Communication in Physical Sciences, 2026, 13(1): 124-138

Development of an Enhanced Predictive Maintenance Model for Industrial Systems using Deep Learning Techniques

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Received : 16 November 2025/Accepted: 26 January 2026 /Published: 30 January 2026

https://dx.doi.org/10.4314/cps.v13i1.11

Abstract: Predictive maintenance has become essential in modern industrial systems for reducing unplanned downtime, lowering maintenance costs, and improving equipment reliability. This study presents a hybrid deep learning framework that combines Long Short-Term Memory (LSTM) and Multilayer Perceptron (MLP) networks for accurate machine failure prediction. The model was trained using multivariate sensor data, including air temperature, process temperature, rotational speed, torque, and tool wear, enabling comprehensive monitoring of machine health. The hybrid architecture integrates LSTM's strength in temporal sequence learning with MLP's capability for nonlinear feature-based classification. Training results showed a steady reduction in loss and convergence in accuracy over 30 epochs, with the model achieving a training accuracy of 98.10%. During testing, the hybrid model achieved an overall prediction accuracy of 99.20%, outperforming standalone LSTM and MLP models. The system effectively detected multiple failure modes, including power failure, overstrain failure, and heat dissipation failure, while maintaining strong performance in distinguishing normal operating conditions. To demonstrate real-world applicability, the model was deployed via a Streamlit-based web interface for real-time monitoring and prediction. An integrated automated email alert system provided immediate notifications when potential failures were detected, supporting proactive maintenance decisions. Although minor performance variation was observed for less frequent failure categories due to class imbalance, the overall results confirm the robustness and scalability of the proposed framework. The findings highlight the significant potential of hybrid deep learning models in transforming maintenance strategies from preventive to data-driven predictive approaches, ultimately enhancing operational efficiency and system longevity in industrial environments.

***Keywords**: Predictive Maintenance, Deep Learning, Long Short-Term Memory (LSTM), Multilayer Perceptron (MLP), Industrial Systems.*

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1.0 Introduction

Unscheduled equipment downtime remains one of the most significant operational challenges in modern industrial systems, leading to substantial financial losses, reduced productivity, and increased safety risks (Smith *et al.*, 2022). Maintaining continuous equipment operation is therefore essential for maximizing asset utilization, reducing maintenance costs, and minimizing health, safety, and environmental risks (Johnson *et al.*, 2021). The goal of a predictive maintenance strategy is to extend the useful service life of the equipment and prevent failures (Li *et al.*, 2020). Anomaly detection is a common approach because it identifies when a device is behaving differently than expected (Ben *et al.*, 2021). Anomaly detection solutions are often more accurate than simple rule-based failure-detection methods and they are useful in the prevention of expensive failures and outages (Hesabi *et al.*, 2021).

Predictive maintenance (PdM) focuses on forecasting equipment failures using operational data collected from sensors embedded in industrial machines during runtime (Smith *et al.*, 2023). Commonly deployed sensors including temperature, vibration, pressure, torque, and voltage sensors provide continuous streams of data that describe machine health and performance.

Predictive maintenance offers several advantages over preventive maintenance and reactive maintenance strategies. It avoids the drawbacks of underutilization of a part's life in preventive maintenance and minimizes unscheduled downtime in reactive maintenance (Hesabi *et al.*, 2021).

By analyzing the historical health data of the equipment, predictive maintenance can anticipate future points of failure, enabling the scheduling of part replacements just before actual failures occur (Bampoula *et al.*, 2021). This proactive approach optimizes maintenance activities, extends the useful service life of the equipment, and prevents costly downtime and risks associated with machine failures (Sohaib & Khan, 2022).

Despite the large volumes of sensor data generated daily on factory floors, much of this information remains underutilized for intelligent maintenance decision-making. This underutilization limits the potential for optimizing equipment reliability and operational efficiency in manufacturing systems. Deep learning (DL) models, particularly Long Short-Term Memory (LSTM) networks and Multilayer Perceptrons (MLPs), have shown strong capabilities in modeling complex nonlinear relationships and temporal patterns in industrial data. LSTM networks are especially effective for time-series forecasting, while MLPs are widely used for classification tasks involving structured features (Bampoula *et al.*, 2021; Fredj *et al.*, 2020). However, many existing predictive maintenance approaches rely on single-model architectures that either focus on temporal dependencies or static feature relationships, but rarely both. Such methods may fail to fully capture the complex interactions present in multivariate industrial sensor data. Furthermore, limited attention has been given to integrating high-performance predictive models into real-time monitoring frameworks suitable for practical industrial deployment. To address these limitations, this study proposes the development of an enhanced hybrid predictive maintenance model that integrates LSTM networks for temporal sequence learning with an MLP classifier for feature-based decision-making. The framework leverages real-time sensor data to improve failure prediction accuracy and optimize maintenance scheduling in industrial systems.

The significance of this study lies in its dual contribution to both research and industry. Scientifically, it demonstrates the effectiveness of hybrid deep learning architectures in predictive maintenance applications. Practically, the model is deployed using a Streamlit-based real-time monitoring interface, enabling proactive maintenance decisions and supporting the transition toward intelligent and automated industrial operations.

1.1 Literature Review

Recent studies indicate that deep learning (DL) models often outperform traditional statistical and machine learning approaches in predicting equipment failures. Li *et al*. (2020) demonstrated the effectiveness of DL techniques for predictive maintenance (PdM), highlighting their ability to capture complex nonlinear degradation patterns in industrial equipment**.** For example, a study conducted at the University of California, Berkeley, reported that a DL-based model achieved 95% accuracy in predicting wind turbine failures. It addressed the underutilization of data generated by manufacturing industrial systems and machines/devices by introducing advanced deep-learning models for predictive maintenance. These models have shown great promise in accurately estimating equipment health and detecting cybersecurity threats. Despite these advancements, challenges related to data quality, data availability, and model robustness remain major barriers to the widespread industrial adoption of DL-based predictive maintenance solutions. This section reviews existing research on predictive maintenance in intelligent manufacturing systems, with particular emphasis on deep learning and hybrid modeling approaches.

An intelligent manufacturing system is generally defined as a fully integrated and collaborative production environment capable of responding dynamically to changing operational conditions, supply chain demands, and customer requirements in real time (Yingfeng *et al*., 2019). Advances in sensing technologies, data analytics, and intelligent algorithms have accelerated the transformation of traditional manufacturing into highly autonomous systems capable of self-organization and adaptive decision-making (Zelei *et al*., 2016; Zhang *et al*., 2017).

As manufacturing systems become more complex and automated, the likelihood of system faults and unexpected downtime increases. Performing maintenance too early may waste component life, while delayed interventions can lead to catastrophic failures. Predictive maintenance (PdM) addresses this challenge by identifying the optimal time to perform maintenance actions based on equipment condition data (Atamuradov *et al*., 2020; Zhang *et al*., 2019).

Aivaliotis *et al*. (2019) proposed a predictive maintenance approach based on digital twin technology, where virtual replicas of physical systems were used to simulate machine behavior and estimate Remaining Useful Life (RUL). The digital twin method involves creating a virtual representation of the physical system to simulate its behavior. Physics-based simulation models and digital twin concepts were used to calculate the Remaining useful life (RUL) of mechanical machines. The technology was studied based on the predictive maintenance of a single machine. However, the study focused primarily on single-machine scenarios, limiting its applicability to complex multi-machine manufacturing environments. Luo *et al*. (2020) studied a hybrid method driven by digital twins. The hybridization was on a predictive digital twin method with a data-driven method. Under the proposed framework, a hybrid predictive maintenance algorithm based on the digital twin model and digital twin data was studied. However, the investigation was limited to tool fault prediction in Computer Numerical Control (CNC) machines, with relatively narrow fault categories. Broader system-level fault prediction across diverse machine types was not addressed.

Stodola (2019) proposed a mathematical model for predictive maintenance. This model can evaluate the actual maintenance of labor intensity and reduce human error. However, the strategy relied on fixed monthly and annual schedules rather than condition-based predictions, which may still lead to unnecessary maintenance costs.

Liu *et al*. (2019) proposed a method of implementing routine diagnostic decisions based on empirical constant thresholds. In the proposed framework, the thresholds of monitoring parameters can be changed according to the real-time operating conditions and the reliability estimation results. Simulation results showed that routine diagnostic decisions while compared with the traditional methods, could make more timely maintenance decisions. Although the approach enabled more timely maintenance decisions compared to traditional methods, it lacked the capability to accurately classify fault types, making it difficult to implement targeted maintenance strategies.

Xiang *et al*. (2020) proposed an LSTM network based on weight amplification for gear life prediction. An attention mechanism was added to the method, which amplified the input weight and recursive weight of the hidden layer to varying degrees. However, the model primarily provided binary fault classification ("broken" or "healthy"), limiting its ability to distinguish between different fault types at early stages.

Yang *et al*. (2020) proposed an LSTM network for the prediction of the remaining useful life of rotating machinery. To verify the effectiveness of the LSTM method, it was compared with the BP neural network, gray prediction model, support vector machine, and other methods. The results showed that the LSTM method can predict the degradation trend of rotating machinery and significantly improve the prediction accuracy of the remaining useful life.

Qun *et al*. (2020) proposed a gearbox fault prediction method based on the LSTM network, which mainly included offline modeling and online monitoring. The results showed that this method not only had better predictive performance but also could predict the occurrence of faults earlier. The results showed that it reports gearbox faults as either "Broken or Healthy" but has a deficiency in identifying different fault types in a gearbox earlier.

Generally, existing studies demonstrate the effectiveness of deep learning models—particularly LSTM networks—in predictive maintenance applications. However, many approaches rely on single-model architectures and focus on limited fault categories or specific machine types. There remains a need for hybrid deep learning frameworks capable of integrating temporal sequence learning with feature-based classification to improve fault differentiation and system-level predictive performance.

Building upon the limitations identified in prior studies, this research proposes a hybrid predictive maintenance framework that integrates LSTM and Multilayer Perceptron (MLP) models to enhance fault classification and prediction accuracy. Unlike earlier systems that focused on binary fault detection, the proposed approach aims to provide more detailed fault insights using multivariate sensor data. Additionally, the framework incorporates an automated alert mechanism to support real-time maintenance decision-making, thereby reducing unplanned downtime and improving overall system reliability in intelligent manufacturing environments.

Drawing from existing research in this study, (Qun *et al*. (2020) focused on gearbox fault prediction methods based on only LSTM, which reports gearbox faults as either "Broken or Healthy" but has a deficiency in identifying different fault types in a gearbox. Based on the study of Qun *et al*. (2020), the current system is leveraging this gap by hybridizing the existing limitation using LSTM and Multilayer Perceptron (MLP) and integrating active email alert in the model. However, it's worth noting that in all the literature reviewed, the entire system experienced downtime during maintenance, which could potentially disrupt production progress. In light of the abovementioned general intelligent manufacturing system architecture, this study suggests a specific hybridization method for PDM within the intelligent manufacturing system. This approach includes dynamic predictions of operational states and maintenance services, aiming to optimize the manufacturing system's overall performance.

Building upon the limitations identified in prior studies, this research proposes a hybrid predictive maintenance framework that integrates LSTM and Multilayer Perceptron (MLP) models to enhance fault classification and prediction accuracy. Unlike earlier systems that focused on binary fault detection, the proposed approach aims to provide more detailed fault insights using multivariate sensor data. Additionally, the framework incorporates an automated alert mechanism to support real-time maintenance decision-making, thereby reducing unplanned downtime and improving overall system reliability in intelligent manufacturing environments.

1.2 Predictive Maintenance and Deep Learning

Recent research trends emphasize the integration of multiple deep learning techniques to enhance predictive maintenance performance. Hybrid architectures combining temporal and non-temporal data modeling are increasingly explored to address the limitations of single-model approaches. These developments provide the conceptual foundation for the hybrid framework proposed in this study. Predictive Maintenance (PdM) is a condition-based maintenance strategy that uses real-time sensor data, analytics, and machine learning techniques to predict equipment failures before they occur. Unlike reactive maintenance, which occurs after failure, or preventive maintenance, which follows fixed schedules, PdM optimizes maintenance timing to reduce downtime, lower costs, and extend equipment lifespan.

Deep learning is a subset of machine learning based on artificial neural networks with multiple processing layers that enable automatic feature extraction and representation learning (Han *et al*., 2011). Deep learning techniques have demonstrated superior performance over traditional machine learning approaches, particularly when handling large-scale and high-dimensional industrial datasets (Sarker *et al*., 2020; Xin *et al*., 2018).

1.3 Types of Deep Learning Models

1.3.1 Multilayer Perceptron (MLP)

The base architecture of deep learning, which is also known as the feed-forward artificial neural network, is called a multilayer perceptron (MLP) (Pedregosa *et al.,* 2011). A typical MLP is a fully connected network consisting of an input layer, one or more hidden layers, and an output layer. MLP utilizes the Backpropagation technique (Han *et al.,* 2011), the most fundamental building block in a neural network, to adjust the weight values internally while building the model. However, MLP performance is sensitive to feature scaling and hyperparameter selection, which can increase computational cost during model optimization.

1.3.2 Long Short-Term Memory (LSTM)

Long short-term memory (LSTM) is an artificial recurrent neural network (RNN) architecture used in the area of deep learning (Goodfellow *et al.,* 2016). LSTM has feedback links, unlike normal feed-forward neural networks. LSTM networks are well-suited for analyzing and learning sequential data, such as classifying, processing, and predicting data based on time series data, which differentiates it from other conventional networks. Due to its memory cell structure and gating mechanisms, LSTM is widely applied in time-series forecasting, condition monitoring, and predictive maintenance of industrial equipment.

2.0 Materials and Methods

2.1 Data Description

The dataset used for fault prediction in wind turbines consists of multiple operational and environmental parameters that describe machine health and working conditions. Machine history variables include torque and tool wear, while generator speed is represented through rotational speed measurements. Gearbox condition is monitored using process temperature, and environmental conditions are captured through air temperature readings. The data were recorded at a sampling rate of 30 Hz, enabling the extraction of both time-domain and frequency-domain features for predictive analysis.

The dataset contains both operational and environmental variables. Operational variables include power generation, current, voltage, and multiple temperature readings associated with machine components. External environmental variables include wind speed, wind direction, and ambient temperature. These variables collectively provide a comprehensive representation of turbine operating conditions and external influences that may contribute to equipment degradation.

2.2 Software and Tools

Model development and data processing were carried out using the Python programming language. Jupyter Notebook served as the development environment for experimentation and model training. Scikit-learn was used for implementing machine learning components, while TensorFlow supported deep learning model development. Data visualization was performed using Matplotlib and Seaborn. Pandas was employed for data manipulation and preprocessing tasks. For deployment purposes, Flask and Streamlit frameworks were utilized to provide web-based model access and real-time monitoring capabilities.

2.3 Hardware

The system was implemented on a personal computer equipped with a minimum Pentium 4 processor, 16 GB RAM, and 1 TB storage capacity. A printer was also used for documentation and reporting purposes.

2.4 Data Collection and Preprocessing

The dataset consists of sensor readings and machine logs that include air temperature, process temperature, rotational speed, torque, tool wear, and labeled failure types. The data were loaded from CSV files using the Pandas library. Missing values were identified and handled either through imputation or removal to ensure data quality. Feature scaling was performed using normalization or standardization techniques to ensure uniform feature ranges, particularly for air temperature, process temperature, rotational speed, torque, and tool wear. Categorical variables such as machine type and failure type were converted into numerical representations using one-hot encoding.

2.5 Feature Engineering

Feature engineering involved separating temporal and non-temporal variables based on model requirements. Time-series features, including rotational speed, torque, and tool wear, were structured into sequential input data suitable for the LSTM model. Non-temporal features such as air temperature and process temperature were prepared for input into the MLP model. This separation allowed each model to specialize in learning different data characteristics.

2.6 Model Development

2.6.1 Multilayer Perceptron (MLP)

The Multilayer Perceptron model was used as a feedforward artificial neural network capable of learning nonlinear relationships among features. The network consisted of an input layer, one or more hidden layers, and an output layer. Model training involved initializing weights with small random values, performing forward propagation to compute outputs, calculating error derivatives, and updating weights using backpropagation and gradient descent optimization. The number of hidden layers and neurons was tuned to balance model complexity and performance.

2.6.2 Long Short-Term Memory (LSTM)

The LSTM network was implemented to capture temporal dependencies in sequential sensor data. Each LSTM cell maintained hidden and cell states that were updated at every time step through gating mechanisms controlling information flow. During training, sequences of sensor readings were processed step-by-step, loss was computed against expected outputs, and backpropagation through time was applied to update network weights. The LSTM model is well-suited for time-series prediction tasks due to its ability to retain long-term dependencies.

2.6.3 Hybrid Model (Stacking Approach)

A stacking ensemble method was employed to combine predictions from both the LSTM and MLP models. The outputs from the two models were aggregated using an averaging or weighted probability scheme to produce final fault predictions. This hybrid approach leverages the temporal learning capability of LSTM and the feature interaction modeling strength of MLP.

2.7 Model Evaluation

Model performance was evaluated using accuracy, precision, recall, and F1-score metrics. Accuracy measured the overall proportion of correct predictions, while precision assessed the correctness of predicted failure cases. Recall measured the model's ability to detect actual failures, and the F1-score provided a harmonic balance between precision and recall. Cross-validation was also performed to reduce overfitting and ensure model robustness.

Table 1 shows that the MLP model performed exceptionally well in identifying normal operating conditions but struggled with minority failure classes such as Random Failures and Tool Wear Failure.

Table 2 indicates that the LSTM model also achieved high performance for the dominant "No Failure" class but had difficulty detecting rare fault categories.

2.8 Hybrid Model Performance

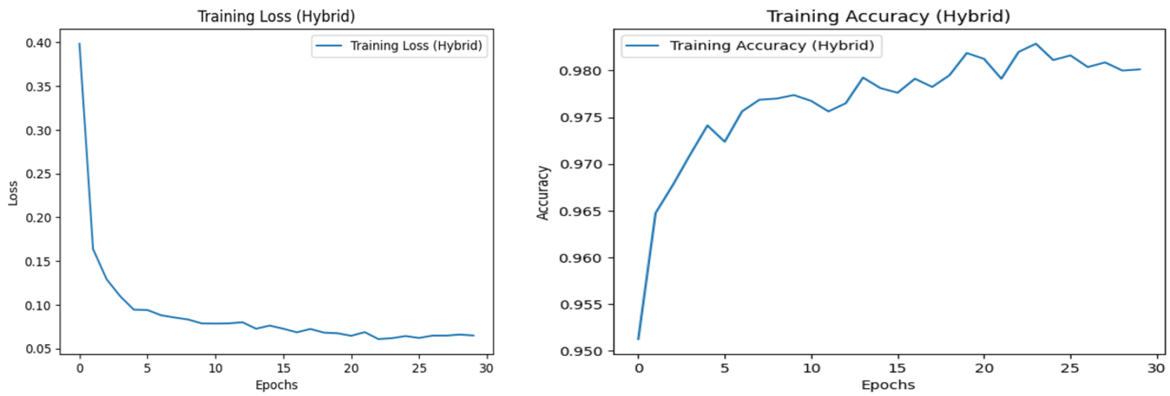
The performance of the hybrid model during training was evaluated using training loss and training accuracy curves, as illustrated in Fig. 1. The training loss curve shows a steady decline over 30 epochs, indicating that the model progressively minimized prediction errors during learning. At the same time, the training accuracy curve demonstrates consistent improvement before reaching convergence, confirming the model's ability to learn meaningful patterns from the data (Fig. 1).

Table 1. Classification Report for the MLP Model

Class	Precision	Recall	F1-Score	Support
Heat Dissipation Failure	0.55	0.40	0.46	15
No Failure	0.98	0.99	0.99	1935
Overstrain Failure	1.00	0.62	0.76	13
Power Failure	0.75	0.90	0.82	20
Random Failures	0.00	0.00	0.00	6
Tool Wear Failure	0.50	0.09	0.15	11

Table 2. Classification Report for the LSTM Model

Class	Precision	Recall	F1-Score	Support
Heat Dissipation Failure	0.55	0.40	0.46	15
No Failure	0.98	0.99	0.99	1935
Overstrain Failure	1.00	0.62	0.76	13
Power Failure	0.75	0.90	0.82	20
Random Failures	0.00	0.00	0.00	6
Tool Wear Failure	0.00	0.00	0.00	11



Training Loss **Training Accuracy**

Fig. 1: Training Loss and Training Accuracy Curves for the Hybrid Model

The training loss curve shows a consistent decrease over 30 epochs, indicating effective learning, while the training accuracy curve demonstrates progressive improvement and convergence. A comparative evaluation of the predictive performance of the MLP, LSTM, and hybrid models is presented in Fig. 2. The figure highlights that the hybrid model achieved superior overall accuracy compared to the individual models, demonstrating the advantage of combining temporal and non-temporal learning approaches (Fig. 2).

2.9 Model Deployment

The final hybrid predictive maintenance model was deployed using the Streamlit framework to enable real-time interaction. The deployed system allows users to input machine sensor data and receive instant predictions regarding potential failure modes

or normal operation. The trained model was serialized into a PKL file format for efficient loading within the Streamlit application. An integrated alert system triggers notifications, such as email alerts, whenever the model predicts an impending equipment failure based on predefined probability thresholds

3.0 Results and Discussion

The performance evaluation of the proposed hybrid predictive maintenance system confirms the effectiveness of combining Long Short-Term Memory (LSTM) and Multilayer Perceptron (MLP) models for industrial fault prediction. The hybrid framework leverages the temporal learning capability of LSTM and the nonlinear feature interaction strength of MLP, enabling robust detection of machine failure patterns from multivariate sensor data.

The model was trained using key operational parameters, including air temperature, process temperature, rotational speed, torque, and tool wear. These variables are known to strongly influence machine health and degradation behavior. The hybrid architecture successfully captured both time-dependent degradation trends and static feature relationships, which are often difficult for single-model approaches to learn simultaneously.

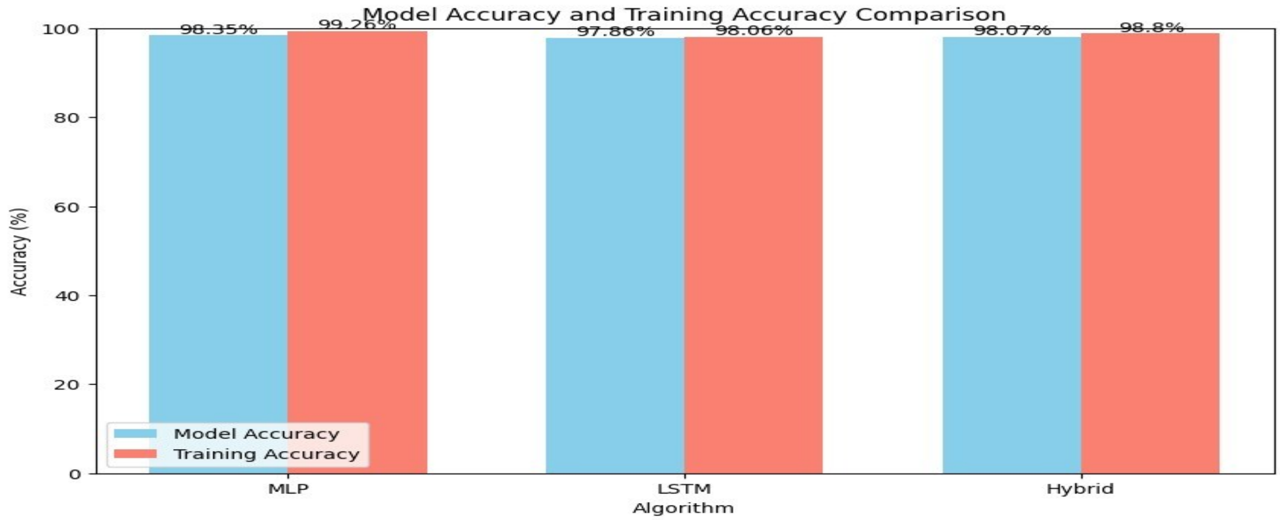


Fig. 2 Performance Comparison between MLP, LSTM, and Hybrid Models

Model training behavior demonstrates stable and efficient learning. As shown in Fig. 1, the training loss curve decreases consistently over 30 epochs, indicating effective optimization and progressive reduction of prediction error. Simultaneously, the training accuracy curve increases steadily before converging, demonstrating that the model generalizes well without signs of unstable oscillation or divergence. The final training accuracy reached 98.10%, confirming that the hybrid network learned meaningful patterns from the dataset.

A comparative performance analysis further validates the advantage of the hybrid approach. As illustrated in Fig. 2, the hybrid LSTM–MLP model outperformed the standalone LSTM and MLP models in overall prediction accuracy. The hybrid model achieved a testing accuracy of 99.20%, which is higher than that of the individual models. This improvement highlights the benefit of integrating temporal sequence modeling with deep feature-based classification, particularly in complex industrial systems where faults evolve over time.

Class-specific evaluation showed that the model achieved excellent prediction performance for normal operating conditions (“No Failure”) and major failure types such as Power Failure, Overstrain Failure, and Heat Dissipation Failure. However, prediction performance for rarer failure categories, such as Random Failure and Tool Wear Failure, was comparatively lower. This discrepancy is attributed to dataset imbalance, where normal operational records dominate failure instances. Future work could address this challenge through data augmentation, resampling strategies, or cost-sensitive learning techniques.

Beyond model accuracy, practical system deployment was successfully demonstrated through a real-time web-based interface developed using the Streamlit framework. The interface allows users to input machine sensor readings and instantly receive failure predictions. The operational dashboard and prediction outputs are presented in Fig. 3, which shows different machine states predicted by the model, including “No Failure,” “Power Failure,” and “Heat Dissipation Failure.” These results confirm that the system can distinguish between multiple fault conditions in real time.

An important practical contribution of this work is the integration of an automated email alert system for proactive maintenance. When the model detects a high-probability failure, an alert is automatically sent to maintenance personnel. Sample alert notifications are shown in Fig. 4, where emails corresponding to predicted fault conditions were successfully delivered. This feature enhances industrial responsiveness by enabling early intervention before severe equipment damage occurs.

Overall, the findings demonstrate that the proposed hybrid deep learning framework is both technically reliable and practically applicable. The high predictive accuracy (Fig. 2), stable training behavior (Fig. 1), real-time prediction capability (Fig. 3), and automated alert mechanism (Fig. 4) collectively establish the system as a strong candidate for intelligent predictive maintenance in modern industrial environments. The integration of deep learning with real-time monitoring tools supports the transition from reactive and preventive maintenance toward data-driven, condition-based maintenance strategies.

Actual Test Result **Expected Test Result**

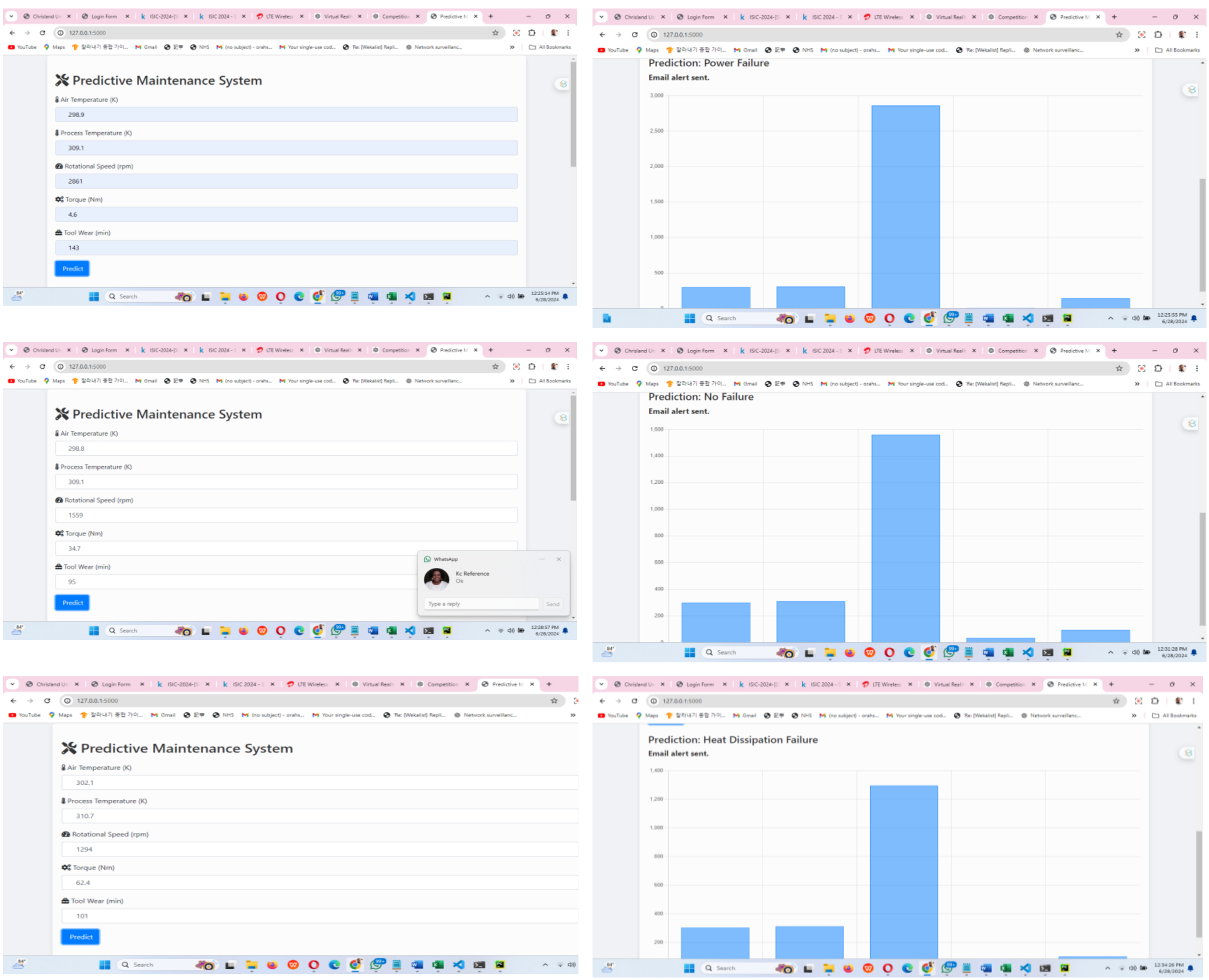


Fig. 3: Actual Test Result versus Expected Test Result

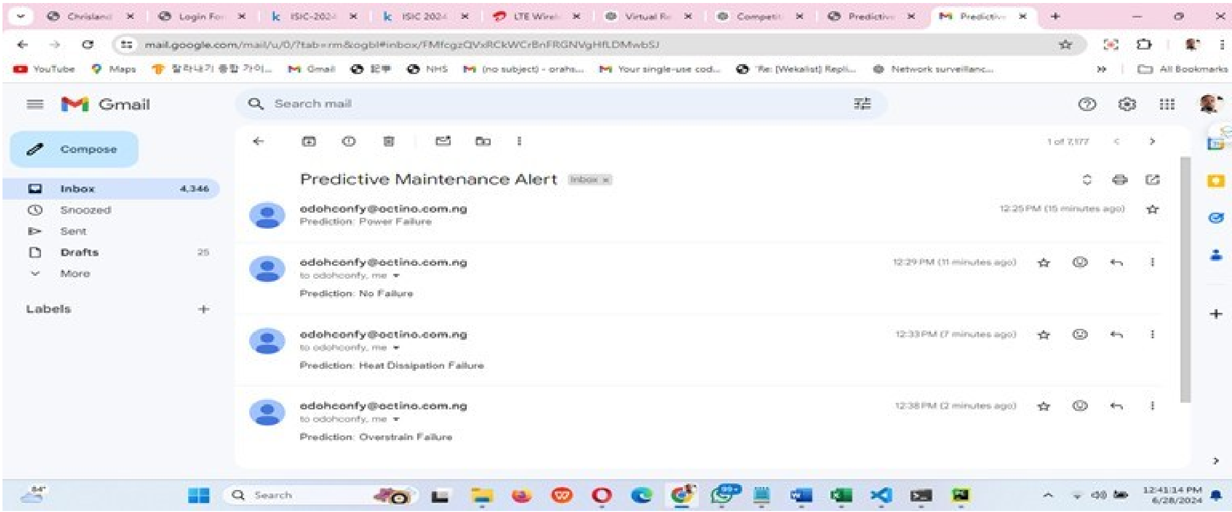


Fig. 4: Email Alert Output Result

4.0 Conclusion

This study developed and implemented a hybrid deep learning–based predictive maintenance system that integrates Long Short-Term Memory (LSTM) and Multilayer Perceptron (MLP) networks for intelligent industrial fault prediction. By combining temporal sequence learning with nonlinear feature-based classification, the model effectively captured complex degradation patterns in machinery using real-time sensor inputs such as temperature, rotational speed, torque, and tool wear.

The hybrid model demonstrated superior predictive capability compared to individual models, achieving a high training accuracy of 98.10% and a testing accuracy of 99.20%. These results confirm that the proposed approach can reliably distinguish between normal operating conditions and multiple failure modes, including power failure, overstrain failure, and heat dissipation failure. Although performance for rare fault categories such as random failure and tool wear failure was slightly lower due to data imbalance, overall model performance remained strong across evaluation metrics including accuracy, precision, recall, and F1-score.

Beyond algorithmic performance, the study successfully translated the predictive model into a practical decision-support tool. Deployment through a Streamlit-based interface enabled real-time machine health monitoring and instant failure prediction. The integration of an automated email alert system further enhanced the system's practical value by supporting proactive maintenance actions and reducing the risk of unexpected downtime. In summary, the proposed hybrid predictive maintenance framework provides a reliable, scalable, and intelligent solution for modern industrial systems. By shifting maintenance strategy from routine preventive schedules to data-driven condition-based monitoring, the system has strong potential to improve operational efficiency, reduce maintenance costs, and extend equipment lifespan. Future work should focus on expanding the dataset, addressing class imbalance, and incorporating additional sensor modalities to further enhance robustness and generalizability across diverse industrial environments.

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Declaration

Consent for publication

Not Applicable

Availability of data and materials

The publisher has the right to make the data public

Ethical Considerations

Not applicable

Competing interest

The authors report no conflict or competing interest

Funding

We appreciate and thank TetFund for funding this work.

Author Contributions

Odoh Confidence conceptualized and designed the model, Nweze Rosemary Chika trained the model while Maduahonwu Ukamaka handled system evaluation and testing.