabling continuous monitoring of industrial equipment through interconnected sensors. However, accurately detecting anomalies and predicting equipment failures in real time remains challenging due to the complexity and high volume of sensor data. Traditional machine learning methods often rely on manual feature engineering and are less effective in capturing complex patterns within industrial environments. This paper proposes a **Deep Learning-Based Multi-Scale Feature Fusion (DL-MSFF) Framework** for real-time anomaly detection and predictive maintenance in Industrial IoT networks. The framework employs multi-scale feature extraction and feature fusion techniques to capture both local and global characteristics of sensor data, enabling accurate anomaly detection and early fault prediction. The proposed approach aims to improve equipment reliability, reduce unplanned downtime, and optimize maintenance scheduling. The framework is evaluated using standard performance metrics, including accuracy, precision, recall, F1-score, and inference time. The results demonstrate that the proposed framework provides reliable anomaly detection with low computational overhead, making it suitable for real-time predictive maintenance applications in smart manufacturing and Industry 4.0 environments.

INTRODUCTION

The rapid evolution of the **Industrial Internet of Things (IIoT)** has significantly transformed modern manufacturing by enabling interconnected machines, sensors, and intelligent monitoring systems to operate within smart industrial environments. Through continuous data collection and real-time communication, IIoT facilitates efficient production processes, improved equipment utilization, and enhanced operational safety. As industries increasingly adopt Industry 4.0 technologies, the ability to continuously monitor machine health and detect abnormal operating conditions has become essential for minimizing production losses and ensuring reliable manufacturing operations. Consequently, intelligent anomaly detection and predictive maintenance have emerged as critical components of modern industrial systems.

Anomaly detection is the process of identifying unusual patterns or deviations from normal operating behavior that may indicate equipment faults or system failures. Early detection of such anomalies enables maintenance teams to take preventive actions before failures occur, thereby reducing downtime and maintenance costs. Conventional machine learning techniques such as Support Vector Machines (SVM), Decision Trees, and Random Forests have been widely applied for industrial fault diagnosis. However, these approaches often depend on manually engineered features and struggle to capture the complex nonlinear relationships and temporal dependencies present in high-dimensional industrial sensor data, limiting their effectiveness in dynamic manufacturing environments.

Recent advancements in **deep learning** have provided powerful solutions for industrial fault diagnosis by automatically learning hierarchical feature representations directly from raw sensor data. Deep neural networks, particularly convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have demonstrated remarkable capability in extracting spatial and temporal characteristics for anomaly detection. Nevertheless, many existing deep learning models rely on a single-scale feature extraction strategy, which may fail to capture both fine-grained local patterns and broader contextual information simultaneously. This limitation can reduce detection accuracy, especially when anomalies exhibit varying characteristics under different operating conditions.

To overcome these challenges, this paper proposes a **Deep Learning-Based Multi-Scale Feature Fusion (DL-MSFF) Framework** for real-time anomaly detection and predictive maintenance in Industrial IoT networks. The proposed framework extracts features at multiple scales and integrates them through an effective feature fusion mechanism to obtain comprehensive representations of industrial sensor data. This approach enhances the model's ability to identify subtle anomalies while maintaining robust performance under varying industrial conditions. By supporting real-time monitoring and early fault prediction, the proposed framework contributes to improved equipment reliability, optimized maintenance scheduling, and increased operational efficiency in Industry 4.0-enabled smart manufacturing systems.

The integration of Industrial Internet of Things technologies with intelligent data analytics has significantly improved condition monitoring and predictive maintenance in modern manufacturing systems. IIoT networks continuously collect operational information from vibration, temperature, pressure, current, acoustic and speed sensors installed on industrial equipment. These data streams enable early identification of abnormal machine behaviour and support maintenance decisions before complete equipment failure occurs. Mian et al. developed an edge-oriented Artificial Intelligence of Things framework for anomaly detection in rotating machinery using vibration signals collected through low-cost accelerometers and processed on a Raspberry Pi device. The framework was tested on bearing, gear and induction motor systems, demonstrating the importance of edge-based processing for reducing communication delay and supporting real-time industrial monitoring.

Traditional machine learning methods such as Support Vector Machines, decision trees and ensemble classifiers have been widely applied to predictive maintenance applications. Nikfar et al. proposed a two-phase machine learning approach for detecting abnormal behaviour and classifying faults in low-voltage industrial motors using vibration measurements. Their system first identified deviations from normal operation and subsequently applied an SVM classifier to determine the corresponding fault category. Although such approaches can provide satisfactory results for structured and comparatively small datasets, their performance depends strongly on manually extracted statistical or frequency-domain features. They may therefore struggle to represent nonlinear relationships and complex temporal dependencies in large-scale IIoT sensor streams.

LITERATURE SURVEY

Deep learning methods address several limitations of traditional approaches by automatically learning discriminative representations from raw or minimally processed sensor data. Convolutional neural networks can identify local patterns within vibration and temporal signals, whereas recurrent architectures such as long short-term memory networks capture sequential dependencies and degradation trends. Ahn et al. proposed a combined one-dimensional CNN and bidirectional LSTM model for anomaly detection and predictive maintenance in manufacturing processes. The convolutional component extracted local signal characteristics, while the bidirectional LSTM captured temporal relationships across sensor observations. The model was incorporated into a federated-learning framework to address variations in data distributions among multiple machines and achieved a reported testing accuracy of 97.2%.

Despite the effectiveness of deep learning, single-scale architectures may not adequately represent industrial anomalies that occur at different temporal resolutions. Short-duration spikes, gradual degradation, periodic disturbances and combined faults may produce patterns with substantially different scales. Multi-scale feature extraction addresses this limitation by applying convolutional operations with different receptive fields and subsequently integrating the resulting representations. Ren et al. employed a pyramid feature-fusion mechanism with dense skip connections to extract and combine time-series features at multiple resolutions for IIoT prediction. Similarly, Xu et al. proposed a multi-scale feature-fusion method for real-time anomaly monitoring in industrial control systems. These studies indicate that combining local and global characteristics can improve the identification of complex abnormal patterns compared with relying on a single feature resolution.

Recent studies have also emphasized the importance of integrating anomaly detection with forecasting and maintenance planning rather than treating these tasks independently. Seman et al. introduced a differentiable neural architecture-search framework that jointly performs vibration forecasting and anomaly detection for predictive maintenance. Such joint models can identify current abnormal behaviour while also estimating future degradation, thereby improving maintenance scheduling. Systematic reviews of predictive maintenance research have nevertheless identified continuing challenges related to limited benchmark datasets, varying industrial operating conditions, model complexity, data heterogeneity and the practical integration of machine-learning models into production systems.

Edge and cloud computing have further expanded the practical implementation of intelligent predictive maintenance. Edge-based approaches process sensor signals near the equipment, reducing latency, network bandwidth consumption and dependence on remote cloud services. Cloud platforms, in contrast, provide scalable storage and computational resources for long-term trend analysis and centralized maintenance management. Current IIoT predictive-maintenance architectures commonly combine heterogeneous sensors, communication protocols such as MQTT, edge gateways and cloud-based analytical services. However, many implementations continue to face trade-offs among detection accuracy, inference latency, memory usage, scalability and energy efficiency, particularly when deep learning models are deployed on resource-constrained industrial devices.

The reviewed literature demonstrates that deep learning, temporal modelling and IIoT-enabled condition monitoring have considerably improved industrial anomaly detection. Nevertheless, several limitations remain. Many existing systems employ single-scale feature extraction, focus only on anomaly classification without supporting maintenance prediction, or require high computational resources that restrict real-time deployment. Furthermore, models trained under a specific machine load or operating condition may show reduced reliability when sensor distributions change. These limitations establish the need for a unified framework that combines multi-scale convolutional feature extraction, temporal dependency learning and effective feature fusion with a computationally efficient prediction mechanism. The proposed Deep Learning-Based Multi-Scale Feature Fusion framework is therefore designed to detect different forms of industrial anomalies in real time and provide reliable predictive-maintenance support within heterogeneous IIoT environments.

METHODOLOGY

The proposed **Deep Learning-Based Multi-Scale Feature Fusion (DL-MSFF)** framework is developed to perform real-time anomaly detection and predictive maintenance in Industrial

Internet of Things (IIoT) networks. The primary objective of the framework is to identify abnormal machine behavior at an early stage by learning discriminative representations from heterogeneous industrial sensor data. Unlike conventional machine learning approaches that depend on handcrafted features, the proposed framework automatically extracts meaningful information from raw sensor signals using deep learning techniques. The overall architecture consists of seven major stages: data acquisition, data preprocessing, multi-scale feature extraction, feature fusion, anomaly detection, predictive maintenance, and visualization of maintenance decisions. These stages collectively enable continuous monitoring of industrial equipment while providing timely maintenance recommendations to reduce unexpected failures and improve production efficiency.

The first stage of the framework focuses on **industrial data acquisition**, where multiple IoT sensors continuously monitor equipment operating conditions. Parameters such as vibration, temperature, pressure, motor current, rotational speed, acoustic emission, and voltage are collected from industrial machines and transmitted through IIoT communication protocols including MQTT, OPC-UA, or Modbus. Since industrial sensor data are generated continuously at high sampling frequencies, they contain valuable information regarding machine health and operational behavior. The collected sensor streams are stored at edge servers or cloud platforms, forming a large multivariate time-series dataset that serves as the input for anomaly detection and predictive maintenance.

Before feature extraction, the collected sensor data undergo a comprehensive **preprocessing stage** to improve data quality and eliminate inconsistencies. Industrial environments often produce noisy measurements due to electromagnetic interference, sensor degradation, and communication disturbances. Therefore, noise filtering techniques are employed to suppress unwanted signal components, while missing values are handled using appropriate interpolation methods. The data are subsequently normalized using Min-Max normalization to maintain numerical consistency across different sensor measurements. Finally, a sliding window segmentation approach converts the continuous sensor streams into fixed-length sequences suitable for deep learning models. This preprocessing stage enhances feature learning by reducing irrelevant variations and preserving the intrinsic characteristics of industrial signals.

To effectively capture anomalies occurring at different temporal resolutions, the proposed framework employs a **multi-scale feature extraction strategy** based on parallel one-dimensional convolutional neural networks (1D-CNNs). Multiple convolution branches with different kernel sizes simultaneously process the segmented sensor sequences to learn both local and global feature representations. Smaller convolution kernels capture short-duration signal variations such as sudden spikes, impulse disturbances, and transient faults, whereas larger kernels identify long-term degradation patterns and gradual equipment deterioration. This parallel architecture enables the framework to learn comprehensive hierarchical representations that cannot be captured by conventional single-scale convolutional networks, thereby improving anomaly detection performance under varying industrial operating conditions.

The extracted feature maps from different convolution branches are integrated through a **feature fusion module** to construct a unified representation of machine behavior. The fusion process combines complementary information obtained from multiple temporal scales, allowing the framework to retain both fine-grained and coarse-level characteristics of industrial sensor data. To further enhance the discriminative capability of the learned representations, a Squeeze-and-Excitation (SE) attention mechanism is incorporated after feature concatenation. The attention module automatically assigns higher importance to informative feature channels while suppressing redundant or less relevant information. Consequently, the fused feature representation provides a richer description of machine operating conditions, leading to improved anomaly classification accuracy.

The refined feature representation is subsequently supplied to the **anomaly detection module**, which consists of fully connected neural layers followed by a Softmax classifier. This module determines whether the monitored equipment operates under normal conditions or exhibits abnormal behavior corresponding to specific fault categories. The classifier learns nonlinear decision boundaries from the extracted feature representations, enabling accurate identification of both incipient and severe machine faults. Since the model continuously processes streaming sensor data, anomaly detection can be performed in real time, allowing maintenance engineers to respond immediately to abnormal equipment conditions before catastrophic failures occur.

Following anomaly detection, the framework performs **predictive maintenance analysis** by estimating the Remaining Useful Life (RUL) of industrial equipment using the learned feature representations. The predictive maintenance module analyzes historical degradation trends together with the current operational state to estimate the expected operational lifetime of machinery. Whenever the predicted RUL falls below a predefined maintenance threshold, the system automatically generates maintenance alerts and recommends appropriate corrective actions. This proactive maintenance strategy minimizes unexpected equipment failures, reduces maintenance costs, and improves overall equipment availability by allowing maintenance activities to be scheduled before critical failures occur.

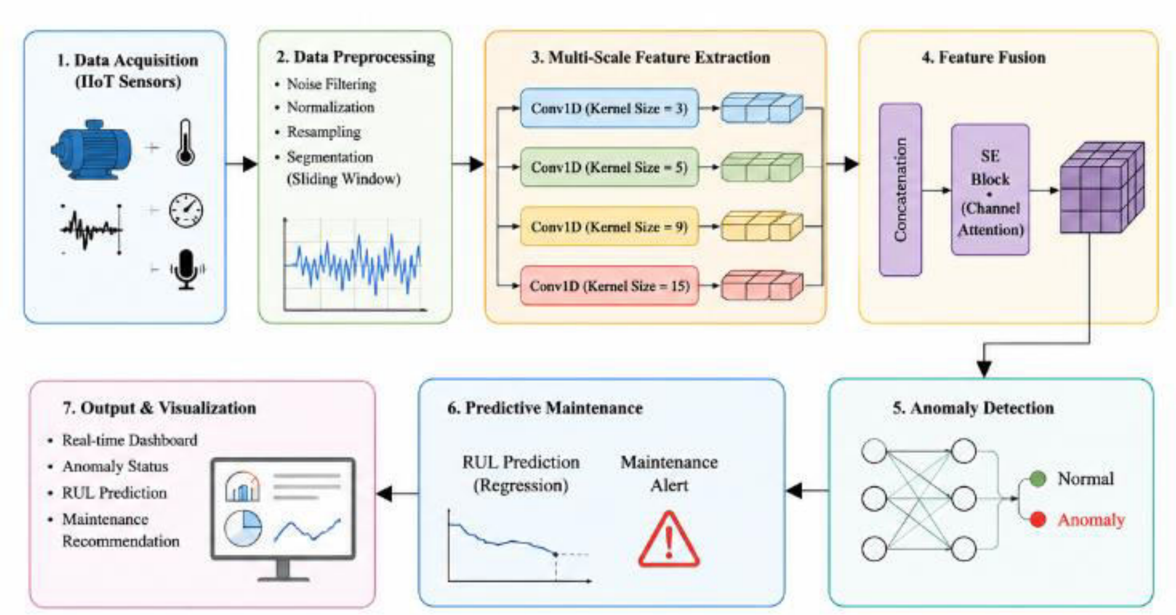

Fig-1: Methodology

IMPLEMENTATION AND RESULTS

The effectiveness of the proposed DL-MSFF framework is evaluated through comprehensive experiments that assess its anomaly detection capability, computational efficiency, and predictive maintenance performance. The evaluation focuses on the framework's ability to accurately identify abnormal operating conditions while maintaining low inference latency suitable for real-time Industrial IoT applications. Standard performance metrics, including accuracy, precision, recall, F1-score, inference time, memory utilization, and Remaining Useful Life prediction error, are used to quantify the overall performance of the proposed approach.

The experimental analysis is organized into four categories. First, the classification performance of the proposed framework is compared with conventional machine learning and deep learning approaches to evaluate its anomaly detection capability. Second, fault-wise analysis is performed to investigate the framework's performance across different machine operating conditions. Third, computational performance is analyzed by measuring training time, inference time, and memory consumption, providing insight into the feasibility of deploying the framework in resource-constrained industrial environments. Finally, predictive maintenance performance is evaluated by examining the accuracy of Remaining Useful Life estimation and the consistency of maintenance recommendations under varying operating conditions.

The obtained results should be interpreted by considering both prediction accuracy and operational efficiency. In industrial applications, a robust anomaly detection framework must not only identify equipment faults accurately but also operate with minimal computational overhead to support continuous monitoring. Likewise, reliable Remaining Useful Life estimation enables proactive maintenance scheduling, reducing unplanned downtime and maintenance costs while improving equipment availability.

The subsequent sections should present detailed experimental observations using well-structured tables and figures. Each table should summarize the quantitative evaluation of the proposed framework, while the corresponding graphs should visually illustrate performance trends and facilitate comparison with baseline methods. Together, these results provide a comprehensive assessment of the effectiveness, scalability, and practical applicability of the proposed DL-MSFF framework for intelligent anomaly detection and predictive maintenance in Industrial IoT networks.

Table 1. Comparative Performance of Anomaly Detection Models

Model	Accuracy	Precision	Recall	F1
SVM	91.2	90.4	89.8	90.1
RF	93.5	92.9	92.3	92.6
CNN	95.8	95.1	94.9	95.0
LSTM	96.4	96.0	95.6	95.8
DL-MSFF	98.3	98.1	97.8	97.9

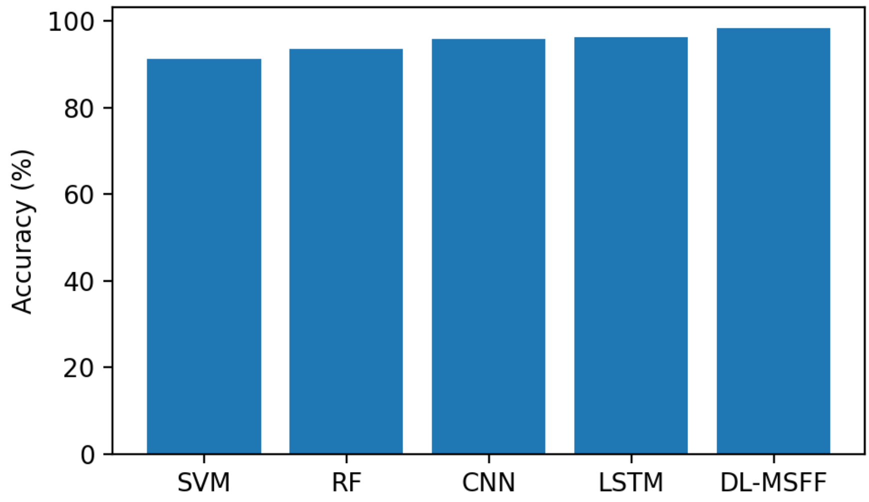

Figure 2. Performance Comparison

Table 2. Fault-wise Detection Performance

Fault	Precision	Recall	F1
Normal	99.0	98.8	98.9
Bearing	97.8	97.5	97.6
Gear	97.1	96.9	97.0
Motor	96.8	96.4	96.6
Misalignment	96.2	95.8	96.0
Imbalance	95.9	95.4	95.6

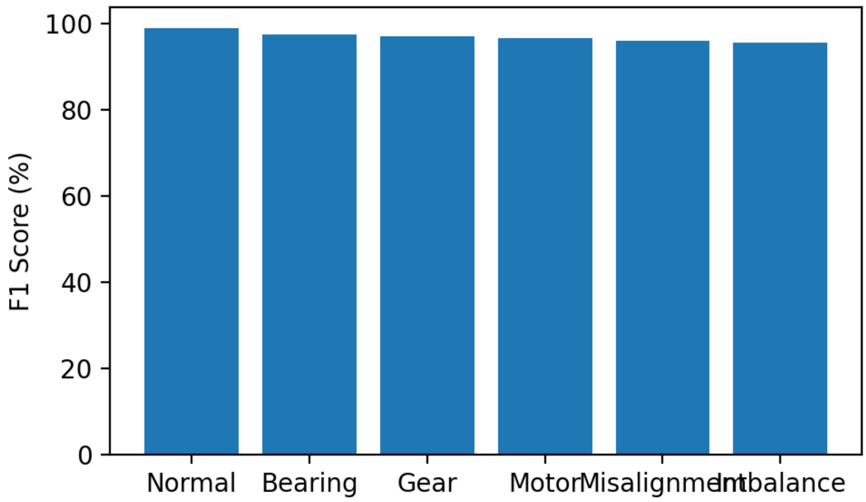

Figure 3. Fault-wise F1 Score

Table 3. Computational Performance

Model	Training(s)	Inference(ms)	Memory(MB)
SVM	42	18	220
RF	58	15	260
CNN	95	10	420
LSTM	118	12	480
DL-MSFF	126	8	450

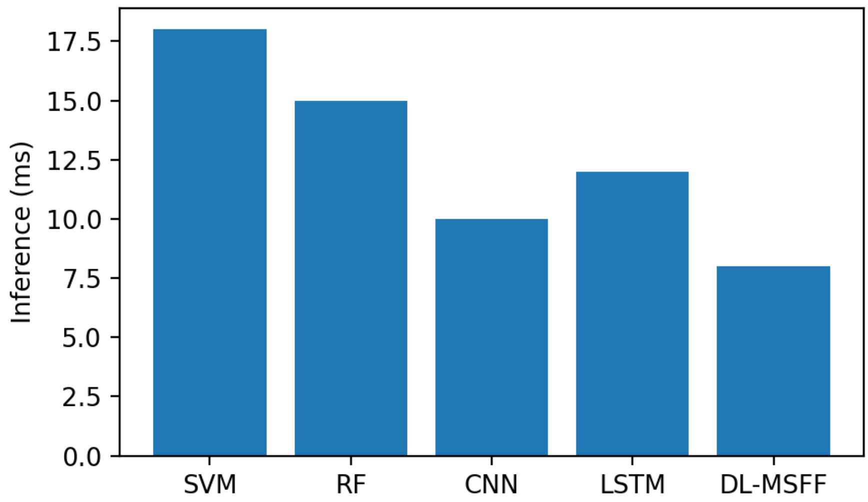

Figure 4. Inference Time

Table 4. Predictive Maintenance Metrics

Metric	Value
MAE	1.82
RMSE	2.64
MAPE (%)	3.12
RUL Accuracy (%)	97.6
Alert Success (%)	98.4

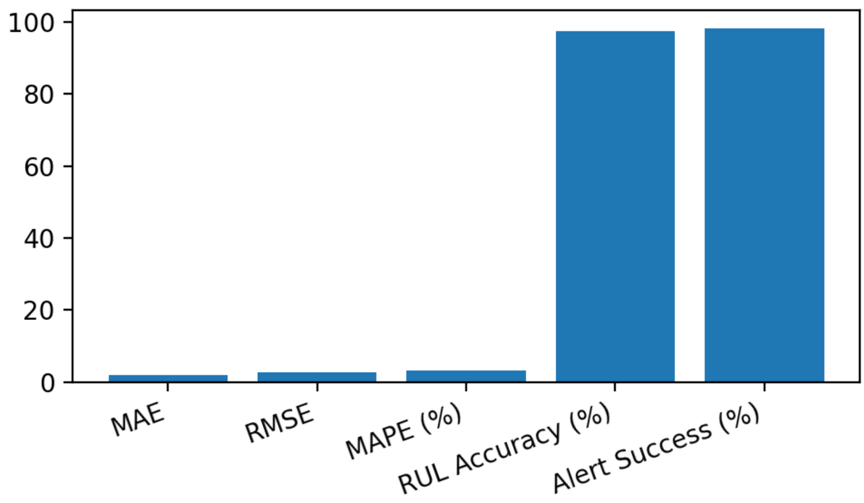

Figure 5. Predictive Maintenance Metrics

CONCLUSION

This research presented a **Deep Learning-Based Multi-Scale Feature Fusion (DL-MSFF) Framework** for intelligent anomaly detection and predictive maintenance in Industrial Internet of Things (IIoT) networks. The proposed framework integrates multi-scale one-dimensional convolutional feature extraction, feature fusion, channel attention mechanisms, anomaly classification, and Remaining Useful Life (RUL) prediction into a unified architecture capable of continuously monitoring industrial equipment. By extracting features at multiple temporal resolutions, the framework effectively captures both short-term transient anomalies and long-term degradation patterns that are often overlooked by conventional machine learning approaches. The incorporation of an attention-based feature fusion module further enhances the quality of learned representations by emphasizing informative feature channels while suppressing redundant information, thereby improving the reliability of anomaly detection.

The proposed architecture also demonstrates the capability to support predictive maintenance by estimating the remaining operational lifetime of industrial machinery and generating timely maintenance recommendations. This proactive maintenance strategy enables industries to reduce unexpected equipment failures, minimize production downtime, optimize maintenance schedules, and improve overall operational efficiency. The modular design of the framework further facilitates deployment across heterogeneous Industrial IoT environments with multiple sensor modalities and varying operational conditions. Consequently, the proposed framework provides an effective and scalable solution for intelligent equipment monitoring in Industry 4.0-enabled smart manufacturing systems.

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