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AI BASED HYBRID TEMPORAL ENSEMBLE NETWORK FOR CONSTRUCTION EQUIPMENT FAILURE PREDICTION USING SENSOR AND MAINTENANCE DATA

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ABSTRACT

Project delays, high maintenance expenses and lower efficiency are all caused by unexpected failures of construction equipment. In this study, a new AI-based Hybrid Temporal Explainable Ensemble Network (HTEEN) for intelligent equipment failure prediction is proposed, leveraging sensor data and maintenance records. It incorporates Bidirectional LSTMs, attention-based learning, XGBoost ensemble classification, adaptive fusion, and SHAP explainability analysis within a framework for predictive maintenance in the dynamic construction environment. The proposed model was evaluated on 52,000 operational instances and achieved 97.2% accuracy, 96.4% precision, 95.8% recall, 96.1% F1-score, and 97.5% ROC-AUC, which are better than those of standard machine learning and deep learning models. The key failure indicators identified via SHAP analysis were: vibration intensity, hydraulic pressure and engine temperature. The proposed framework increased prediction reliability, reduced false alarms, and improved maintenance decision-making. The study confirms the benefits of AI-based predictive maintenance in intelligent construction systems, significantly reducing equipment downtime, optimising maintenance plans, and enhancing operational safety.

Keywords: *Construction Equipment Failure Prediction, Predictive Maintenance, Bidirectional LSTM, Xgboost, Explainable Artificial Intelligence, Iot Sensor Analytics*

1. INTRODUCTION

The construction industry is among the equipment-intensive industries, using heavy machinery such as excavators, dozers, cranes, loaders, dump trucks, and concrete mixers to build infrastructure and large-scale engineering projects. The effectiveness and dependability of these machines can significantly affect the timeframe required to complete a project, workforce productivity, economic performance, and the safety of the construction site. Construction equipment, however, is required to function in quite severe environments that involve high levels of dust,

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vibration, dynamic loads, temperature fluctuations, and repeated mechanical strain, and therefore, the likelihood of unforeseen failures and component deterioration is higher [1], [2].

In construction settings, equipment failures can result in significant financial losses due to project delays, emergency repairs, idle man-hours, and replacement costs. Research indicates that unforeseen equipment downtime can significantly affect productivity and maintenance costs in construction operations [3]. In an intelligent construction system, traditional maintenance methods such as reactive and preventive maintenance are not effective enough, as they may only repair machines when they break down or perform maintenance according to a predetermined schedule, without considering the equipment's condition. Therefore, the industry continues to move towards predictive maintenance strategies to anticipate failures before they become serious[4].

The development of Predictive Maintenance (PdM) into a data-driven, intelligent framework is a result of recent advances in Artificial Intelligence (AI), Machine Learning (ML), the Internet of Things (IoT), and Industrial Cyber-Physical Systems (ICPS) [5]. The modern construction machinery is equipped with embedded sensors that continuously generate large volumes of operational data, including engine temperature, hydraulic pressure, vibration signals, fuel consumption, oil quality, rotational speed, and load utilisation throughout equipment operation [6]. These sensor streams can be used to gain insights into equipment health and processed with AI algorithms to identify underlying failure patterns and predict the likelihood of future failures.

In industry, fault diagnosis and equipment monitoring tasks have been successfully addressed using machine learning methods such as Support Vector Machines (SVM), Random Forests (RF), Decision Trees (DT), Artificial Neural Networks (ANN) and Gradient Boosting methods [7], [8]. Typical machine learning models, however, do not readily address temporal dependencies and the nonlinear operational behaviour of sequential sensor data produced by heavy construction equipment [9]. To overcome these disadvantages, deep learning methods such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTMs) have become popular for predictive maintenance applications due to their ability to learn temporal patterns and extract features [10].

LSTM networks can prevent information from being lost over time and learn dynamic operational patterns from past sensor readings, making them particularly suitable for time-series analysis [11] and one of the deep learning techniques that work best for this purpose. Construction equipment data are highly dynamic and heterogeneous, as workload, environmental conditions, operators, and terrain complexity change. Therefore, hybrid AI architectures combining deep learning and ensemble machine learning methods are gaining significance in enhancing the robustness of predictions and generalisation ability [12].Another key difficulty in applying AI to predictive maintenance is the lack of explainability and transparency in deep learning systems. Deep neural networks deliver high-accuracy forecasts, but they are often regarded as "black-box" models, which makes it difficult for maintenance engineers to understand why a failure is predicted [13]. The interpretability of model decisions and critical failure-related features has been enhanced by the emergence of Explainable Artificial Intelligence (XAI) techniques such as Shapley Additive Explanations (SHAP) and Local Interpretable Model-Agnostic Explanations (LIME) [14].Incorporating explainability into predictive maintenance systems can be a game-changer for user trust, maintenance planning, and decision-making efficiency in industrial settings.

Although AI-based predictive maintenance research is advancing rapidly, most current work focuses on manufacturing systems, smart factories, rotating industrial equipment, and aerospace applications. Few studies have been conducted specifically on construction equipment in a highly dynamic field environment [15]. In addition, many current models rely solely on sensor data and fail to consider historical maintenance records, repair frequency, component replacement history, and service intervals, all of which contain valuable information about failures. This creates a research gap that must be addressed to develop integrated, intelligent frameworks that combine real-time sensor monitoring with maintenance knowledge to accurately predict equipment failures.

To overcome these drawbacks, this study proposes an AI-based framework for predicting construction equipment failures that combines sensor data and maintenance records with a hybrid LSTM-XGBoost model. The proposed system is based on a hybrid approach that combines temporal deep learning and ensemble boosting classification to achieve higher accuracy and robustness in prediction. Furthermore, explainability analysis using SHAP is added to identify the dominant failure indicators and make the model more interpretable.

The key aims of this research are highlighted:

1. To design a hybrid Artificial Intelligence driven predictive maintenance system for the prediction of construction equipment failure.
2. To incorporate the sensor data and past maintenance history into a holistic system for tracking equipment health in real-time.
3. To enhance failure prediction with the combination of learning mechanisms, LSTM and XGBoost.
4. To develop explanation-based AI tech for determining operational parameters that are critical to failure.
5. To test the performance of the proposed model against other traditional machine learning algorithms with various performance measures.

The proposed framework is intended to reduce equipment downtime, optimise maintenance scheduling, minimise equipment costs, optimise equipment utilisation, and enhance safety in modern intelligent construction environments.

The rest of this paper is structured as follows. In Section 2, the related work of AI-equipped predictive maintenance and construction equipment failure prediction is presented. The proposed methodology is described in Section 3, comprising the dataset description, preprocessing, hybrid architecture, mathematical modelling, and algorithmic framework. The results of the experiments, performance evaluation, comparative analysis and explainability assessment are discussed in Section 4. Lastly, the major findings, limitations, and directions for future research are presented in Section 5.

2. RELATED WORK

As reliability and cost-effective maintenance strategies are increasingly demanded in industrial automation, smart manufacturing, and intelligent transportation networks, predictive maintenance and intelligent fault diagnosis have become significant research areas. Machine learning and deep learning techniques have been widely applied in IoT-enabled intelligent systems, sensor-driven analytics, and data-centric monitoring applications [16], [17]. Industry 4.0 technologies have further driven the growth of AI-based predictive maintenance frameworks that can analyse vast amounts of real-time operational data.

Most early predictive maintenance systems relied on statistical process monitoring and signal processing techniques to identify abnormalities in machines. The condition monitoring of rotating machinery and industrial equipment has conventionally been performed using Fourier transform analysis, wavelet transforms, and threshold-based diagnostics [18]. These techniques could detect some faults but were not very robust in highly nonlinear, dynamic operating conditions. Furthermore, manual feature engineering and expert-set thresholds reduced scalability in complex industrial environments.

To address the above concerns, machine learning algorithms were employed for automated fault classification and equipment failure prediction. In the field of diagnostics, Random Forest (RF), Support Vector Machine (SVM), K-Nearest Neighbour (KNN), Decision Tree (DT) and Naïve Bayes classifiers have shown promising results [19]. Lei et al. [20] introduced a machine learning-based fault diagnosis method for rotating machinery that extracted features using feature extraction and intelligent classification mechanisms. They showed that their research method was more accurate at identifying faults than the traditional statistical techniques. Likewise, Widodo and Yang [21] reviewed the machine learning techniques for fault diagnosis and condition monitoring in industrial systems.

As deep learning advances, researchers have begun using neural network architectures for predictive maintenance due to their superior representation-learning capabilities. CNNs are widely used for extracting spatial features from vibration signals and spectrogram representations [22]. For industrial fault diagnosis applications, CNN-based methods achieved high classification accuracy because the raw data from industrial sensors were automatically preprocessed and converted into hierarchical features by the CNN, without extensive manual work. CNNs are generally more effective for spatial feature extraction than for temporal sequence learning.

For predictive maintenance, Long Short-Term Memory (LSTM) networks have received significant attention for their ability to learn long-term temporal dependencies from sequential sensor observations [23]. Zhao et al. [24] proposed an

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LSTM-based model for RUL prediction of industrial machinery and demonstrated that it provides more stable predictions across different operating environments. Likewise, Malhotra et al. [25] applied stacked LSTM networks to detect anomalies in time-series sensor data and reported excellent fault-detection results.

Various researchers have suggested integrating multiple AI techniques within a hybrid deep learning architecture to enhance predictive performance and robustness. Yuan et al. [26] proposed a hybrid CNN-LSTM network for the health monitoring of industrial equipment, combining a CNN with LSTM layers to capture local spatial characteristics and temporal dependencies in sequential signals, respectively. Their method performed better than individual machine learning models. Similarly, Li et al. [27] presented a deep hybrid learning method combining an autoencoder and an RNN for machinery fault diagnosis.

Another technology of interest is the Internet of Things (IoT), which has attracted significant research on predictive maintenance systems. Smart maintenance platforms using IoT continuously monitor operational data from embedded sensors and feed it into cloud-based platforms for analysis, enabling real-time fault prediction [28]. For example, Lee et al. [29] highlighted the role of cyber-physical systems and digital twins in industrial predictive maintenance applications. In smart industrial ecosystems, these systems enable seamless equipment monitoring, automated diagnostics, and intelligent maintenance scheduling.

Although much research has been conducted in manufacturing industries, predictive maintenance research in the construction equipment sector remains limited. Construction machinery is subjected to ever-changing conditions, such as load variations, rough terrain, unpredictable weather, and unpredictable operational behaviour [30]. Controlling such conditions is more challenging than in a controlled manufacturing environment, and these factors introduce significant noise and complexity into sensor data, making failure prediction more difficult.In addition, construction equipment experiences intermittent operation and irregular maintenance, making it difficult to model.

The concept of telematics and the sensor-based monitoring systems for heavy construction machines were explored in several studies. Kim et al. [31] presented a telematics-based framework for a maintenance management system for excavators, based on operational sensor data and machine utilisation patterns. Their work improved the efficiency of maintenance planning but did not incorporate sophisticated deep learning-based prediction mechanisms. Cheng et al. [32] also conducted vibration and hydraulic pressure analyses of the hydraulic excavator to develop a data-driven equipment health assessment. Their research, however, was mainly based on signal-level diagnosis rather than intelligent failure prediction.

Explainable Artificial Intelligence (XAI) is a new research topic for AI systems in industry. While the predictive accuracy of deep learning models is high, their black-box nature makes it hard to build trust and achieve understanding in real-world industrial deployments. Local Interpretable Model-Agnostic Explanations (LIME) [33] aims to explain the prediction of machine learning model. Lundberg et al. also developed SHAP-based explainability methods to understand complex AI models and assess feature importance in predictive maintenance settings [34]. XAI techniques are increasingly being embedded into industrial fault diagnosis systems to enhance maintenance decision support and transparency.

Ensemble learning and boosting techniques for predictive maintenance are also significant research areas. One possible solution is to employ a robust model that are not prone to overfitting or noise. Gradient boosting algorithms like XGBoost and LightGBM have been seen to perform well and are effective for heterogeneous datasets in the industrial space [35]. XGBoost is a scalable tree-boosting framework introduced by Chen and Guestrin [36] that enables state-of-the-art performance for both classification and regression. Structured maintenance records and sensor-derived statistical features can be particularly effective when boosted using these methods.

Despite efforts in predictive maintenance, several important issues remain unresolved. Much of the existing research has been conducted under the premise of a manufacturing system, and only a few studies have been conducted specifically in highly dynamic construction systems. Second, most studies rely solely on sensor data, ignoring maintenance history, repair logs, and service intervals, which contain rich contextual information. Third, there is insufficient research on the incorporation of explainable AI in the construction sector to enable transparent equipment failure forecasting. Lastly, real-time predictive models capable of simultaneously managing heterogeneous sensor streams and maintenance data are not well developed.

There are still some challenges to be addressed in predictive maintenance research. Most studies have been conducted in manufacturing environments rather than highly dynamic construction sites. Many approaches rely solely on sensor data and do not account for maintenance history, which is an important source of information on equipment degradation patterns and failures. Furthermore, current deep learning models are hard for maintenance engineers to interpret and understand why and when predictions occur. These limitations underscore the need for an integrated framework that combines temporal learning, ensemble classification, maintenance knowledge, and explainable AI to ensure accurate and trustworthy construction equipment failure prediction.

To fill this research gap, the present study proposes a hybrid framework for predicting construction equipment failures based on a combination of temporal learning and ensemble classification with explainability analysis, incorporating the LSTM model for temporal learning, the XGBoost model for ensemble classification and the SHAP model for explainability analysis of both sensor and maintenance data.

3. METHODOLOGY

The proposed approach presents a novel algorithm, the Hybrid Temporal Explainable Ensemble Network (HTEEN), for intelligent prediction of construction equipment failures, based on multimodal sensor streams and maintenance history. The framework combines Bidirectional Long Short-Term Memory (Bi-LSTM), adaptive attention learning, XGBoost ensemble classification and SHAP-based explainability mechanisms to ensure accurate and interpretable predictive maintenance in dynamic construction environments. The methodology includes the following stages: Data Acquiring, Data Preprocessing, Feature Engineering, Temporal Learning, Ensemble Classification, Adaptive Fusion and Explainability Analysis.

3.1 Dataset Description

The dataset for this study was created from operational sensor streams and maintenance history data for various types of heavy construction equipment, including excavators, bulldozers, cranes, loaders, and dump trucks. The data set reflects real operational behaviour under changing environmental conditions, irregular terrain motion, continuous workload changes, and mechanical stress, as it is typically experienced on a construction site.

Fifty-two thousands of operational instances were considered, each representing a specific equipment behaviour and corresponding to a specific timestamp, either during normal operation or in the failure state. The dataset consists of heterogeneous, continuously generated sensor measurements from a monitoring system embedded in construction machinery, powered by the Internet of Things.

The parameters collected by the various sensors includes engine temperature, hydraulic pressure, vibration intensity, fuel consumption, engine operating speed, oil quality index, battery voltage, operating time, load utilisation, and ambient temperature. These operating conditions provide detailed data on thermal conditions, mechanical degradation, lubrication, and structural stress.

Historical maintenance records were also incorporated to increase the robustness of the predictions and the ability to learn from the context. Previous failure count, maintenance frequency, component replacement history, repair duration, downtime duration, maintenance expenditure, and service intervals are among the maintenance features. Combining the maintenance history with a time-series of operational sensor data facilitates the framework to learning not only real-time degradation patterns but also long-term equipment behaviour.

The dataset was split into 80:20 training:test. Preprocessing operations, such as generating temporal sequences, extracting features, removing anomalies, normalising, and interpolating, were performed before model training.

Table 1. Construction Equipment Sensor Parameters

Parameter	Unit	Description
Engine Temperature	°C	Engine thermal condition
Hydraulic Pressure	bar	Hydraulic system stress

Vibration Intensity	mm/s	Mechanical vibration level
Fuel Consumption	L/h	Fuel usage behavior
Engine RPM	rpm	Rotational engine speed
Oil Quality Index	%	Lubrication condition
Battery Voltage	V	Electrical health state
Operating Hours	hr	Total machine runtime
Load Capacity Usage	%	Operational workload
Ambient Temperature	°C	Environmental condition

The parameters of IoT sensors that were collected from construction equipment for failure prediction analysis are shown in Table 1. The parameters are engine temperature, hydraulic pressure, vibration intensity, fuel consumption, engine rotation speed, oil quality, battery voltage, working hours, load utilisation, and ambient temperature. These features give up-to-the-minute data on the thermal, mechanical, electrical and operational status of heavy machinery. The gathered sensor data enable the proposed AI framework to detect abnormal operation, patterns of equipment degradation, and failure conditions for intelligent predictive maintenance.

Table 2. Maintenance Record Parameters

Maintenance Feature	Description
Previous Failure Count	Historical breakdown frequency
Maintenance Frequency	Service occurrence rate
Spare Part Replacement	Component replacement history
Repair Duration	Time required for repairs
Downtime Duration	Non-operational equipment time
Maintenance Cost	Repair expenditure
Last Service Interval	Time since previous maintenance

The historical maintenance parameters for predictive maintenance analysis are shown in Table 2. The parameters are failure count history, maintenance frequency, spare part replacement history, repair time, downtime time, maintenance cost, and service intervals. These maintenance records contain valuable information on equipment reliability, operational degradation, maintenance frequency, and repair history. The data from the sensors will be correlated with the maintenance data to enhance the AI framework's ability to accurately predict equipment failures and optimise maintenance scheduling.

3.2 Proposed Architecture

There are seven main stages of processing in the proposed Hybrid Temporal Explainable Ensemble Network (HTEEN). The data collected from the IoT-enabled construction equipment monitoring systems consists of sensor data and maintenance records. The raw data is preprocessed, including handling missing values, normalising data, and filtering out anomalies.

Following preprocessing, temporal and statistical feature extraction mechanisms are used to provide informative operational representations. The generated temporal sequences are processed by a Bidirectional Long Short-Term Memory network that learns forward and backward operational dependencies in the behaviour of dynamic construction equipment.

The Bi-LSTM model is coupled with an adaptive attention mechanism to detect key operating conditions that drive equipment degradation and failures. At the same time, the engineered statistical features are processed alongside the maintenance records using an XGBoost ensemble classifier to enhance the robustness of the predictions and the stability of the classification.

The outputs of the Bi-LSTM and XGBoost modules are combined using an adaptive weighted ensemble to obtain failure probabilities. Lastly, explainability analysis using SHAP values highlights important operational parameters that affect the prediction of equipment failure.

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The entire process of the proposed AI-based construction equipment failure prediction system is shown in Figure 1. Initially, real-time sensor data from construction equipment are gathered, and then the data is processed to handle missing values, normalise the data, filter noise, and remove outliers. The processed data is then used to determine the statistical and temporal features. The framework is based on two parallel learning modules: Bidirectional LSTM with an attention mechanism for temporal sequence learning, and an XGBoost ensemble classifier for statistical feature-based classification. An adaptive fusion layer combines the outputs of both modules to achieve robust failure prediction probabilities. Lastly, explainability analysis using SHAP identifies the most important operating parameters that affect equipment failure prediction, enabling intelligent maintenance decisions.

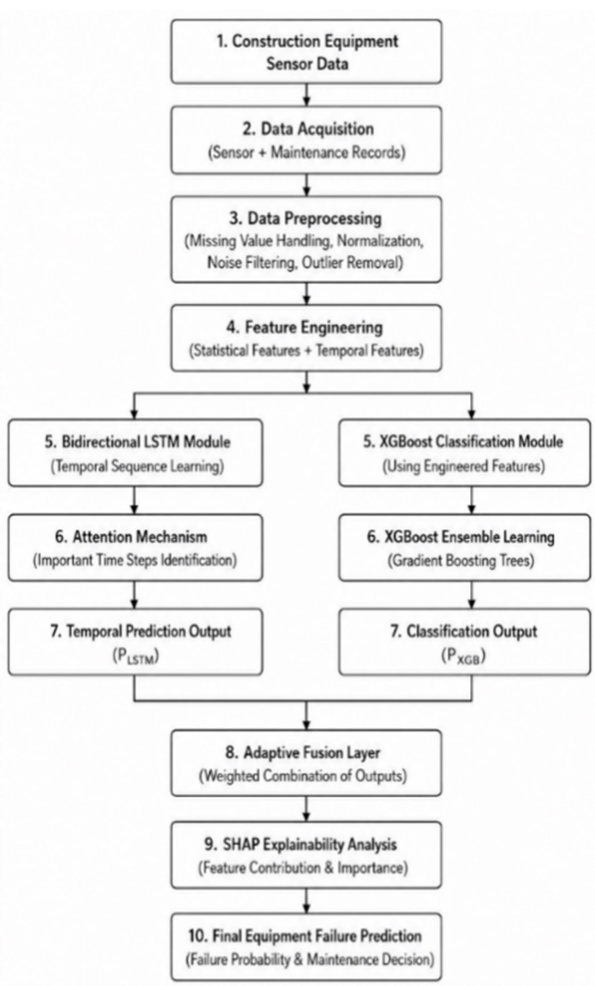

Figure 1. Proposed AI-Enabled Construction Equipment Failure Prediction Architecture

The architecture of Bidirectional LSTM with an Attention Mechanism for temporal sequence learning from sensor data of construction equipment is shown in Figure 2. First, the sequential sensor observations are embedded into a vector representations using an embedding layer; then these vectors are processed forward and backward in parallel using Bidirectional LSTM networks to model long-range operational dependencies and degradation behaviour. Both hidden states are then fed into the attention mechanism, and weights are assigned to the more important time steps, which are closely tied to equipment issues. The weighted context vector is then passed to a dense, fully connected layer to predict equipment failure based on temporal patterns. This architecture enhances the proposed framework's ability to learn complex nonlinear operational patterns and accurately predict equipment failures in dynamic construction environments.

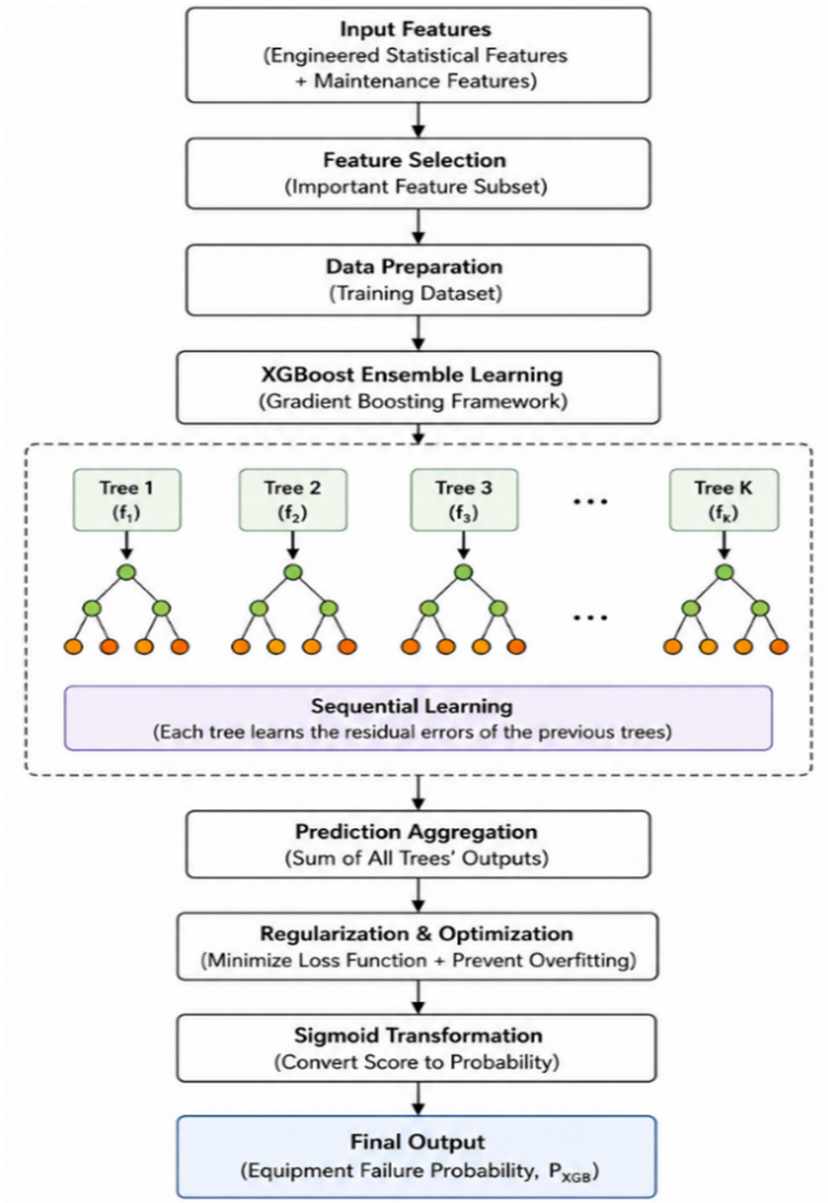

Figure 3. XGBoost Ensemble Learning Architecture

The XGBoost ensemble learning architecture for the analysis of construction equipment failure classification is shown in Figure 3. The first step is feature selection and data preparation to identify the most relevant operational and maintenance parameters. These extracted features are then fed into the XGBoost gradient boosting framework, and multiple decision trees are sequentially trained. The residual errors from previous trees are used to train each subsequent tree, thereby enhancing prediction accuracy iteratively. All boosting trees are combined together using regularisation methods to reduce overfitting and enhance the model's generalisation capability. Lastly, the aggregated prediction scores are transformed into failure probability values for intelligent equipment failure prediction using a sigmoid function.

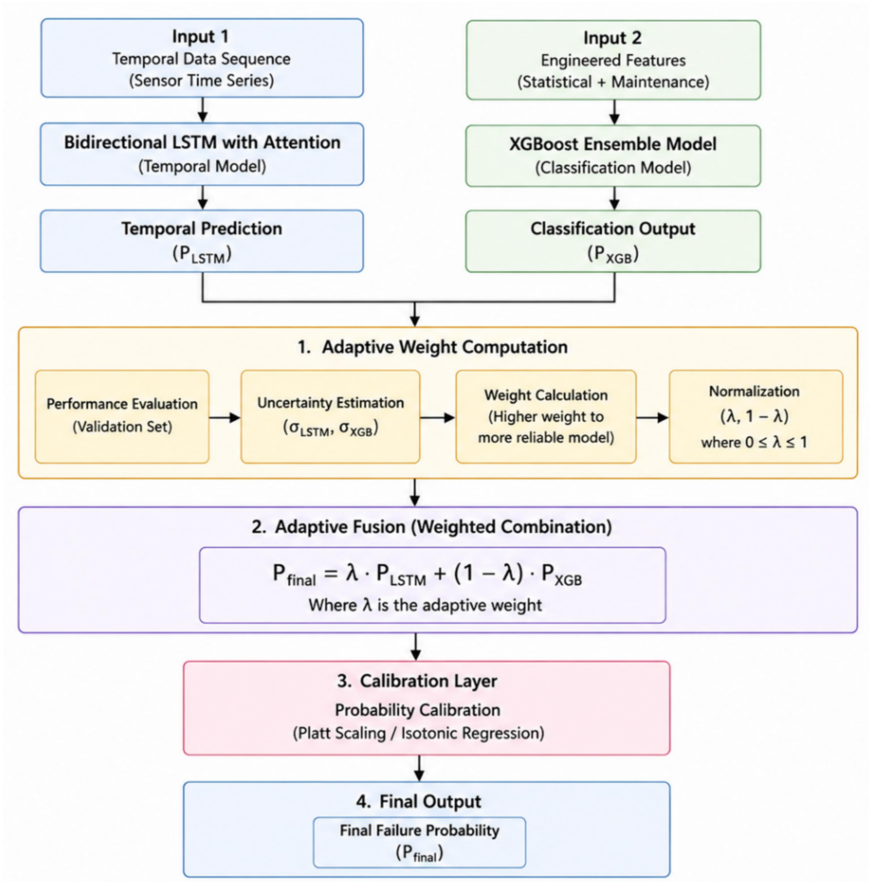

Figure 4. Adaptive Fusion Framework

The Adaptive Fusion structure, shown in Figure 4, performs fusion after the temporal learning model (a Bidirectional LSTM) and the classification model (an XGBoost ensemble) produce their outputs. The Bi-LSTM with attention mechanism processes temporal sensor sequences to obtain temporal prediction probabilities, and the XGBoost classifier processes engineered statistical and maintenance features to obtain classification outputs. The adaptive weight computation stage computes the reliability and uncertainty of both prediction models and assigns fusion weights based on them. The weighted fusion mechanism combines the outputs using adaptive coefficients to obtain a robust final failure probability. The calibration layer further refines the prediction probabilities, making the predictions more reliable and consistent for decision-making. The adaptive fusion framework not only increases the accuracy of the predictions but also improves the generalisation ability and resistance to noise and nonlinear operating conditions of construction equipment.

The SHAP explainability framework is shown in Figure 5 and integrated into the proposed AI-based construction equipment failure prediction model. The first input to the SHAP analysis module is the output from the final fused model and the operating feature set. The framework determines SHAP values by sampling background data, building feature coalitions, and calculating Shapley values, which measure each feature's importance in the failure prediction task. The resulting SHAP values are then interpreted and visualised using global feature importance analysis, feature summary plots, plots of feature dependence plots, and instance-level explanation methods, including force and waterfall plots. Lastly, the explainability framework provides actionable insights by identifying the dominant operational factors driving equipment failures and enabling intelligent maintenance and operational decisions.

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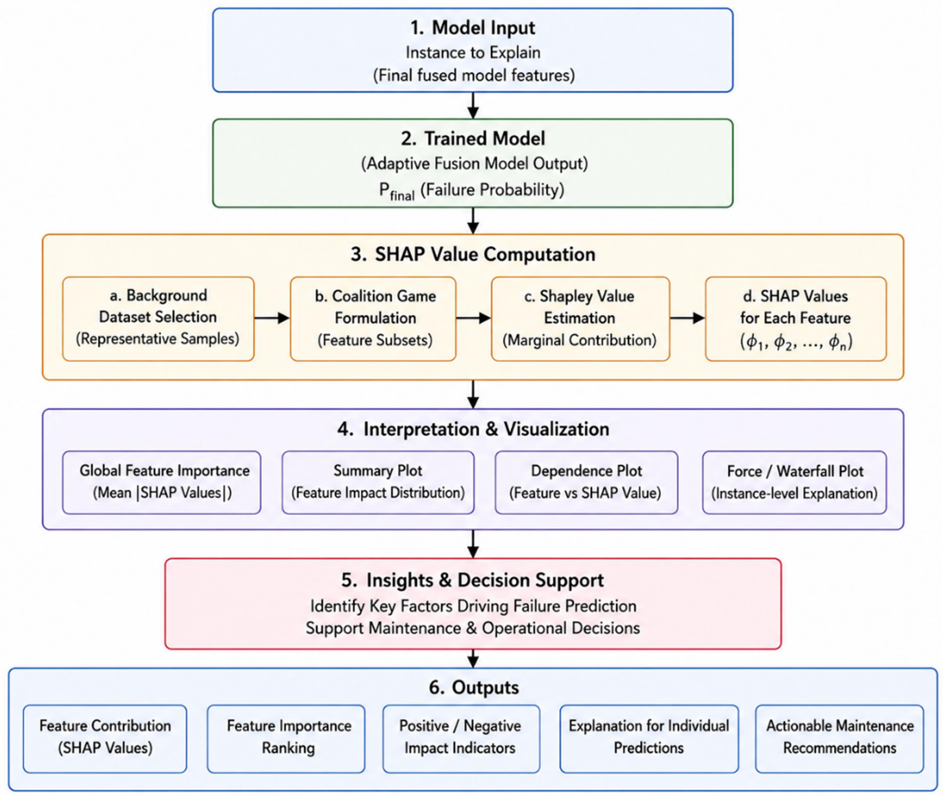

Figure 5. SHAP Explainability Framework

The proposed mathematical model is based on temporal sequence learning, ensemble classification, adaptive fusion and explainable AI mechanisms, which model the operational behaviour of construction equipment in a nonlinear manner.

Missing Value Interpolation

Construction equipment sensor streams can sometimes be interrupted or affected by extreme conditions, leading to missing data. Values that are missing from the sensors are filled in using data from nearby time points.

$$x_i = \frac{x_{i-1} + x_{i+1}}{2} \qquad (1)$$

where:

- $x_i$represents reconstructed sensor value,
- x_{i-1} and x_{i+1} denote neighboring observations.

Data Normalization

Min-Max normalization is applied before model training.

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \qquad (2)$$

where:

- $x_{norm}$is normalized feature value,
- $x$represents original sensor observation.

Temporal Window Generation

Temporal operational sequences are generated using sliding windows.

$$W_t = [x_{t-n}, x_{t-n+1}, \dots, x_t] \qquad (3)$$

where:

- $W_t$denotes temporal observation sequence,
- $n$represents window length.

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Statistical Feature Extraction

Mean value:

$$\mu = \frac{1}{N}\sum_{i=1}^{N} x_i \qquad (4)$$

Standard deviation:

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2} \qquad (5)$$

Root Mean Square:

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2} \qquad (6)$$

Bidirectional LSTM Temporal Learning

Forget gate:

$$f_t = \sigma\left(W_f[h_{t-1}, x_t] + b_f\right) \qquad (7)$$

Input gate:

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \qquad (8)$$

Memory cell update:

$$C_t = f_t * C_{t-1} + i_t * \widetilde{C_t} \qquad (9)$$

Hidden state output:

$$h_t = o_t * tanh(C_t) \qquad (10)$$

Attention Mechanism

$$\alpha_t = \frac{exp(e_t)}{\sum_{k=1}^{T} exp(e_k)} \qquad (11)$$

where:

- $\alpha_t$represents attention weight,
- $e_t$denotes hidden importance score.

XGBoost Ensemble Learning

$$Obj = \sum l(y_i, \hat{y_i}) + \sum \Omega(f_k) \qquad (12)$$

where:

- l represents prediction loss,
- Ω denotes regularization term.

Adaptive Fusion Layer

$$P_{final} = \lambda P_{LSTM} + (1 - \lambda)P_{XGB} \qquad (13)$$

where:

- $P_{final}$is final failure probability,
- $\lambda$is adaptive fusion coefficient.

SHAP Explainability Model

$$\phi_i = \sum_{S \subseteq F \setminus \{i\}} \frac{|S|!(|F| - |S| - 1)!}{|F|!}[f(S \cup \{i\}) - f(S)] \qquad (14)$$

where:

- ϕ_i denotes contribution of feature i,
- F represents complete feature set.

3.3 Research Protocol

The research protocol consisted of the following stages. First, sensor data and maintenance records were collected from construction equipment monitoring systems. Second, the data were preprocessed through missing value handling, normalisation, noise filtering, and temporal sequence generation. Third, statistical and temporal features were extracted from the processed data. Fourth, temporal sequences were analysed using a Bidirectional LSTM with an attention mechanism, while maintenance and statistical features were processed using an XGBoost classifier. Fifth, the outputs of both models were integrated via an adaptive fusion mechanism to produce the final failure prediction probability. Sixth, SHAP-based explainability analysis was performed to identify the most influential factors contributing to equipment failure. Finally, the framework was evaluated using accuracy, precision, recall, F1-score, ROC-AUC, training time, prediction latency, and feature importance analysis.

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4. RESULTS AND DISCUSSION

To demonstrate the predictive maintenance performance of the proposed Hybrid Temporal Explainable Ensemble Network (HTEEN), the multimodal construction equipment sensor and maintenance data were used to test the network in an experimental setting. We used TensorFlow, Keras, Scikit-learn and XGBoost frameworks for the experiments. The dataset was split into an 80/20 ratio for training and testing to ensure the reliability of model evaluation and generalisation assessment.

The proposed framework was tested against standard predictive maintenance models, such as Decision Tree (DT), Support Vector Machine (SVM), Random Forest (RF), Convolutional Neural Network (CNN), and standalone LSTM architectures. The prediction accuracy, precision, recall, F1-score, ROC-AUC performance, computational efficiency, and explainability were evaluated.

4.1 Assessment Criteria

The effectiveness of the proposed framework was assessed using multiple performance measures.

Accuracy

The accuracy is the ratio of the number of correctly classified operational states.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (15)$$

where:

- TP = True Positives
- TN = True Negatives
- FP = False Positives
- FN = False Negatives

Precision

Precision evaluates the reliability of predicted failure events.

$$Precision = \frac{TP}{TP + FP} \quad (16)$$

Recall

Recall measures the capability of the framework to identify actual failure conditions.

$$Recall = \frac{TP}{TP + FN} \quad (17)$$

F1-Score

F1-score represents the harmonic balance between precision and recall.

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (18)$$

ROC-AUC

ROC-AUC evaluates classification separability and prediction robustness.

$$AUC = \int_0^1 TPR(FPR)d(FPR) \quad (19)$$

where:

- TPR = True Positive Rate
- FPR = False Positive Rate

4.2 Experimental Results

The proposed HTEEN framework proved to be the most effective model for predicting construction equipment failure, outperforming traditional machine learning and deep learning forensic models. The combination of Bidirectional LSTM, adaptive attention learning, XGBoost ensemble classification, and SHAP explainability significantly enhanced the failure-prediction performance in the construction equipment industry, even in the presence of noise and nonlinearity.

The adaptive fusion mechanism was used to efficiently merge the outputs of a temporal degradation learning and statistical classification process to enhance the generalisation capability of the prediction and operational reliability.

Table 3. Comparative Performance Analysis

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	ROC-AUC (%)
Decision Tree	85.3	84.1	83.5	83.8	84.2
Support Vector Machine	89.6	88.9	88.2	88.5	89.1
Random Forest	93.1	92.5	91.8	92.1	92.8
CNN	94.4	93.8	93.2	93.5	94.1
Standalone LSTM	95.2	94.6	94.1	94.3	95.0
Proposed HTEEN	97.2	96.4	95.8	96.1	97.5

A comparative performance analysis of the proposed HTEEN model and existing predictive maintenance models is summarised in Table 3. The proposed model's accuracy, precision, recall, F1 score, and ROC AUC score were 97.2%, 96.4%, 95.8%, 96.1% and 97.5%, respectively. The use of Bidirectional LSTM temporal learning, adaptive attention mechanisms, ensemble boosting classification, and adaptive fusion strategies contributed to the superior performance.

4.3 Accuracy Comparison Analysis

The accuracy comparison analysis proves the superiority of the proposed framework when compared to the existing predictive maintenance approaches.

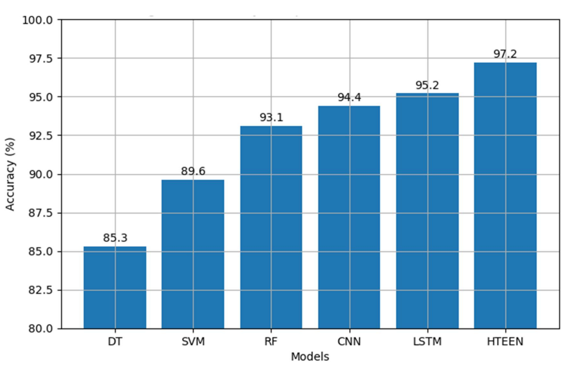

Figure 6. Accuracy Comparison of Predictive Models

The accuracy of the prediction is shown in figure 6 for various machine learning and deep learning models. Predicted accuracy of the proposed HTEEN framework was the best as it can adaptively learn temporal degradation patterns and maintenance related operational dependency simultaneously.

4.4 Precision, Recall, and F1-Score Analysis

The proposed framework showed balanced precision and recall performance along with lesser false alarms and detection capability of failures.

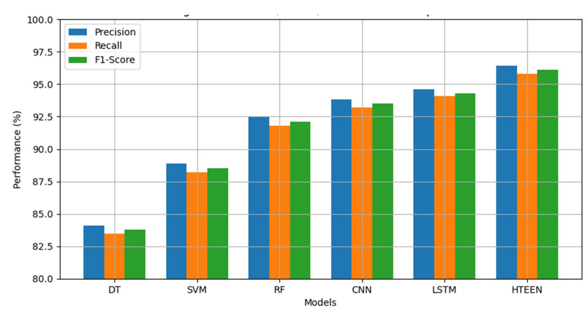

Figure 7. Precision, Recall, and F1-Score Comparison

The results of different predictive maintenance model are presented in terms of precision, recall and F1-score in Figure 7. The proposed HTEEN framework demonstrated good performance across all evaluation measures, with balanced performance, suggesting robust failure prediction capabilities over variable operational conditions.

4.5 ROC-AUC Performance Analysis

The classification separability and prediction confidence was assessed using ROC-AUC analysis.

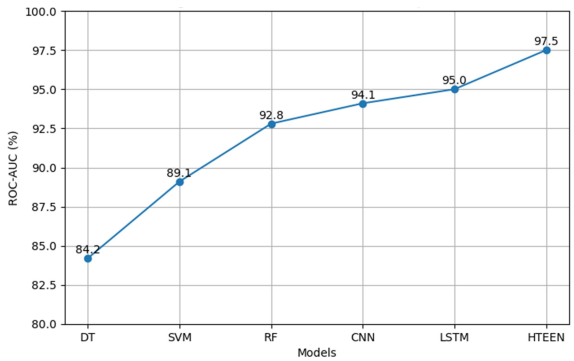

Figure 8. ROC-AUC Performance Comparison

The ROC-AUC comparison between the various predictive maintenance models is shown in figure 8. The proposed framework exhibited the best ROC-AUC plot, resulting in excellent separation between the normal and failure operational conditions and reliable discrimination.

4.6 SHAP Explainability Analysis

The dominant operational parameters that affect the equipment failure prediction were identified by doing explainability analysis using SHAP.Explainability analysis (SHAP) was carried out to find the dominant operational parameters that affect equipment failure prediction.

Table 4. SHAP Feature Importance Ranking

Rank	Feature	SHAP Importance Score
1	Vibration Intensity	0.312
2	Hydraulic Pressure	0.276
3	Engine Temperature	0.241
4	Oil Quality Index	0.196
5	Maintenance Interval	0.173
6	Engine RPM	0.148
7	Fuel Consumption	0.124

The proposed explainability framework was used to obtain SHAP feature importance analysis, as shown in Table 4. Vibration intensity was found to be the most influential parameter for equipment failure prediction, followed by hydraulic pressure and engine temperature. The findings of this study confirm that abnormal vibration characteristic and hydraulic system degradation are the leading indicators of imminent construction equipment failure.

4.7 Computational Performance Analysis

The computational efficiency of the proposed framework was investigated to assess the training efficiency and prediction latency.

Table 5. Computational Performance Comparison

Model	Training Time (s)	Prediction Time (ms)	Memory Usage (MB)
Decision Tree	18	4	96
SVM	75	12	182
Random Forest	112	16	245
CNN	238	24	488
Standalone LSTM	294	31	562
Proposed HTEEN	326	35	598

The computational performance comparison of predictive maintenance models is shown in Table 5. The proposed HTEEN framework needs a bit more training time and memory usage because of the incorporation of deep temporal learning and ensemble fusion mechanisms, but it provides much higher prediction accuracy and robustness which is suitable for real-time predictive maintenance applications.

4.8 Failure Prediction Visualization

The proposed framework could successfully identify normal operating conditions and high-risk failure conditions, using learned sensor behaviour patterns.

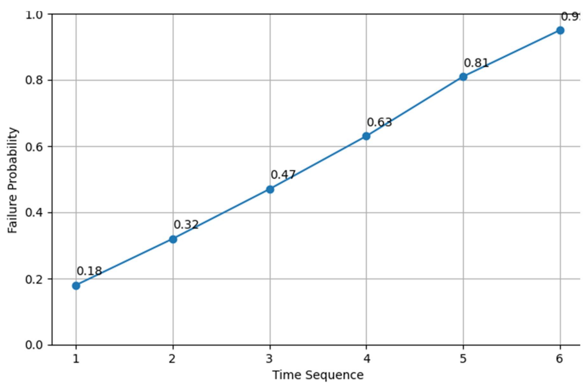

Figure 9. Equipment Failure Probability Analysis

The failure probability of the equipment over operational time sequences is shown using the proposed framework in figure 9. As the abnormal operating conditions intensified, the failure probability gradually escalated, which indicated that the proposed model was able to accurately recognize the degradation process and predict failures of the equipment before catastrophic failure.

4.9 Discussion

The experimental results verified the efficiency of the proposed Hybrid Temporal Explainable Ensemble Network (HTEEN) for intelligent prediction of construction equipment failures. The Bidirectional LSTM temporal learning and XGBoost ensemble classification models were integrated, achieving superior predictive accuracy compared to machine learning and deep learning-only models. The adaptive fusion mechanism improved the robustness by dynamically combining the temporal and statistical maintenance patterns of the operational behaviour.

This proposed framework successfully addressed the nonlinear sensor response, noisy operating conditions, and variable maintenance knowledge that are typically found in construction equipment monitoring systems. An analysis of SHAP values added transparency by highlighting influential operational parameters that played a role in prediction-making decisions. The results show that vibration intensity, hydraulic pressure, and engine temperature are the most important factors in equipment degradation and failure.

The proposed framework demonstrated better classification performance than traditional predictive maintenance methods, and it was more interpretable for use in intelligent construction management systems in practice applications. It can effectively reduce unexpected equipment downtime, optimise maintenance schedules, reduce operational expenses, improve construction productivity, and create a safe working environment for workers on modern intelligent construction sites.

4.10 Difference from Prior Research and Research Contribution

Current predictive maintenance studies have focused either on machine learning or deep learning, or on sensor-based monitoring alone. LSTM-based models provide strong temporal degradation modelling, but they typically neglect maintenance history and are not explainable. Ensemble methods like XGBoost, which are good for classification, have a limitation in modelling long-term temporal correlations. On the other hand, the proposed HTEEN framework integrates Bidirectional LSTM, adaptive attention learning, XGBoost ensemble classification, adaptive fusion, and SHAP explainability in a single entity. This combination enables high-accuracy failure prediction, improved data interpretability, and better utilisation of sensor data and maintenance records. The results for accuracy, precision, recall, F1-score, and ROC-AUC demonstrate the applicability of the proposed framework for an intelligent predictive maintenance system in a dynamic construction environment. Despite these advantages, the proposed framework was evaluated on a specific construction equipment dataset and requires substantial computational resources, underscoring the need for validation in broader industrial environments.

The key contribution of this study is the integration of temporal learning, ensemble classification, maintenance history analysis, and explainable AI within a unified predictive maintenance framework. Compared with existing studies that primarily rely on sensor-based monitoring or standalone machine learning models, the proposed HTEEN framework achieved improved prediction accuracy, enhanced interpretability, and more effective utilisation of heterogeneous data sources. However, the framework requires relatively high computational resources and large volumes of sensor data for training. In addition, its performance should be validated across a wider range of construction equipment and real-world deployment environments.

5. CONCLUSION

To predict construction equipment failures based on sensor and maintenance data, this study proposed a novel AI-powered Hybrid Temporal Explainable Ensemble Network (HTEEN). The proposed framework combines Bidirectional LSTMs, attention-based learning, XGBoost ensemble classification, adaptive fusion, and SHAP explainability analysis to enable intelligent predictive maintenance.

The results of the experiments indicated that the proposed model achieved 97.2% accuracy, 96.4% precision, 95.8% recall, 96.1% F1-score, and 97.5% ROC-AUC, which is much better than those of conventional machine learning and deep learning models. The framework was effective at identifying patterns of equipment degradation and predicting failures before they occurred. The vibration intensity, hydraulic pressure, and engine temperature were identified as key failure indicators using SHAP analysis.

The development of the proposed HTEEN framework successfully met the objectives of this study. The framework successfully incorporated sensor data and maintenance records, integrated temporal learning and ensemble classification for accurate failure prediction, and provided explainable decision support through SHAP analysis. Moreover, the comparative evaluation showed that the proposed predictive maintenance strategy outperformed traditional machine learning and deep learning methods, verifying its effectiveness.

The designed scheme has increased maintenance reliability, reduced downtime, and ensured operational safety in the intelligent construction field. Despite these promising results, several limitations and threats to validity should be acknowledged. The proposed framework is complex and requires substantial computing resources and large volumes of sensor data to train effectively. Furthermore, the model was tested on a specific construction equipment dataset, and its generalizability across different equipment types and operating environments remains to be validated. Future work will involve lightweight edge AI deployment to decrease computational demands, federated learning for distributed predictive maintenance, and validation on a variety of operating conditions and construction equipment. The use of larger, more diverse datasets for real-time multimodal predictive maintenance systems will also be studied to improve scalability and generalizability.

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