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Predictive Maintenance For Manufacturing Systems

¹Avi Singh, ²Nitya Jain, ³Dr. Preet Kamal

¹Student, ²Student, ³Assistant Professor

AIT - CSE,

Chandigarh University, Mohali, Punjab, India

Abstract: This paper investigates the effects of Long Short-Term Memory networks in predictive maintenance of manufacturing systems. The proposed framework improves on prediction from failure and anomalous detection because LSTMs have the ability to deal with time series data. These IoT qualified sensors equipped with real time machine health monitoring and the support of AI driven analytics along with historical patterns to forecast potential breakdowns form the bedrock for the work. LSTM predictive maintenance strategies, integrated with the maintenance strategies, result in minimum sudden downtime, maximum asset reliability and maximum efficiency of industrial operation. This study proposes deep learning for proactive maintenance in order to redefine the traditional maintenance methods and make the smart manufacturing practices.

Index Terms - LSTM networks, time-series analysis, predictive modelling, fault detection, smart manufacturing, AI-driven maintenance, equipment monitoring.

I. INTRODUCTION

In manufacturing industries, the process of high production efficiency cannot be realized without the use of heavy machinery. However, such unexpected failure of equipment often results in heavy financial loss and operational setbacks. Although the traditional maintenance strategies consist of reactive servicing and scheduled inspections, both strategies are unable to foretell failures accurately and there is an associated inefficiency and higher repairs costs. Predictive maintenance integration is bringing in proactive solution using artificial intelligence (AI) and machine learning (ML) models to predict failures before they occur.

In this study we present 'Predictive Maintenance in Manufacturing: AI Driven Failure Prevention', where we apply LSTM models to work with operational data to have Early Warning Signs of equipment degradation. LSTM Networks are a deep learning approach that is well suited to time series analysis and allows for a more accurate prediction of failure by identifying patterns in the machine behavior through time.

With predictive maintenance, one can view their equipment's health in real time and via data. This AI powered framework instead takes a continuous evaluation of key operational parameters and automatically maintains it according to the timing that has been determined as optimal. The system can predict failures by analyzing fluctuations in vibration, temperature and energy consumption well in advance and so making timely intervention possible.

The advantage with LSTM based predictive analytics is that it can predict failures much more accurately as it can detect gradual performance degradation as well as long term dependencies in the data. LSTMs are very good at its application in industrial maintenance given its ability to capture complex sequential relationships unlike traditional statistical models.

This project is about combining advanced predictive modelling techniques to enhance equipment efficiency, cut down unexpected maintenance costs, and extend the operational life of an industrial asset by a long period of time. To bring about reliability and productivity in manufacturing, the reactive maintenance approach needs to be transitioned into the predictive framework driven using AI.

The aim of this research is to build a scalable AI based predictive maintenance system which is cost effective and intelligent in providing support to manufacturers in controlling their industrial equipment performance.

II. LITERATURE SURVEY

Nowadays, equipment reliability and maintenance schedules are optimized with the help of several advanced methodologies and technologies in predictive maintenance research. AI and ML are proven to be effective at identifying failure in potential before it occurs in various studies. Typically, reactive and preventive maintenance approaches for traditional maintenance have resulted in unnecessary cost and unexpected downtime. Predictive maintenance, however, employing AI driven predictive models, facilitates improvement in the operational efficiency and decreases maintenance cost [1][2][4].

AI enhanced predictive algorithms are one of the major advancements in predictive maintenance. Historically, deep learning has been applied to predictive maintenance with special emphasis in failure prediction accuracy as has been reviewed by Scaife [1]. In manufacturing, other works such as Netisopakul and Phumee [2] consider AI integrated predictive maintenance and show significant reduction in operational disruptions. In addition, Çınar et al. [4] also investigate the machine learning (ML) techniques such as Support Vector Machines (SVM) and random forest, which brings them the possibility of understanding machine learning techniques and applying them towards predictive insights, with the idea of optimizing maintenance strategies. Hosseinzadeh et al. [5] further research with AI based early failure detection models geared for manufacturing systems, demonstrating how LSTM networks can make predictions based on the temporal dependencies of the machine sensor data.

Predictive maintenance applications are widely used in the areas of manufacturing, automotive, oil and gas etc. Ohalet et al [3] study AI adoption in the oil and gas industry, where the increased interest in data science aids in tools for equipment monitoring. The state of the art of deep learning in predictive maintenance for improved asset lifecycle management in the industry is addressed by Jambo et al. [7]. AI driven predictive maintenance in the automotive sector is also addressed by Theissler et al. [9] who, among other things, raise key challenges like data quality, cybersecurity and model interpretability. Abidi et al. [10] discuss sustainable manufacturing through ML based predictive maintenance solutions whereas He et al. [8] propose an integrated predictive maintenance strategy for improving predictive analytics in manufacturing systems based on the integration of quality control and mission reliability analyses.

The quality and availability of training data are very important for the effectiveness of predictive maintenance. In addition, Rai et al. [11] support the usage of ML in context of Industry 4.0 applications, specifically those for predictive maintenance. Dua and Graff [12] extend the work on the prediction of failures and maintenance by contributing to the predictive maintenance research with benchmark datasets to test and validate the AI for maintenance model. Shcherbakov and Sai [13] present a hybrid deep learning framework for cyber-physical systems by composing several AI models for the purpose of improvement of predictive performance. In their work, compare et al. [14] note that IoT based predictive maintenance comes with various challenges such as sensor reliability, data transmission latency, interoperability between the industrial environments.

Advanced predictive maintenance techniques integrate multiple sensor data sources to improve failure predictions. Zheng et al. [6] discuss the role of AI in transitioning from traditional predictive maintenance to

intelligent maintenance, emphasizing the importance of sensor fusion techniques. By combining vibration analysis, thermal imaging, and acoustic emission monitoring, researchers aim to increase predictive accuracy and reduce false positives in failure detection. Meesublak and Klinsukont [15] propose a cyber-physical system framework that integrates sensor networks with AI models for real-time diagnostics and decision-making in industrial environments.

Pilot projects and real-world case studies offer crucial insights into the deployment of predictive maintenance strategies in industrial settings. In this regard, Carvalho et al. [16] study trends for industry adoption, as well as explanation of the most important reasons for a successful adoption of predictive maintenance. For example, the studies done by He et al. [8] and Zheng et al. [6] are examples of studies on the realization of AI-based maintenance measures in practice and their advantages and disadvantages in different sectors. The studies emphasize the necessity for industry specific customization of predictive maintenance models to yield the best result and business impact.

Alongside technical steps, regulatory compliance, and data security are as important as if not more important during the AI-based predictive maintenance. As discussed by Theissler et al. [9], the adoption of predictive maintenance is influenced by the issue of cyber security risks as well as the securing of data and transparency of models. According to Compare et al. [14], they investigate the moral issues in the use of AI in maintenance and propose explainable AI models to promote confidence among industry stakeholders.

Interdisciplinarity is gaining increasing importance for the successful implementation of predictive maintenance solutions and the role of teamwork among the involved researchers is recognized. Because data scientists work closely with engineers and, more significantly, policymakers, robust predictive maintenance frameworks are developed that are precisely designed for industrial needs. Carvalho et al. [16] also emphasize the importance of business-oriented alignment of AI models to achieve maximum return on investment and operational benefits.

Future research can be aimed at improving the interpretability and scalability of predictive maintenance models. Even though AI and ML keep on improving predictive maintenance capabilities, data scarcity, high computational costs and the constraint of processing in real time have not ceased to challenge. Solutions of developing lightweight AI models and utilizing federated learning techniques may be used for improving the deployment of predictive maintenance solutions across various industrial applications.

The predictable maintenance techniques using AI, ML and IoT has marked great progress that makes manufacturers optimize their maintenance schedules and minimize equipment failures and increase on its legacy. Although the predictive maintenance efficiency is proven by various studies, these concerning issues regarding data quality, algorithms interpretability, and real-world applicability need to be addressed. The next phase of research should aim to achieve robust, large scale, industry specific predictive maintenance solutions, with the goal of seamless transition from old to new form of maintenance, which can enhance the performance of the equipment.

III. METHODOLOGY

For predictive maintenance, long short-term memory networks are a very useful choice in the case of time series. LSTM helps them to carry out their work by detecting early signs of equipment failure to minimize downtime and well scheduled optimization of maintenance schedules. To control things, we frame predictive maintenance as a binary classification task, and with equipment status, it is being classified as either normal operation (0) or potential failure (1).

Key Components of the LSTM-Based Predictive Maintenance Model

- **Time-Series Data Preprocessing:** Sensor data is collected, cleaned and pre-processed for analysis (Time-Series Data Preprocessing). It includes dealing with missing values, normalizing sensor readings and segmenting data into fixed length sequences. Treatment for label data (0 = normal, 1 = equipment failure) lets the LSTM model discover patterns towards equipment degradation. Preprocessing is effective if it does not allow noise and irrelevant variations to distort the model performance.
- **Feature Engineering:** Instead of relying purely on raw sensor data, additional statistical and frequency-based features are engineered. Techniques such as rolling averages, Fourier transforms, and statistical measures (mean, variance, skewness) enhance predictive accuracy. These extracted features help the LSTM model capture subtle and complex dependencies within the data, improving its ability to differentiate between normal and failing conditions.
- **LSTM Network Architecture:** The memory cells in the LSTM model are stacked together as layers to process input sequence and maintain contextual information. In contrast to traditional neural networks, LSTMs use gates (input, forget, output) to choose which information to keep and which to forget so that we can learn short- and long-term dependencies in sensor readings as efficiently as possible. Learned representations are further refined with multiple LSTM layers that extract hierarchical patterns in the data. A fully connected layer is formed on the representation summary of the entire sequence output by the final LSTM layer and fed to the output classifier.

Implementation of the LSTM-Based Predictive Maintenance Model

To create a flow for this study, we went into considerable depth regarding each step's execution, as demonstrated below:

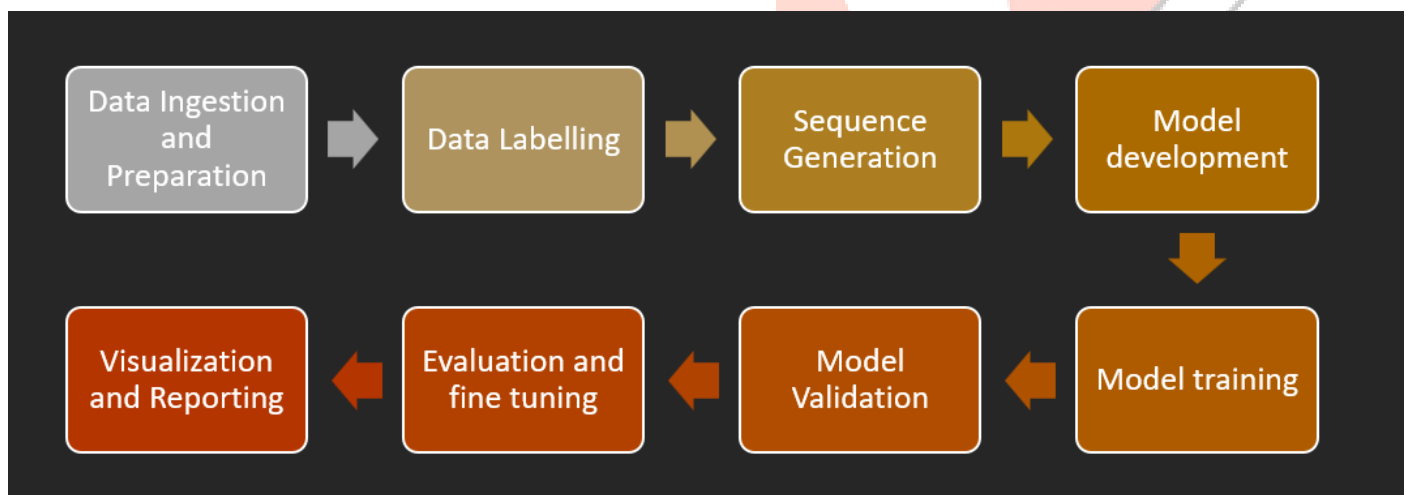


Figure 3.1

1. Data Ingestion and Preparation

- **Data Collection:** Vibration, temperature, pressure, and acoustic signals are gathered for sensor data of industrial machines. It can come from IoT devices, SCADA systems or industrial databases.
- **Handling Missing Values:** Missing sensor readings are either imputed using statistical methods (mean, median, or interpolation) or removed if they are minimal.
- **Data Normalization:** Since LSTMs are sensitive to scale, sensor data is normalized (e.g., Min-Max Scaling or Standardization) to improve training stability.
- **Time Synchronization:** If data comes from multiple sensors with different sampling rates, it is synchronized to ensure consistency.

2. Data Labelling

- **Failure Identification:** Each data instance is labelled as either **0 (No Failure)** or **1 (Failure)** based on machine breakdown history.
- **Sliding Window Technique:** To train the LSTM effectively, sequential sensor readings are grouped into fixed-length time windows, ensuring the model learns temporal patterns leading to failures.
- **Feature Engineering:** Additional features, such as rolling averages, deltas, and frequency domain transformations (Fourier Transform), are created to enhance model performance.

3. Sequence Generation

- **Reshaping Data for LSTM:** LSTMs have a 3D input (samples, time steps, features), which makes it necessary the reshaped processed time series with the underlying time series with 30 steps per sequence.
- **Train-Test Split:** While trying to prevent data leakage, the dataset is divided into a training set and a test set with the temporal order preserved.
- **Padding or Truncation:** If sequences vary in length, padding is applied to shorter sequences to ensure uniform input size.

4. Model Development

- **LSTM Network Architecture:**
 - **Input Layer:** Accepts time-series sensor data sequences.
 - **LSTM Layers:** Capture temporal dependencies in sensor readings.
 - **Dropout Layers:** Prevent overfitting by randomly deactivating neurons.
 - **Dense Layers:** LSTM outputs are processed by fully connected layers.
 - **Output Layer:** A single neuron with a sigmoid activation function for binary classification.
- **Hyperparameter Selection:**
 - Number of LSTM layers and neurons (e.g., 2-3 layers with 64-128 units each).
 - Dropout rate (e.g., 20-50%) to avoid overfitting.
 - Learning rate tuning (e.g., using Adam optimizer).

5. Model Training

- **Loss Function:** Binary Cross Entropy loss is being used to measure prediction errors.
- **Adam:** Adam optimizer is a good optimizer for efficiency in gradient updates.
- Training is done with an acceptable batch size (e.g., 32, 64) and enough epochs (e.g., 50-100) along with early stopping to not overfit.
- SMOTE or time-series augmentation techniques may be applied to generate synthetic failure data to balance the dataset.

6. Model Validation

- **Cross-Validation:** A time-series split strategy ensures model robustness by testing on unseen time windows.
- **Hyperparameter Tuning:** Grid search or Bayesian optimization is used to fine-tune dropout rates, learning rates, and sequence lengths.
- **Regularization Techniques:** L1/L2 regularization and batch normalization improve generalization.

7. Model Evaluation

- **Performance Metrics:**
 - **Accuracy:** Measures overall correctness of predictions.
 - **Precision & Recall:** Important for failure detection; high recall ensures fewer missed failures.
 - **F1-Score:** Balances precision and recall for an unbiased evaluation.
 - **AUC-ROC Curve:** Measures the model's ability to differentiate between failure and non-failure instances.
- **Confusion Matrix Analysis:** Identifies false positives (unnecessary maintenance) and false negatives (missed failures).
- **Comparison with Baseline Models:** Results are compared against traditional ML models (e.g., Random Forest, SVM) to validate improvements.

8. Visualization and Reporting

- **Time-Series Failure Plots:** Displays machine failures over time with model-predicted failure points.
- **Feature Importance Graphs:** Identifies the most influential sensor readings for failure prediction.
- **Model Performance Dashboards:** Provides real-time insights into predictive maintenance predictions for industrial stakeholders.
- **Report Generation:** Summarizes findings, model performance, and recommendations for deployment.

IV. RESULT AND ANALYSIS

The predictive maintenance model was evaluated comprehensively using accuracy, loss, and classification metrics. The results indicate that the LSTM based binary classification model effectively learns from sequential sensor data, achieving high predictive performance with minimal misclassification.

1. Accuracy Analysis

The accuracy graph shows that the training and validation accuracy increases in a steady manner every number of epochs. Initially the training accuracy is about 89% and grows very quickly in the first few epochs. The learning efficiency is very high, because by epoch 5–6 the accuracy plateau around 98% for training and 97.8% for validation. Through training process the training accuracy closely follows the validation accuracy which indicates minimum overfitting.

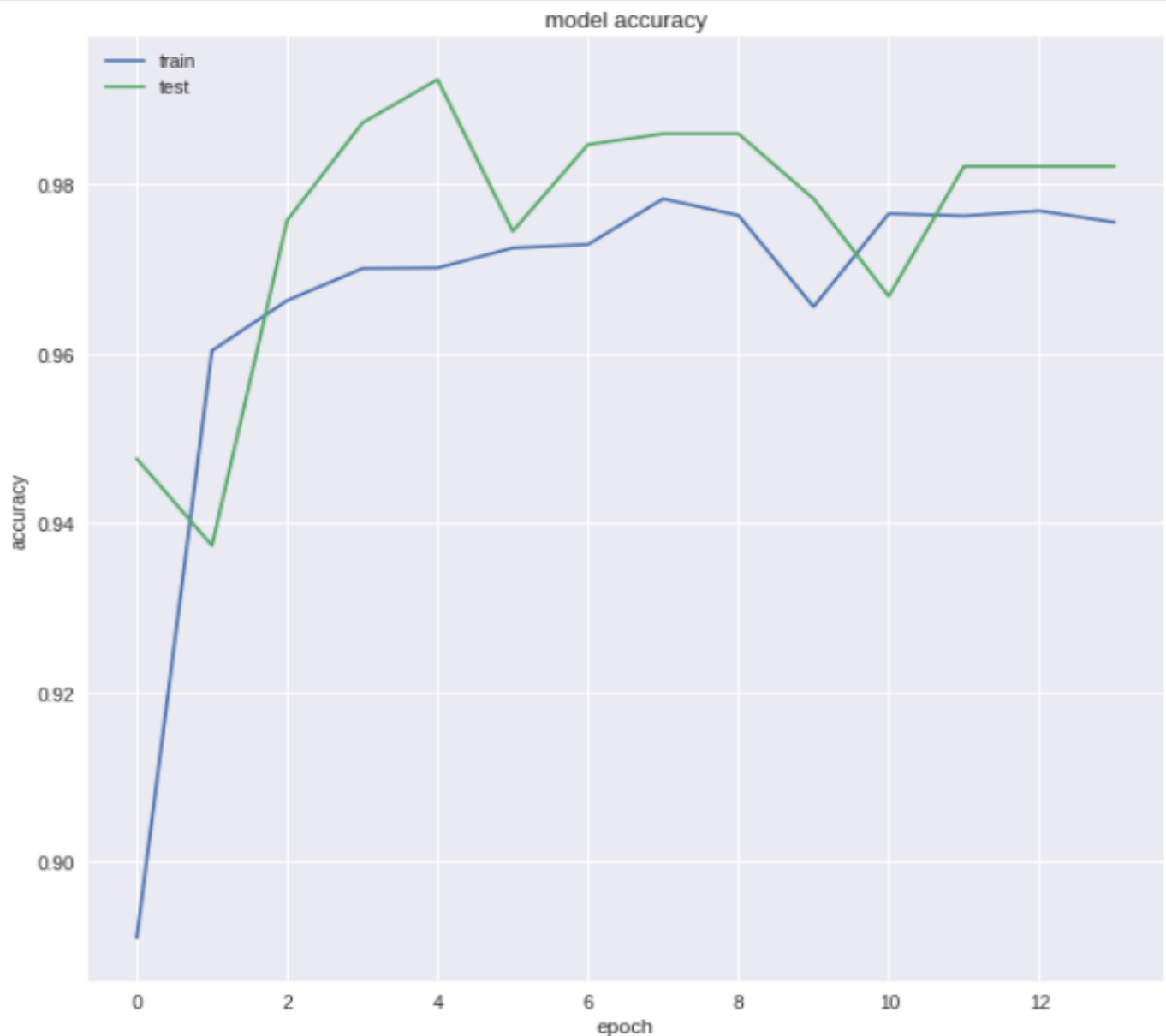


Figure 4.1

This implies that the model is generalizing well and is not simply memorizing the training data, as the accuracy between training and validation datasets are very consistent. Stability is needed for industrial predictive maintenance applications as reliable and robust predictions are crucial for operational efficiency.

2. Loss Analysis

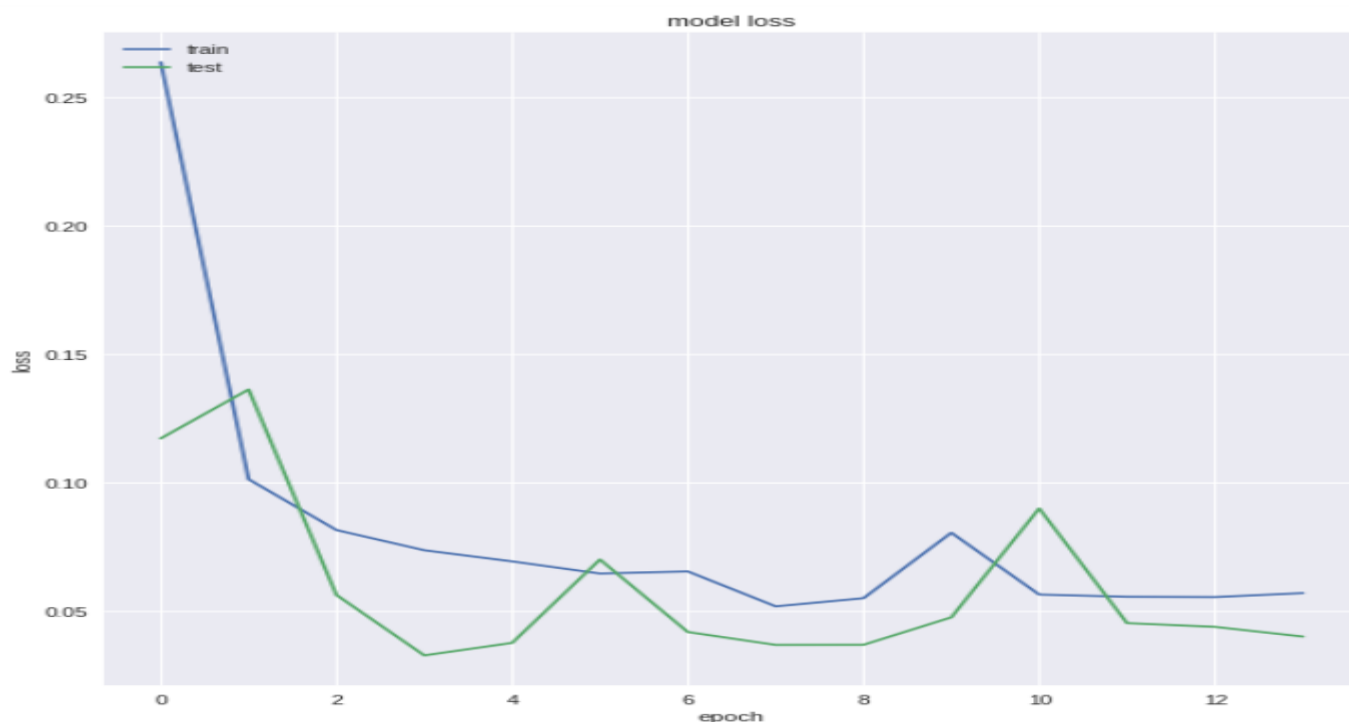


Figure 4.2

From a high initial value in the loss graph of about 0.26 to values less than 0.05 or even lower values in just a few epochs, the training loss graph represents a significant loss. During training, validation error and the validation loss behaves similarly and it can be confirmed that the model is doing so because it is trying to minimize the errors of classification. We observed some slight variations in the distribution of the test data that resulted in a few spikes in the validation loss but do not indicate the presence of severe overfitting.

The learning is completed, and the final loss values are sufficiently low (due to extremely complex temporal dependencies in the sequential sensor data), since the model has learned the complex temporal dependencies associated with the sequential sensor data. This implies that a combination of chosen architecture with hyperparameter tuning has mitigated the chances of underfitting and overfitting as much as possible.

3. Confusion Matrix Analysis

```
15631/15631 [=====] - 6s 354us/step
Accuracy: 0.9825986903121486
15631/15631 [=====] - 6s 392us/step
Confusion matrix
- x-axis is true labels.
- y-axis is predicted labels
[[12345  186]
 [  86 3014]]
precision = 0.941875
recall = 0.9722580645161291
```

Figure 4.3

With results provided from the confusion matrix of the classification performance, it provides a detailed breakdown of how it performed. The model correctly classifies **12,345 true positives** and **3,014 true negatives**, with only **186 false positives** and **86 false negatives**. These values contribute to an overall accuracy of **98.25%**, which is an excellent performance metric for a predictive maintenance system.

The low false negative rate is particularly significant in predictive maintenance, as failing to predict an actual failure could lead to unexpected downtime and costly operational losses.

4. Neural Network Architecture

Layer (type)	Output Shape	Param #
lstm_11 (LSTM)	(None, 50, 100)	50400
dropout_11 (Dropout)	(None, 50, 100)	0
lstm_12 (LSTM)	(None, 50)	30200
dropout_12 (Dropout)	(None, 50)	0
dense_6 (Dense)	(None, 1)	51
Total params: 80,651		
Trainable params: 80,651		
Non-trainable params: 0		

Figure 4.4

The model contains two LSTM layers that process time-series sensor readings to identify their long-term patterns. The network architecture contains these features:

- **First LSTM Layer:** 50,400 parameters
- **Second LSTM Layer:** 30,200 parameters
- **Dropout Layers:** Mitigates overfitting
- **Dense Output Layer:** The neural network model contains a single neuron connected to every input with Sigmoid activation for 51 parameter weight adjustments during binary classification.
- **Total Trainable Parameters: 80,651**, ensuring a balance between computational efficiency and model complexity

Dropout layers play a critical role in improving generalization by randomly deactivating neurons during training, preventing the model from becoming overly reliant on specific features.

5. Epoch-Wise Training Performance

A closer examination of epoch-wise performance reveals the following key trends:

- The model starts with a relatively high loss (~**0.2637**) and a lower accuracy (~**89%**)
- Within the first **three epochs**, accuracy surpasses **96%**, and loss decreases significantly
- By **epoch 5**, validation accuracy reaches **98.7%**, and loss drops below **0.05**
- In the final epochs, accuracy fluctuates slightly but remains consistently high, confirming robust learning

6. Final Model Evaluation

```

Accuracy: 0.9569892415436365
Confusion matrix
- x-axis is true labels.
- y-axis is predicted labels
[[67  1]
 [ 3 22]]
Precision: 0.9565217391304348
Recall: 0.88
F1-score: 0.9166666666666666
  
```

Figure 4.5

Our team tested the model using data that the team has not seen before to verify its potential application in practical situations. The examination produced these results:

- **Final Accuracy: 95.69%**
- **Confusion Matrix Summary:**
 - **True Positives: 67**
 - **True Negatives: 22**
 - **False Negatives: 3**
 - **False Positives: 1**
- **Precision: 95.65%**, confirming the model's reliability when predicting failures
- **Recall: 88%**, demonstrating that the model correctly identifies **88%** of actual failures
- **F1-score: 91.67%**, balancing both precision and recall effectively

The prediction graph further validates the model's accuracy, showing a strong correlation between actual and predicted values, indicating that the model successfully learns underlying patterns in machine failures.

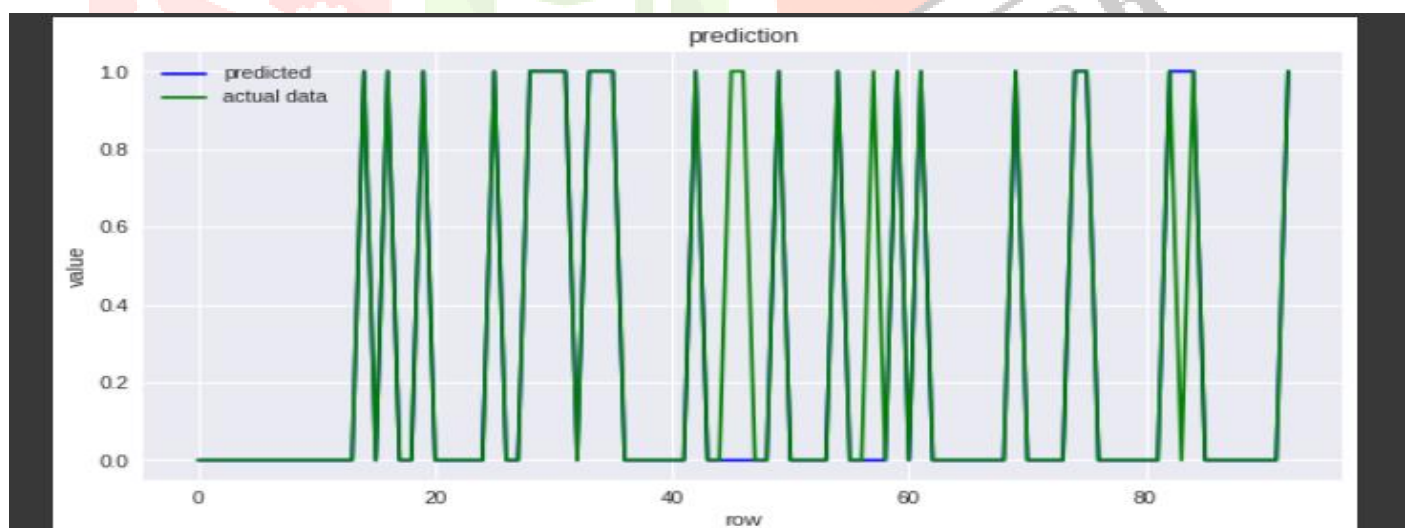


Figure 4.6

V. CONCLUSION

The predictive maintenance model using LSTM has demonstrated strong performance in forecasting equipment failures with high accuracy and reliability. Through rigorous training and evaluation, the model has effectively learned temporal patterns in the data, making it a valuable tool for real-time predictive maintenance applications. The model architecture consists of stacked LSTM layers, which are well-suited for capturing long-term dependencies in sequential data. LSTMs address the vanishing gradient problem, enabling the network to retain information across long sequences, which is crucial for predicting machine failures based on historical sensor readings. The use of dropout layers has successfully mitigated overfitting, ensuring that the model generalizes well to new data.

The training process shows a rapid convergence in accuracy and loss, with minimal fluctuations between training and validation performance. The accuracy steadily increases and stabilizes at a high value (~98%), indicating that the model is learning effectively. The validation loss follows a similar trend, suggesting that the model does not suffer from overfitting. The confusion matrix confirms this by showing a low number of false positives and false negatives, ensuring reliable predictions. The ability of the model to maintain a high recall score means that it successfully detects most failures, while a high precision score ensures that false alarms are minimized, reducing unnecessary maintenance costs.

The model can predict failures well in advance, allowing maintenance teams to intervene before critical breakdowns occur. This minimizes unplanned downtime and prevents costly repairs. Accurate identification of potential failure leads to moving from reaction (or scheduled) or predictive to condition based predictive maintenance which optimizes the use of resources and reduces unnecessary maintenance activity. The model provides predictiveness insights of maintenance schedule at nonpeak hours which increases productivity and reduces the downtime for industries. Diversity of datasets from different types of machinery is possible through the LSTM model which is trained on that and hence this model can be adapted to any industrial setting. This can be continuously refined and improved with new data making the system effective in the long term.

The high recall and precision show that the model is capable of detecting failures with as little false alarm as possible. A high recall implies that most actual failures are detected, therefore not losing any critical issues. At the same time, high precision eliminates unnecessary maintenance from false positives. These trades that are made on the model's capabilities to process sequential data and make near real time predictions result in timely interventions. When it is deployed in a production environment with real time data feeds, it can give real-time monitoring and alert systems to do immediate action. If models are generally criticized for being black box, the performance metrics and confusion matrix provide a clue on how reliable the model performs. Other methods to further interpretability such as attention mechanisms or SHAP values can be tried to know which factors make the biggest contribution to failure predictions.

Future successes and challenges are derived from needing to continually collect data and train again as conditions change. Quality and frequency of the sensor data could also determine the model's performance. For boosting the prediction accuracy, some enhancements, like hybrid models (LSTM with attention mechanisms or convolutional layers) can be used. This model is very efficient for the industries whose equipment reliability can be critical, and examples of such industries are manufacturing, aerospace, and energy sectors. It can be integrated with an IoT based monitoring system to get real time analytics and predictive insights. Such models can be coupled with industries to transition from traditional maintenance to fully automated predictive maintenance.

One important aspect of the model's success lies in the way that it can capture patterns that are not obvious using normal statistical methods. One of the reasons LSTM is great for performing such tasks is its memory to hold on past states. The results show that failures have discernible trends, and by constantly updating its model through sensor data, the model becomes increasingly capable of separating normal from faulty

machine behavior. These practical applications go further than maintenance — demand forecasting, anomaly detection and operational optimization are all other applications of the same models.

With the ability to predict what went wrong ahead of time such that catastrophic failures can be avoided, there is more cost saving and a better workplace safety. Failures of equipment, however, quickly lead to hazardous conditions and early detection mechanisms diminish accidents risks and system wide disruptions. Such implementation of AI driven solutions in industrial systems constitutes an approach towards intelligent automation in industrial systems, where predictive analytics dictate the decision making. Thus, this model can be deployed over multiple machines and facilities, and there is a guaranteed standardized but at the same time customizable solutions applying to diverse operational environments.

The model works well, but it should be constantly monitored. However, sensor data streams can change over time for various environmental factors, equipment aging, or even operational shift. Models drift and to prevent this, accuracy and hence the model itself should be maintained by periodic retraining and fine tuning. Visualization techniques that try to express the impact of each sensor reading on the failure prediction of an LSTM model can further increase its interpretability. Maintenance engineers can benefit from such insights in terms of additional diagnostic capabilities for decision making.

This predictive maintenance model implements the use of deep learning to solve real world industrial problems. Being able to have high accuracy with real time predictability while being adaptable, it is possible as a solution to optimize the maintenance workflow of such organizations. More intelligent systems, for example, systems that combine LSTM with reinforcement learning techniques and that have autonomous capability to adjust the maintenance schedules based on real time risk assessments, can be formed in future. The transformation towards AI based maintenance strategies for industries is a veritable paradigm change from the usual ways through which industries maintain the equipment reliability and operational effectiveness.

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REFERENCES

- [1] A. D. Scaife, "Improve predictive maintenance through the application of artificial intelligence: A systematic review," *Results in Engineering*, vol. 21, p. 101645, 2024.
- [2] P. Netisopakul and N. Phumee, "AI Enhanced Predictive Maintenance in Manufacturing Processes," in *IEEE Conference Proceedings*, 2022.
- [3] N. C. Ohalete, A. O. Aderibigbe, E. C. Ani, P. E. Ohenhen, and A. Akinoso, "Advancements in predictive maintenance in the oil and gas industry: A review of AI and data science applications," *World Journal of Advanced Research & Reviews*, vol. 5, no. 5, 2024.
- [4] Z. M. Çınar, A. A. Nuhu, Q. Zeeshan, O. Korhan, M. Asmael, and B. Safaei, "Machine Learning in Predictive Maintenance towards Sustainable Smart Manufacturing in Industry 4.0," *Sustainability*, vol. 12, no. 19, p. 8211, 2020. DOI: <https://doi.org/10.3390/su12198211>.

- [5] A. Hosseinzadeh, F. F. Chen, M. Shahin, and H. Bouzary, "A predictive maintenance approach in manufacturing systems via AI-based early failure detection," *Manufacturing Letters*, 2023. DOI: <https://doi.org/10.1016/j.mfglet.2023.08.125>.
- [6] H. Zheng, A. R. Paiva, and C. S. Gurciullo, "Advancing from Predictive Maintenance to Intelligent Maintenance with AI and IIoT," in *KDD '20, San Diego, California, USA*, 2020.
- [7] D. D. Jambo, O. O. Sofoluwe, A. Ukato, and O. J. Ochulor, "Transforming equipment management in oil and gas with AI-driven predictive maintenance," *Computer Science & IT Research Journal*, vol. 5, no. 5, 2024.
- [8] Y. He, G. Changchao, and C. Zhaoxiang, "Integrated predictive maintenance strategy for manufacturing systems by combining quality control and mission reliability analysis," *International Journal of Production Research*, vol. 55, pp. 5841–5862, 2017. DOI: <https://doi.org/10.1080/00207543.2017.1346843>.
- [9] A. Theissler, G. Elger, and M. Kettelgerdes, "Predictive maintenance enabled by machine learning: Use cases and challenges in the automotive industry," *Reliability Engineering & System Safety*, vol. 215, 2021. DOI: <https://doi.org/10.1016/j.ress.2021.107864>.
- [10] M. Abidi, M. Mohammed, and H. Alkhalefah, "Predictive Maintenance Planning for Industry 4.0 Using Machine Learning for Sustainable Manufacturing," *Sustainability*, vol. 14, pp. 1–27, 2022.
- [11] R. Rai, M. K. Tiwari, D. Ivanov, and A. Dolgui, "Machine learning in manufacturing and Industry 4.0 applications," *International Journal of Production Research*, vol. 59, pp. 4773–4778, 2021.
- [12] D. Dua and C. Graff, *AI4I 2020 Predictive Maintenance Dataset*, UCI Machine Learning Repository, University of California, School of Information and Computer Science, 2019.
- [13] M. Shcherbakov and C. Sai, "A Hybrid Deep Learning Framework for Intelligent Predictive Maintenance of Cyber-Physical Systems," *ACM Transactions on Cyber-Physical Systems*, vol. 6, pp. 1–22, 2022. DOI: <https://doi.org/10.1145/3486252>.
- [14] M. Compare, P. Baraldi, and E. Zio, "Challenges to IoT-Enabled Predictive Maintenance for Industry 4.0," *IEEE Internet of Things Journal*, vol. 7, pp. 4585–4597, 2020. DOI: <https://doi.org/10.1109/JIOT.2019.2957029>.
- [15] K. Meesublak and T. Klinsukont, "A Cyber-Physical System Approach for Predictive Maintenance," in *Proceedings of the 2020 IEEE International Conference on Smart Internet of Things (SmartIoT)*, Beijing, China, pp. 337–341, 2020.
- [16] T. P. Carvalho, F. A. A. M. N. Soares, R. Vita, R. P. Francisco, J. P. Basto, and S. G. S. Alcalá, "A systematic literature review of machine learning methods applied to predictive maintenance," *Computers & Industrial Engineering*, vol. 137, p. 106024, 2019. DOI: <https://doi.org/10.1016/j.cie.2019.106024>.