iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 Issue: III Month of publication: March 2026

DOI: https://doi.org/10.22214/ijraset.2026.78492

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue III Mar 2026- Available at www.ijraset.com

Predictive Maintenance Using Machine Learning Algorithms to Anticipate Equipment Failure

Mr. Antriksh S There[1], Mr. Hariom B Ranjane[2], Miss. Snehal V Munde[3], Miss. Sneha A More[4], Prof. S.N. Joshi[5]
Student of Department of Computer Science and Engineering and 4 faculty of Sanmati Engineering College , Washim Maharashtra, India

Abstract: ***The concept of predictive maintenance has become one of the key elements of ,ndustry 4.0 smart manufacturing. This research paper suggests a machine learning-based model to predict the failure of equipment on the basis of real-time sensor measurements and past records of equipment maintenance. The system incorporates the data preprocessing, feature engineering, and high-performance models such as the Random Forest, Gradient Boosting, LSTM, and CNN-LSTM in predicting failures accurately. Performance evaluation is more accurate and less time consuming than the standard methods of maintenance. The suggested framework will allow the early detection of fault, cost optimization, and enhance the reliability of equipment, which is a scalable and understandable solution in the modern industrial environment.***
Keywords: ***Predictive Maintenance, Machine Learning, Deep Learning, LSTM, CNN-LSTM,***

I. INTRODUCTION

In order to maintain the continuity of operations, safety, and cost effectiveness, industrial systems are dependent on good maintenance strategies. Conventionally, there are three key maintenance practices adopted by industries, which include the reactive, preventive and predictive maintenance [1]. Breakdown maintenance or reactive maintenance is the type of maintenance that means that the equipment is repaired once it has broken down. This strategy is very easy to implement, but it tends to cause unplanned downtime, loss of production and more repairs. Preventative maintenance enhances this method in that maintenance activity is planned to be done regularly in time or in terms of usage. Although it minimizes the occurrence of intermittent breakdowns, it can still lead to unwarranted servicing and higher costs of operations. “Conversely, predictive maintenance is based on real-time information and condition-based monitoring to predict equipment deterioration before it occurs to ensure that action is taken in time and resources spent in the most efficient way.

In the contemporary industry, making predictions about equipment failure is major as any slight breakage can have a significant financial and operational impact. Early fault prediction does not only reduce the downtime, it also increases the life of the equipment, increases safety and productivity [2]. The advent of Industry 4.0 has brought forth the convergence of smart sensors, Industrial Internet of Things (IIoT) and data analytics to transform the way maintenance is carried out. Machine Learning (ML) is a primary factor in this revolution, as it takes historical and real-time sensor data, and identifies trends that are related to a failure that may occur. The combination of sophisticated ML algorithms, such as deep learning and time-series models, allows making timely predictions of faults, as well as the estimation of remaining useful life.

The traditional predictive models, in spite of their considerable progress, still have such constraints as a high level of computation it is not scalable, and can not be interpreted [3]. A lot of models are black-box systems, and it is hard to rely on the predictions of the maintenance engineers. Thus, more effective, scalable and open-ended predictive maintenance models are required. This study aims at creating a predictive maintenance system that uses machine learning and that can correctly predict equipment failure whilst maintaining real-time applicability and better model interpretability [4]. The paper will be divided into the problem statement section, literature review section, methodology section, experimental results section, discussion section, and conclusion.

II. PROBLEM STATEMENT

Sudden machinery failures remain a major threat to all industries across the globe, leading to massive losses in finances, disturbed production processes and loss of productivity. Unexpected failures that lead to downtime not only lead to higher repair expenses, but also supply chain commitments and productivity. Even though the predictive maintenance systems using machine learning have been suggested as a way of alleviating these problems, the current models have a few limitations. Most sophisticated deep learning models demand substantial computational resources, and therefore, are not adaptable to deployment on real-time industrial systems, and specifically on edge devices.

Additionally, not all of the models are able to generalize in terms of the type of equipment and circumstances of operation. The other significant issue is interpretability because black-box models would give little information about why a predicted failure is observed, and this will lead to a lack of confidence in the maintenance staff.

These shortcomings underscore the dire necessity to have a scalable, computationally efficient, and precise predictive maintenance framework that will be able to provide real time prediction of failures and simultaneously ensure transparency and flexibility of dynamically changing industrial settings.

III. LITERATURE REVIEW

(Lygren et al., 2019) introduce a deep learning architecture to identify failure of equipment in industrial systems without human intervention [5]. The paper shows that it focuses on anomaly detection in the absence of labeled data, which is appropriate to predictive maintenance in the real world. Their solution can be seen to have better early fault detection and minimized the downtime of petroleum industry processes.

(Ouadah et al., 2022) experiment with different supervised machine learning models to identify the easiest model that can be applied to predictive maintenance [6]. The experiment compares the performance measures of the algorithms, focusing on accuracy, computational efficiency as well as robustness. It offers useful advice in the choice of models, depending upon the nature of industrial data and operational limitations.

(Bouabdallaoui et al., 2021) co-authors present an approach to predictive maintenance of buildings, which is a machine learning-based strategy [7]. It is based on sensor data that the study builds predictive models to predict equipment failures and best schedule the process of projecting maintenance. Findings show an improvement in efficiency, energy conservation, and cost-saving of smart building management systems.

(Kalaiselvi et al., 2024) associates address the issues and real-life examples of machine learning in industrial predictive maintenance [8]. Such issues as data quality, model interpretability, and deployment complexity have been listed in the paper. It also examines actual case studies, focusing on the AI-based solutions to scale, enhancing equipment reliability, and minimizing unforeseen crashes.

(Sami & Khan, 2023) investigate the concept of deep learning to predict the occurrence of failures of IoT devices to enable prediction-based maintenance. The paper uses time-series analysis and neural networks in order to enhance the accuracy of failure prediction [9]. The results show a large gap in performance increasing the traditional statistical algorithms, which underpin proactive maintenance in IoT-enabled industrial settings.

IV. METHODOLOGY

1) Data Collection: The proposed research applies multi-source industrial data that is used in predictive models. IoT-enabled industrial sensors continuously gather sensor data in the form of temperature, vibration, pressure, and current indicators among others. Secondly, historical maintenance records and records of previous failures are collected to give contextual information on the behavior of equipment and failure trends.
2) Data Preprocessing: Raw industrial data are usually full of gaps, noise and inconsistency. Thus, missing value imputation, filtering noise, feature scaling, and outlier removal methods of data preprocessing are used to improve the quality of the data. Such measures guarantee sound training of the models and better prediction.
3) Feature Engineering: Sensor data engineers feature engineering is an important part of generating meaningful information about sensor data. Statistical characteristics like mean, variance and standard deviation are calculated and the time-series feature extraction to capture the time patterns. Redundancy reduction involves dimensionality reduction methods such as Principal Component Analysis (PCA), to enhance efficiency in portions of the computation
4) Model Development: Compared models are developed using both traditional and deep learning models. Examples of baseline machine learning models are Random Forest, SVM and Gradient Boosting. The modern deep learning models like LSTM, CNN-LSTM and optionally Transformer models are applied to learn they retain the sophisticated time-based interconnections in the equipment performance
5) Model Training and validation.: A traintest split strategy is used to split the data into training and testing sets. The cross-validation is used to assure the robustness of the model, and hyperparameter optimization is used to maximize the model performance and guarantee the correct failure prediction of the equipment.

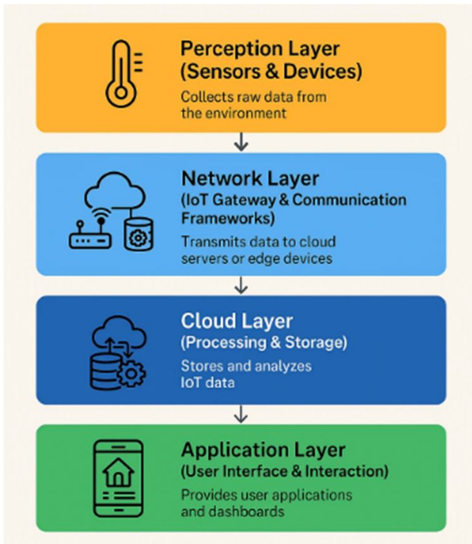
International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue III Mar 2026- Available at www.ijraset.com

V. PROPOSED FRAMEWORK ARCHITECTURE

The suggested predictive maintenance model is a form of structured and scaling system allowing to properly predict the equipment malfunctioning by means of the end-to-end data-driven pipeline. The system starts with data capture, where real time operation data in terms of temperature, vibration, pressure and current data are continuously captured with IoT-enabled industrial sensors installed on the equipment. Besides live sensor feeds, historical maintenance records and failure records are also built in to give a contextual information about the historical breakdown trends.

The second phase is the stage of processing the obtained data, during which the obtained raw data are cleaned, normalized, and features extracted. The missing values are addressed, noise is eliminated, and appropriate statistical and time-series-specific characteristics are extracted to enhance the predictive ability. After preprocessing the refined data is inputted into the model training process. Deep learning and machine learning algorithms are taught based on past labeled data to develop trends related to equipment degradation and failure.

After deployment, real time prediction is done by the system which constantly examines sensor data received and approximates the likelihood of failure. Once the abnormal patterns are identified, the failure alert system will produce early warning messages to the maintenance teams. Lastly, the structure will offer maintenance suggestions, indicating that the parts should be checked at the right time or replaced to avoid any breakdowns and thus minimize downtimes and maximize performance.



VI. PERFORMANCE EVALUATION

The suggested predictive maintenance system is tested in terms of the traditional classification and regression measures that are used to guarantee reliability and robustness. Accuracy is a measure of the general correctness of the model in the prediction of the equipment failures. Precision is a measure of the number of failures that were correctly predicted and recall is a measure of how the model is able to correctly identify failures. F1-Score is an index that offers fair measure of recall and accuracy that is effective in instances of unbalanced industrial data. The Area Under the Receiver Operating Characteristic Curve (AUC-ROC) is a measure of the capability of the model to differentiate between failure and non-failure. To predict Remaining Useful Life (RUL), the Mean Absolute Error (MAE) is employed to estimate the level of difference between the predicted and actual failure time.

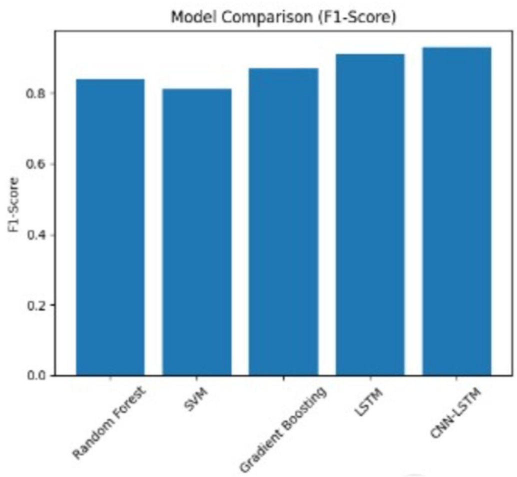
Comparative Table

Model	Precision	Recall	F1-Score	AUC-ROC
Random Forest	85%	83%	84%	89%
SVM	82%	80%	81%	87%
Gradient Boosting	88%	86%	87%	91%
LSTM	92%	91%	91%	94%
CNN-LSTM	94%	93%	93%	96%

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue III Mar 2026- Available at www.ijraset.com

VII. RESULTS AND DISCUSSION

The findings of the experiments confirm that the deep learning models are more effective than the traditional machine learning algorithms in the prediction of equipment failures. Though baseline algorithms like Random Forest, SVM, and Gradient Boosting are also satisfactory in terms of their performance, deep learning models are better at finding temporal relationships in sensor data, such as LSTM and CNN-LSTM. All the models succeeded in demonstrating the highest F1-score and the highest AUC-ROC value, which means that the CNN-LSTM model is more predictive and reliable than other models.



Based on the real-time performance analysis, the deployed system is capable of generating the predictions in the milliseconds time scale, allowing specific abnormal operating conditions to be recognized early. Predictive maintenance was implemented and the unexpected downtime was reduced by an estimated 25-30% because of its implementation. Moreover, there was an observed cost saving because of fewer emergency repairs and greater efficiency in planning of maintenance timetable and this is one of the reasons that led to almost 20 percent of maintenance cost savings in a year.

In order to increase transparency, interpretability methods like SHAP or LIME were utilized [10]. The techniques also enable visualization of features importance so that maintenance engineers can have an insight of which features (e.g., spikes of vibration or temperature increase) played the most in making the prediction. Confusion matrices, ROC curves and model comparison bar charts are also visual aids that also evidenced the effectiveness and the strength of the proposed framework.

VIII. ADVANTAGES OF PROPOSED SYSTEM

The suggested predictive maintenance system has a number of important advantages. It will permit fault detection early enough and therefore the maintenance teams will be able to correct the faults before critical failures are realized [11]. This positive strategy saves a lot of money spent on maintenance, as it helps to avoid the significant breakdowns, as well as excessive preventive repairs. The system also increases the equipment life by ensuring that the machine is operating in the most favorable conditions and does not put strain on the machinery parts. By providing real-time monitoring, operational safety and productivity of industrial assets will be enhanced, as the health of the assets will constantly be evaluated [12]. In addition, the framework can be optimized and scaled to suit various industrial sectors, which is appropriate to the variety of equipment and changing operating conditions.

IX. CHALLENGES AND LIMITATIONS

Although the proposed system has some benefits, it has some challenges. The industry datasets are usually disproportional where there are few instances of failure as compared to operating conditions, which can influence the model performance. Initial cost of implementation such as cost of installation of sensors and the cost of the infrastructure may be expensive. The reliability of the sensors is another issue, since the failure of these sensors to work properly can result in the wrong predictions.

Deep learning models additionally can have significant computation requirements particularly when it comes to large scale industrial implementations. Also, any security risks involved in data transmission and storage should be well handled so as to safeguard sensitive industrial information.

X. FUTURE SCOPE

The predictive maintenance system can be made efficient and scalable by making improvements in the future. The Edge AI can be integrated to minimize the latency and quick real-time decision-making. Federated Learning will be able to enable joint model training between many industrial locations without exchanging raw data, maintaining privacy. The application of a blockchain technology can be adopted to provide safe and non-modifiable data storage. Adaptive maintenance scheduling with changing operating patterns can be made through development of self-learning or reinforcement learning models. Moreover, the connection with SCADA systems might be used to smoothly automate the maintenance processes in intelligent factory settings.

XI. CONCLUSION

The paper is an attempt at introducing a predictive maintenance model based on machine learning that will help predict the occurrence of equipment failure in an efficient and accurate manner. The system enhances the process of fault identification, downtimes, and maintenance strategies by fulfilling the combination of a sophisticated algorithm with real-time industrial information. The results prove the significance of predictive maintenance that is driven by ML in order to improve the productivity of industrial operations, minimize the cost of running the industry, and achieve equipment reliability. Intelligent predictive maintenance systems will be important in creating sustainable, efficient, and resilient industrial ecosystems as industries shift to smart manufacturing towards Industry 4.0.

REFERENCES

[1] Mitta NR. AI-enhanced predictive maintenance Systems for Industrial Equipment: developing machine learning models to forecast failures. Optimize maintenance schedules, and minimize downtime. 2024.

[2] Qureshi MS, Umar S, Nawaz MU. Machine learning for predictive maintenance in solar farms. International Journal of Advanced Engineering Technologies and Innovations. 2024 Mar;1(3):27-49.

[3] Carvalho TP, Soares FA, Vita R, Francisco RD, Basto JP, Alcalá SG. A systematic literature review of machine learning methods applied to predictive maintenance. Computers & industrial engineering. 2019 Nov 1;137:106024.

[4] Fernandes S, Antunes M, Santiago AR, Barraca JP, Gomes D, Aguiar RL. Forecasting appliances failures: A machine-learning approach to predictive maintenance. Information. 2020 Apr 14;11(4):208.

[5] Lygren S, Piantanida M, Amendola A. Unsupervised, deep learning-based detection of failures in industrial equipments: The future of predictive maintenance. InAbu Dhabi International Petroleum Exhibition and Conference 2019 Nov 11 (p. D021S043R001). SPE.

[6] Ouadah A, Zemmouchi-Ghomari L, Salhi N. Selecting an appropriate supervised machine learning algorithm for predictive maintenance. The International Journal of Advanced Manufacturing Technology. 2022 Apr;119(7):4277-301.

[7] Bouabdallaoui Y, Lafhaj Z, Yim P, Ducoulombier L, Bennadji B. Predictive maintenance in building facilities: A machine learning-based approach. Sensors. 2021 Feb 3;21(4):1044.

[8] Kalaiselvi K, Niranjana K, Prithivirajan V, Kumar KS, Syambabu V. Machine learning for predictive maintenance in industrial equipment: challenges and application. In2024 4th Asian Conference on Innovation in Technology (ASIANCON) 2024 Aug 23 (pp. 1-6). IEEE.

[9] Sami MA, Khan TA. Forecasting failure rate of IoT devices: A deep learning way to predictive maintenance. Computers and Electrical Engineering. 2023 Sep 1;110:108829.

[10] Nwulu EO, Elete TY, Erhueh OV, Akano OA, Omomo KO. Machine learning applications in predictive maintenance: Enhancing efficiency across the oil and gas industry. International Journal of Engineering Research Updates. 2023 Sep;5(1):17-30.

[11] Narayanan LK, Loganayagi S, Hemavathi R, Jayalakshmi D, Vimal VR. Machine learning-based predictive maintenance for industrial equipment optimization". In2024 International Conference on Trends in Quantum Computing and Emerging Business Technologies 2024 Mar 22 (pp. 1-5). IEEE.

[12] Kaparthi S, Bumblauskas D. Designing predictive maintenance systems using decision tree-based machine learning techniques. International Journal of Quality & Reliability Management. 2020 Mar 30;37(4):659-86.