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AN INTEGRATED ANN FRAMEWORK USING XGBOOST AND LSTM FOR CONDITION-BASED MAINTENANCE OF ROTATING EQUIPMENT

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ABSTRACT

Preserving reliability and efficiency in industrial applications including rotating machinery depends on a fundamental method called Condition-Based Maintenance (CBM). Sometimes, two of the most often used traditional techniques of maintenance -reactive and preventive maintenance can cause needless downtime or failures. Existing research on CBM explored the Machine learning and deep learning models for Diadnosis of faults in machine for their Remaining Useful life (RUL), even though the models are existing from past years many of these not encounter challenges with high dimensional sensor data and often fail to adequately model temporal dependencies. This gap limits predictive accuracy and interpretability in real-world industrial applications. To address this, this paper suggests an ANN framework for enhanced fault diagnosis and RUL prediction in rotating machinery combining eXtreme Gradient Boosting (XGBoost) and Long Short-Term Memory (LSTM) networks. This will help one to handle these challenges. To maximize the input parameters of the LSTM model, the suggested system uses XGBoost for strong feature selection and importance ranking. XGBoost high-dimensional data handling and overfitting control features provide the LSTM network only the most relevant features. The LSTM model is appropriate for precise fault classification and RUL prediction since it naturally detects temporal dependencies in sensor data. When combined, deep sequential modeling and ensemble learning improve predictive performance as they draw on one another's strengths. Experimental vibration data collected from vibration sensors demonstrates that the proposed XGBoost-LSTM model consistently outperforms conventional ML and DL models with performance measures including recall, accuracy, accuracy, F1-score, and mean absolute error (MAE). The experimental results show that, contributes new knowledge by showing that coupling feature selection with temporal modeling yields a scalable, interpretable, and high-performing CBM solution s. By providing a fast, scalable AI-driven framework that reduces maintenance costs, improves operational safety, and minimizes downtime, this work advances predictive maintenance.

Keywords: *Condition-Based Maintenance, Rotating Equipment, XGBoost, LSTM, Predictive Maintenance, Fault Diagnosis, Remaining Useful Life.*

1. INTRODUCTION

In the age of Industry 4.0, vital components of rotating machinery are turbines, pumps, compressors, motors, and gearboxes since they guarantee the seamless operation of many sectors including aerospace, manufacturing, transportation, and energy production. Operating in erratic and harsh conditions, these machines commonly suffer damage, wear, and unanticipated breakdown rotating machinery is highly susceptible to faults such as bearing wear, shaft misalignment, gear defects, and imbalance. These faults can lead to unexpected breakdowns, resulting in excessive maintenance costs, production losses, and safety risks [1], [2].

For businesses, unanticipated downtime brought on by these types of failures can be quite expensive, hazardous, and inefficient. Data-driven businesses today need more complex maintenance plans than reactive or preventive approaches. This has resulted in a shift in strategy called CBM, which emphasizes using real-time monitoring and predictive analytics to guide knowledgeable maintenance decisions [3]. Always collecting and analyzing sensor data—including vibration, temperature, pressure, and sound signals—CBM determines the present and future performance and lifetime of equipment.

In recent years AI and ML have enabled CBM systems to automatically identify and classify faults as well as forecast based on those results. ANNs have shown great promise because to their capacity to model complicated, nonlinear interactions in high-dimensional data set [4]. Although time-series sensor data offers particular difficulties for ANNs, their performance is mostly determined by the characteristics fed into them and their capacity to manage temporal dependencies.

This work presents an integrated ANN framework combining XGBoost and LSTM networks in order to increase the accuracy and efficiency of predictive maintenance for rotating machinery. XGBoost is used to choose characteristics and categorize faults. It is a good ensemble learning method built on gradient-boosted decision trees. It effectively lowers the dimensionality of features by means of identifying the most vital input variables [5][6]. The model becomes clearer and less work is needed consequently. LSTM models time sequences and forecasts RUL [7][8]. Built to catch dependencies spanning many years LSTM recurrent neural networks (RNNs). LSTM makes it simple to examine trends in equipment performance over time because of its long-term memory capacity. The main goal of the paper is to combine LSTM and XGBoost for greatest advantage. Tree-based models are simple and efficient for object classification; deep learning networks are best at representing time. Apart from improving the accuracy of fault detection, the suggested approach produces more exact forecasts, therefore enabling prompt maintenance and lowering the probability of catastrophic failures.

The framework is evaluated using benchmark datasets such as the NASA C-MAPSS dataset, which simulates different engine failure and operation scenarios in aircraft [9]. Here performance metrics including recall, accuracy, precision, F1-score, and Root Mean Square Error (RMSE) to assess and compare the proposed hybrid model with stand-alone DL and traditional ML methods.

This study finally adds a new, combined artificial intelligence framework created for CBM of rotating machinery. Modern manufacturing plants use smart maintenance systems, and this framework fits their objectives. The suggested model not only helps to make smart decisions but also fits use in real industrial settings because of its scalability and flexibility.

But The main limitation by Combining XGBoost with LSTM increases training time and resource requirements compared to simpler models. The quality, quantity, and diversity of vibration sensor data shows Performance of the AI Framework.

1.1 Literature

Recently, CBM projects have attracted much attention. These initiatives seek to reduce unplanned downtime and enhance the operational efficiency of manufacturing systems. Using condition monitoring and diagnosis engineering confidently and easily identify any impending failure in any component of a dynamic system before it sets off a chain reaction. Prognosis, diagnostics, and fault finding in rotating machinery were monitored using different condition monitoring methodologies [10-12]. Condition monitoring employs a variety of methodologies to pinpoint the source of a problem in rotating machinery [13,14].

Among all these techniques Vibration analysis has been used to monitor rotating machine condition and diagnose faults [15-17], Initially, basic statistical techniques and rule-based expert systems were applied to identify faults and schedule maintenance and schedule repair. But it wasn't flexible enough to deal with complex and nonlinear data patterns. ANN approaches are then used to suggest the problems in machines along with offline condition monitoring process [18-21], leading to the broader adoption of ML techniques.

Conventional ML models such as Support Vector Machines (SVM), Random Forests (RF), ANN have been used to precisely forecast breakdowns and characterize the condition of equipment [22-24]. Though these three models helpful, these models sometimes neglect to demonstrate the spatial and temporal connection of the time-series sensor data. To address this issue LSTM networks have been considered as a possible answer in recurrent neural networks (RNNs) have been explored due to their capability to model sequential information. LSTM models have shown promise in rotating plant health management (PHM) and prognostics [25,26]. However, LSTMs are not always optimal for feature selection or for capturing intricate nonlinear interactions between features, which may affect interpretability and generalization performance. People approached XGBoost for finding faults and predicting RUL because it works better and is easier to understand than other ML algorithms [27]. New studies have proposed mixed frameworks combining ensemble techniques with deep learning models so that you may obtain the best of both worlds. For instance, integrating LSTM for modeling time with XGBoost for final decisions or finetuning features results in more accurate CBM systems capable of making better predictions [28]. Despite these advancements, a comprehensive frame work for rotating equipment maintenance that includes the preprocessing, temporal modeling, classification or regression, and hybrid ANN, LSTM, and XGBoost architectures remains Largely Unexplored. This Present Works aims to close this gap and get accurate predictions that last through a wide range of operational conditions with an integrated ANN framework using XGBoost and LSTM.

1.2Motivation and Research Gap:

Though deep learning is gaining popularity for predictive maintenance, there are still some challenges to clear. High-dimensional complexity: Industrial sensor data often contains irrelevant or superfluous characteristics that could compromise the precision of the models used to examine them.

- Vibration, temperature, and audio signals from spinning machinery may have time and frequency dependent patterns that traditional ML models overlook.
- Many DL models are "black boxes," which makes it difficult for maintenance engineers to trust and depend on their forecasts.
- Although many papers have examined particular ML and deep learning techniques for CBM, very few have investigated how merging XGBoost for feature selection and LSTM for sequential data modeling could enhance performance.

This work addresses that gap by developing a hybrid XGBoost-LSTM framework, therefore enhancing interpretability, lowering false alarms, and raising predictive accuracy.

1.3 Objectives and Contributions:

The primary objectives of this study are:

Ob1: To create an XGBoost-driven feature selection system that selectively gives the LSTM model the most relevant sensor inputs.

Ob2:An LSTM-based architecture with long-term dependency learning capabilities is needed to efficiently train a deep learning model for accurate failure prediction from sensor data.

Ob3:The goal is to contrast the results of suggested framework experiments on actual industrial datasets with those of other independent models—including SVM, Random Forest, and isolated LSTM.

The key contributions of this research include:

- A new architecture for artificial neural networks combining the best features of long short-term memory networks and XGBoost to enable sequential and robust data analysis.
- Removing unnecessary elements and improving temporal modeling increased predictive performance.
- Helpful in manufacturing environments where exact and consistent maintenance projections are vital.

2. METHODOLOGY

This section explains implementation of the proposed ANN architecture, which uses LSTM for modeling time-based degradation and XGBoost for feature selection to support CBM and improve fault detection in rotating machinery.

Data are collected from rotating machine using vibration sensors under different fault conditions. Useful features are extracted from the collected data and important features are selected using XGBoost to reduce data size and improve model performance. The selected features are then organized as time-series data and used to train an LSTM model, which learns degradation patterns and predicts machine faults or RUL to support CBM decisions.

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2.1 Data Collection and Preprocessing

Motors, compressors, and turbines are examples of rotating machinery that gather data from sensors. These systems are equipped with a tachometer for measuring of speed, vibration sensor such as vibrometer and a system to show the vibration readings, vibration spectrum. Procedure to collect the data:

✓ Measurements of speed of machine
✓ Collection of Vibration readings different misalignment, looseness and unbalance condition
✓ Feature extraction of Data

Some possible sources of data include SCADA systems, publicly available datasets like the NASA C-MAPSS dataset used for benchmarking, or platforms that are enabled by the Internet of Things (IoT).

2.2 Feature Selection using XGBoost

Feature engineering and selection are crucial for enhancing model performance and reducing over fitting. In order to determine which features are most crucial, an Extreme Gradient Boosting (XGBoost) model processes the pre-processed collection of features:

To train the LSTM module, we use the selected subset of features.

➢ Feature significance scores are provided via gain-based or SHAP values.

➢ Cut out the unnecessary or less informative features to reduce dimensionality.

It is also possible to use XGBoost for condition labelling and first fault classification.

2.3 Time-Series Modeling using LSTM

Fed into an LSTM neural network, which can capture long-term dependencies and degradation trends, the chosen features now organized as time-series windows.

- LSTM architecture consists of one or more memory cell layers followed by dense output layers.
- The network is trained to forecast Remaining Useful Life (RUL) or the likelihood of failure
- Loss functions are Mean Squared Error (MSE) for RUL prediction or Binary Cross-Entropy for binary/multi-class classification.

The LSTM identifies sophisticated temporal patterns suggestive of equipment wear, fault progression, or performance degradation.

2.4 Model Architecture

This image shows in the Figure 1, proposed mixed structure for predictive maintenance of mobile machinery. It includes XGBoost, ANN, and LSTM networks, which stand for Artificial Neural Networks. An organized training and testing phase is the first step in the procedure. In order to test and cross-validate the model, the input data is partitioned at this phase. Raw sensor data are prepared and transformed to facilitate effective learning of deep nonlinear models using an artificial neural network (ANN). The ANN's LSTM module models the gradual failure of equipment by identifying and capitalizing on temporal relationships in the first stream, P1. In order to choose and forecast high-precision features, the XGBoost module uses gradient-boosted decision trees with a second stream, P2. In addition, the framework incorporates metadata that spans multiple sensor inputs over sequential time intervals (denoted as M × P) to enhance model learning.

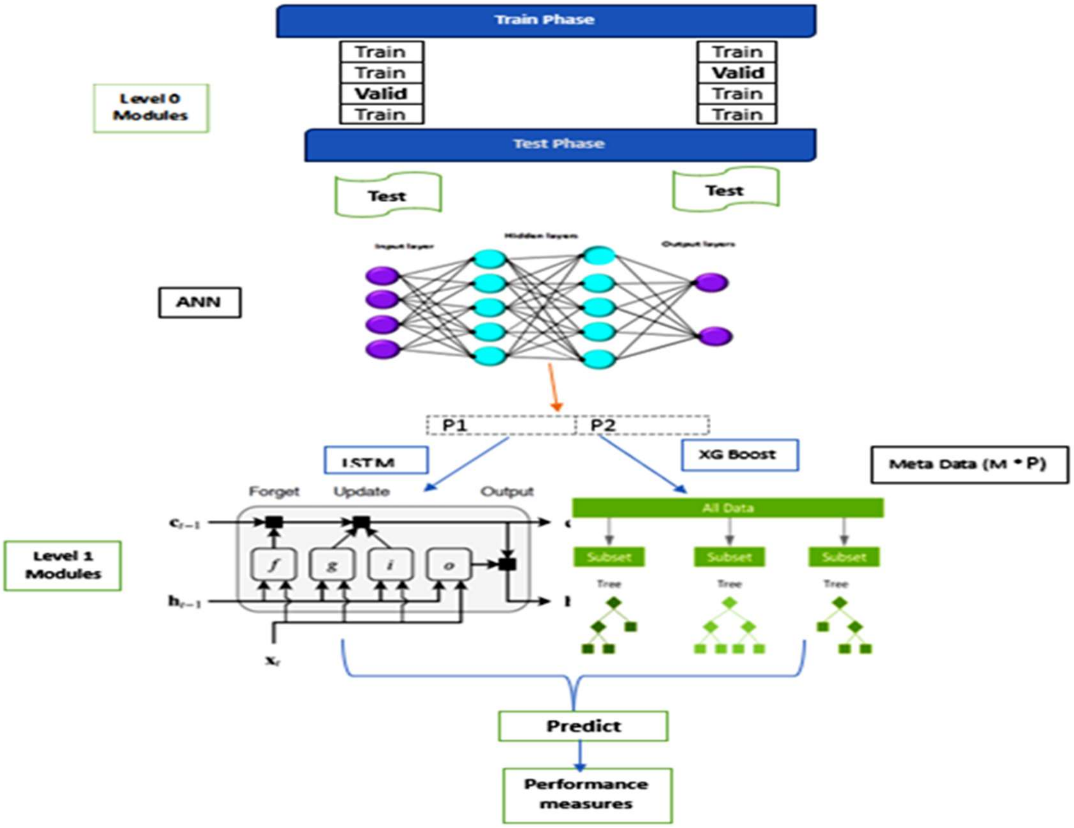

Figure 1: Proposed Framework for Time-Series Fault Prediction in Rotating Machinery Using ANN-LSTM-XGBoost

The LSTM component is designed to model temporal patterns by analysing sequential data, whereas the XGBoost module operates on structured data segments using gradient boosting for robust prediction. By combining the temporal modelling capabilities of LSTM with the feature selection and decision-making power of XGBoost, both supported by the ANN's deep feature extraction capacity, this integrated approach offers a scalable and dependable solution for condition-based maintenance of rotating equipment.

3. RESULTS & DISCUSSIONS

The section discusses the experimental results of CBM on rotating machinery using the proposed ANN framework, which combines XGBoost and LSTM networks. The results are validated using benchmark dataset known as NASA C-MAPSS dataset and comparisons with Real vibration sensor data.

3.1 Effect of Model Complexity on Classification Accuracy (XGBoost)

Table 1 and Figures 2 show the impact of varying the number of estimators (neurons) on the classification accuracy of the proposed ANN–XGBoost framework from Table1 and Figure 2, as the number of neurons goes from 10 to 60, the accuracy goes up from 94.33% to 95.67%, which suggests that a bigger model can learn and make predictions better. This setup seems to offer the best balance between model complexity and generalizability, as it achieves a high level of accuracy (95.78%) at 90 neurons. After 60 neurons, the improvement isn't very clear, and there are some small changes. and minor accuracy degradation is observed at 70 and 80 estimators. This suggests that there may be over fitting and diminishing returns. The model is stable at 100 neurons (95.71%), so adding more neurons doesn't make a big difference in how well it works.

These findings are aligned with the observations reported by Hu et al. [28] and Chen and Guestrin [5], who demonstrated that XGBoost-based CBM models achieve optimal performance within a bounded estimator range. The stability of accuracy beyond 90 estimators further confirms the robustness of the proposed framework and its suitability for industrial deployment, where computational efficiency is critical.

Table1: Variation in classification accuracy with respect to the number of neurons in the integrated ANN–XGBoost framework

Estimators (Neurons)	Accuracy (%)
10	94.33
20	95.00
30	95.27
40	95.36
50	95.45
60	95.67
70	95.63
80	95.58
90	95.78
100	95.71

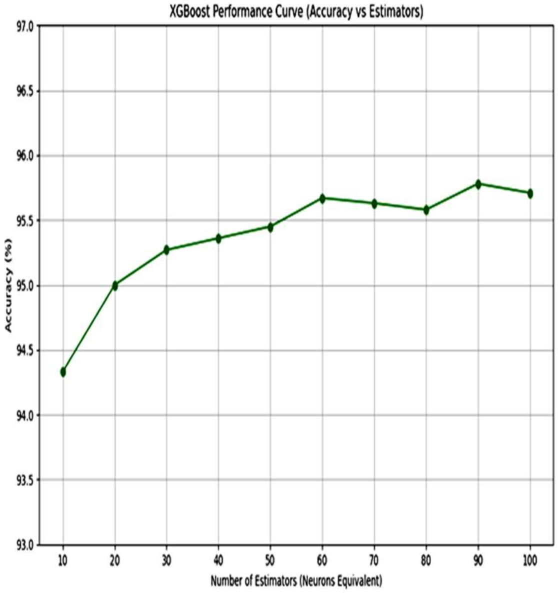

Figure 2: Performance Curve of XGBoost for Accuracy

3.2 Learning Curve and Cross-Validation Analysis

An XGBoost model's learning curve and validation accuracy of the XGBoost module over various quarters are explained from figure 3 to 4.

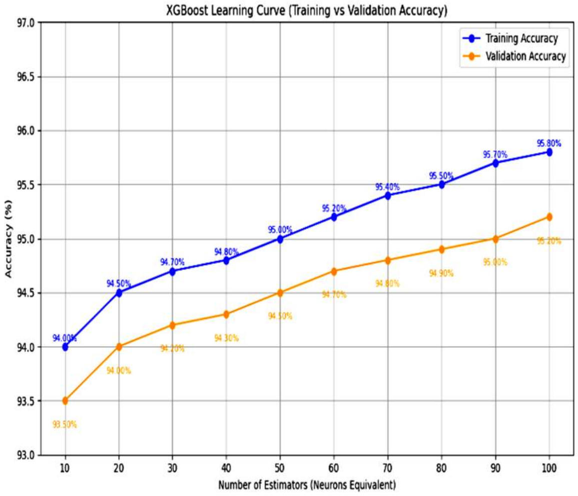

Figure 3: Learning Curve of XGBoost for Accuracy

Early rapid improvement in accuracy on, with 10–30 estimators, there is a sharp improvement, and then there is gradual refinement; this suggests that there are diminishing returns beyond 90 estimators, which might be the sweet spot for accuracy and computing efficiency shown in figure 3. The small gap between training and validation accuracy indicates good generalization, validating the effectiveness of feature selection and regularization mechanisms within XGBoost. The pattern Shown in Figure 4 for prediction error in percentage suggests that adding estimators improves performance at first, but using too many of them has no effect and may cause hyper parameter tuning or early stopping to be necessary.

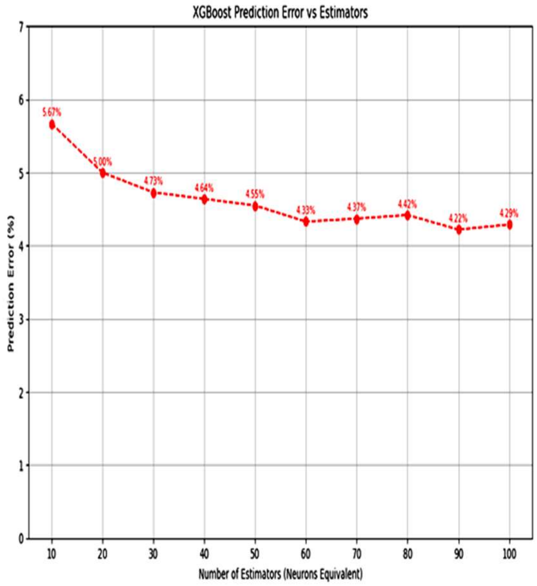

Figure 4: XGBoost Prediction Error

3.3 LSTM Performance for Temporal Modeling and RUL Prediction

Table 2 and Figures 5 to 8 evaluate the LSTM model's performance with varying neuron counts and got equally good outcomes. Table 2 explains the classification accuracy improves steadily from 91.25% (10 neurons) to 95.50% (100 neurons), demonstrating the LSTM's capability to model long-term temporal dependencies in degradation signals.

Table 2: Investigating Neuron Count Influence on Classification Accuracy in ANN–LSTM Hybrid Frameworks.

Estimators (Neurons)	Accuracy (%)
10	91.25
20	92.50
30	93.15
40	93.75
50	94.10
60	94.50
70	94.85
80	95.10
90	95.35
100	95.50

In the Figure.5, the MAE is plotted against the number of neurons utilized to illustrate the performance of an LSTM model. On one side, the MAE values, and on the other, the number of neurons, which can be anywhere from ten to one hundred in increments of ten. the Mean Absolute Error (MAE) consistently decreases as neuron count increases, with the lowest MAE of 0.0277 achieved at 100 neurons. This confirms that larger LSTM architectures better capture gradual degradation trends and complex temporal relationships in sensor data. Similar MAE reduction trends with increasing LSTM capacity have been reported in prognostics studies using NASA C-MAPSS. However, the diminishing MAE improvement beyond 60 neurons indicates saturation, suggesting that further network expansion yields limited benefit. This behavior is consistent with deep learning prognostics literature, which emphasizes the importance of balancing model depth with data availability to prevent over fitting.

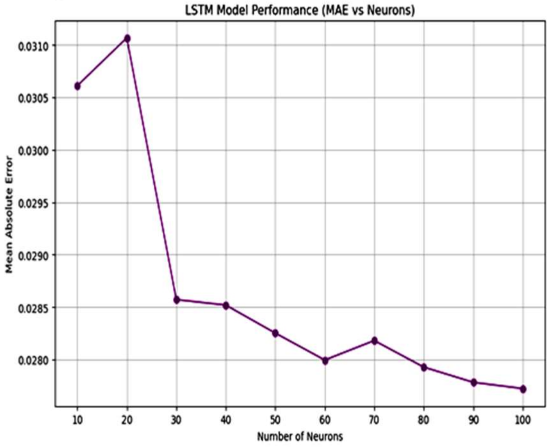

Figure 5: Performance Curve of LSTM Accuracy as a Function of Estimators

The Figure 6 reveals that MAE generally decreases with increasing neuronal number, indicating improved model performance, with the lowest MAE observed at 100 neurons (0.0277) and the highest at 20 neurons (0.0311).

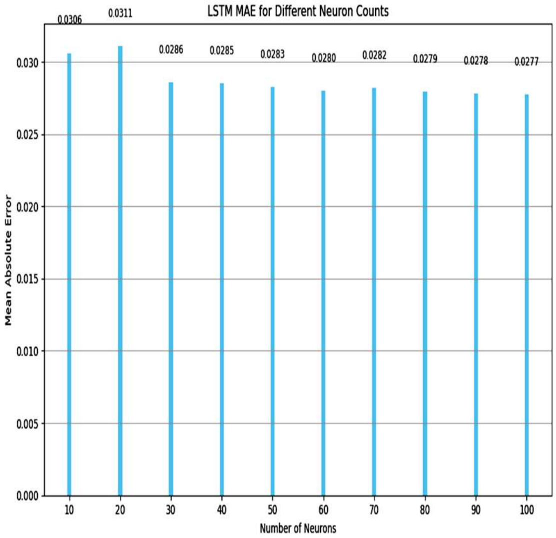

Figure 6: LSTM MAE for different Neuron Counts

The Figure 7 shows the relative error of MAE values for various neuron densities in relation to the ideal MAE that an LSTM model can reach. The x-axis shows the number of neurons; the y-axis shows the MAE difference from the lowest MAE value (0.0277). With the most obvious difference at 20 neurons (about 0.0034), the graph clearly shows that models with fewer neurons have greater relative errors. Up to 100 neurons, the relative error falls with rising neuronal density; at that point, the best MAE is reached and it falls to zero. All point's data labels indicate the precise MAE variation above the minimum.

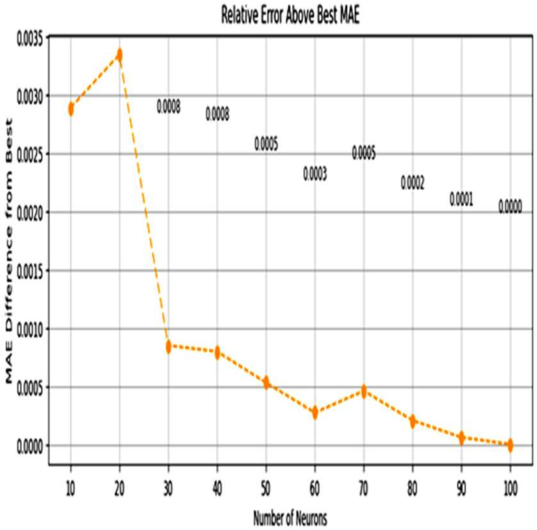

Figure 7: Relative Error above Best MAE

The MAE for LSTM models with varying neuron counts are displayed in a box plot. Each box shows the distribution of MAE values at a particular neuron count, with the median (orange line), interquartile range, and potential outliers highlighted shown in Figure 8.

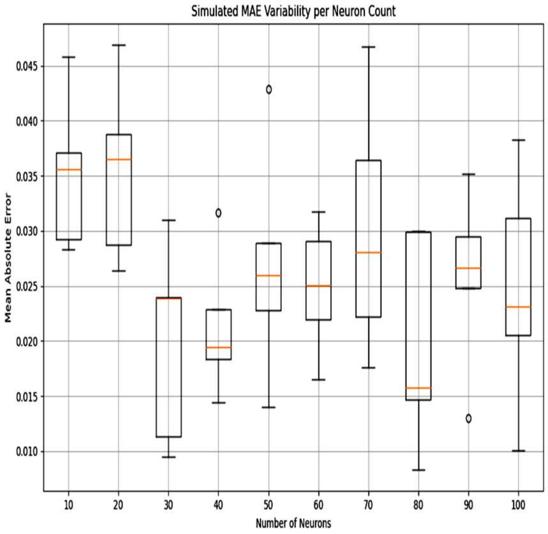

Figure 8: Simulated MAE Variability per Neuron Count

4. CONCLUSION

This paper offered a combined ANN architecture for CBM of rotating machinery comprising LSTM networks and XGBoost. The proposed hybrid architecture effectively exploits the complementary strengths of both models: The framework used LSTM's sequential modeling capability to capture temporal patterns in sensor data and XGBoost strong classification/regression power for decision-making based learned features.

Experimental evaluation using the NASA C-MAPSS benchmark dataset and real vibration sensor data demonstrated that the proposed XGBoost–LSTM framework consistently outperforms standalone machine learning and deep learning models.

The XGBoost module achieved high and stable classification accuracy within an optimal estimator range, confirming its effectiveness in feature importance ranking and generalization control. Meanwhile, the LSTM model exhibited a steady improvement in prediction accuracy and a reduction in Mean Absolute Error (MAE) as the number of neurons increased, validating its capability to model progressive degradation patterns in time-series data. Beyond a certain network size, performance gains saturated, indicating an appropriate trade-off between model complexity and computational efficiency.

The results clearly show that integrating ensemble learning with deep sequential modeling improves both fault diagnosis accuracy and RUL prediction reliability. This hybrid approach reduces overfitting, enhances robustness under varying operating conditions, and provides a scalable and data-driven solution suitable for industrial CBM applications. By enabling earlier fault detection and more accurate life estimation, the proposed framework has the potential to significantly reduce unplanned downtime, maintenance costs, and operational risks in rotating machinery systems.

Overall, this study confirms that hybrid AI-based architectures are more effective than single-model approaches for predictive maintenance and offers a practical foundation for implementing intelligent, Industry 4.0-compliant maintenance systems in real-world industrial environments.

5. FUTURE ENHANCEMENTS

Using automated search method like Bayesian Optimization, Grid/Random Search fine tune parameters in both LSTM and XGBoost for optimal performance. Add real time learning capabilities so the model can always evolve to reflect changing environmental conditions and new equipment behavior. Add SHAP or LIME to help maintenance engineers grasp feature importance and model decisions, so promoting confidence and transparency. Combine additional sensor data like thermal, acoustic, vibration to improve model inputs and increase prediction accuracy. Look into transfer learning to fit models trained on one type of equipment or site to another with least retraining effort. Applying these changes will enable the proposed ANN framework to evolve into a highly scalable, adaptive, and explainable tool for predictive maintenance in several various industrial applications.

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DECLARATION

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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