



## International Journal of Artificial Intelligence and Machine Learning

Publisher's Home Page: <https://www.svedbergopen.com/>



Research Paper

Open Access

# Machine Learning–Enabled Predictive Maintenance for Industrial Sensor Networks: A Hybrid Deep Learning Approach for Real-Time Anomaly Detection and Asset Health Management

<sup>1</sup>Ramya P, <sup>2</sup>Vinay Joshi\*, <sup>3</sup>Ashwin Pathak, <sup>4</sup>Md. Shakil Ahmad and <sup>5</sup>Ajit Kumar Singh

<sup>1</sup>Assistant Professor and HOD, Department of Computer Science, Jain College (Autonomous), VV Puram, Bangalore, India, [ramya2624@gmail.com](mailto:ramya2624@gmail.com)

<sup>2</sup>Founder, InfinAlverse Pvt. Ltd., Jaipur, Rajasthan, India, [vinay.joshiii@gmail.com](mailto:vinay.joshiii@gmail.com)

<sup>3</sup>Associate Professor, Thakur College of Engineering and Technology, Mumbai, Maharashtra, India, [ashwin.pathak@thakureducation.org](mailto:ashwin.pathak@thakureducation.org)

<sup>4</sup>Assitant Professor, Department of Electrical Engineering, Government engineering College, Arwal, Bihar-804409, India, [shakileegec@bihar.gov.in](mailto:shakileegec@bihar.gov.in)

<sup>5</sup>Assistant Professor, Department of Electrical Engineering, Government Engineering College Gopalganj, Tola Sipaya, Bihar, [singhajit@bihar.gov.in](mailto:singhajit@bihar.gov.in)

**Corresponding mail:** [vinay.joshiii@gmail.com](mailto:vinay.joshiii@gmail.com)

### Abstract

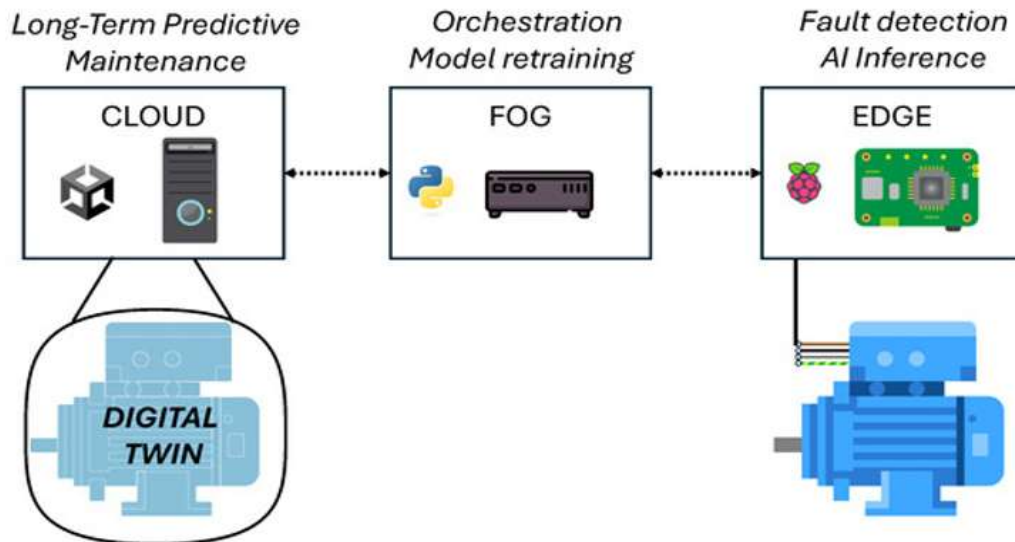
This study shows machine learning-based predictive maintenance architecture for industrial sensor networks and the design of a hybrid CNN–LSTM model for real-time anomaly detection and equipment health monitoring. The study is based on the Condition Monitoring of Hydraulic Systems dataset consisting of 2205 operational cycles, each with 60 seconds of sampling and 43,680 measurements from various sensors. Pressure, flow, temperature, vibration and motor-power signals under various equipment states are measured and provided. The sensor data were pre-processed using the following stages: missing value treatment, noise and outlier removal, sensor data synchronization, sensor data normalization, time series segmentation and feature engineering before the model was developed. The CNN learns and extracts the local patterns from the sensor signals and the LSTM learns and captures evolutions over time. The proposed model precision, recall and F1 score were 97.1%, 96.5% and 96.2%, respectively. The accuracy of the component level classification was 94.36% for cooler, valve, pump and accumulator. Additionally, the model's anomaly scores of 0.87 and 0.68 were found on abnormal operating time, demonstrating that the internal model can detect faults early and help to make decisions for timely maintenance.

**Keywords:** Predictive Maintenance; Industrial Sensor Networks; CNN–LSTM; Real-Time Anomaly Detection; Asset Health Management.

## 1. INTRODUCTION

Industrial Internet of Things (IIoT) has enabled the transformation of modern manufacturing processes with the ability to continuously monitor, intelligently control and make decisions based on data in complex industrial environments [1]. The industrial sensor networks produce a huge amount of data for nodes in various units of measurement and are very dynamic in terms of data frequency, covering temperature, vibration, pressure, current, acoustic signals and operating state [2]. These data are useful for understanding the equipment behaviour, but the traditional maintenance approaches such as reactive and schedule-based are inefficient, may lead to unexpected equipment failure, unnecessary maintenance activities, loss of productivity and equipment costs [3]. Therefore, intelligent predictive maintenance has yielded as a crucial method to give a notice of an abnormal operating condition and estimate asset health prior to critical failure [4].

Machine learning (ML) methods have proven to be of enormous potential to mine valuable information from the sensors of industrial systems and assist the automatic fault diagnosis [5]. The traditional ML models such as random forest, decision tree and gradient boosting algorithms work well when features provide useful information for classification of equipment conditions [6]. But these methods are depending on handcrafted features and have limited performance in dynamic industrial environments [7]. For learning nonlinear and sequential representations directly from sensor observations, deep learning methods, such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), long short-term memory (LSTM) networks and gated recurrent units (GRUs) offer more powerful capabilities [8]. However, this may not always be sufficient to cover the various spatial, temporal and contextual properties of industrial sensor streams [9] with only one type of deep learning architecture.



**Figure 1:** Edge-Fog-Cloud Architecture for Predictive Maintenance and Asset Health Management [10]

Adopting a complementary approach to design a hybrid deep learning framework would can address these deficiencies, featuring both deep learning and classic statistical methods for more comprehensive real-time detection of anomalies and asset health assessment [11]. CNN-based feature extraction models can represent local patterns and inter-sensor relations and recurrent networks can represent temporal dependencies between different equipment states used for progressive equipment degradation [12]. Attention mechanisms can also be used to highlight the most relevant sensor observations and degradation modes, enhancing the interpretability and sensitivity of the predictive maintenance system. This integration can help to develop the abnormal behavior detection, health monitoring and very reliable maintenance decision making in a changing industrial operation environment [13-15].

Although significant advances have been made, there are still issues to be addressed such as noisy and disparate sensor readings, the class imbalance problem between normal and faulty operations, moving equipment behavior patterns, real-time computational load and asset health indicators that must be guaranteed to be accurate. This study presents a hybrid deep learning approach to real-time anomaly detection and asset health management in industrial sensor networks using machine learning. The aim of the framework is to improve the accuracy of the predictions, minimize false alarms and facilitate early detection of faults and better maintenance planning. The recent advancements in AI-powered IoT monitoring also highlight the benefits of combining diverse sensor data, machine learning, and real-time analytics to detect risks early and provide intelligent decision support. These integrated solutions can continuously analyze sensor data, detect anomalies, and facilitate timely interventions, closely related to the goals of predictive maintenance and asset health management [16].

The main objectives of this study are:

- To develop a hybrid deep learning model for extracting spatial and temporal patterns from heterogeneous industrial sensor data.
- To detect equipment anomalies in real time with improved accuracy, precision, recall and F1-score.
- To estimate asset health conditions and identify early degradation patterns for predictive maintenance planning.

- To evaluate the proposed framework against conventional ML and individual deep learning models in terms of predictive performance, robustness and computational efficiency.

## 2. LITERATURE REVIEW

In their work Asim et al., (2026) [17] introduced an anomaly detection system that integrates enhanced TransGAN, Transformer temporal modelling, BiLSTM-GRU and statistical validation for industrial predictive maintenance. This framework is tested with the Machine Failure and SWaT data sets as well as unlabeled crane data set. When applied to Machine Failure dataset it had an accuracy rate of 84.09%, a precision of 68.95%, a recall of 84.32% and an F1 of 75.86%, with SWaT having an accuracy of 92.25% and an F1 of 69.37%. Khan et al., (2026) [18] proposed a TCN model that combines multimodal sensor fusion and XAI method for estimating RUL and tool health classification, yielding an overall accuracy of 86% on the NASA Ames milling dataset. Kumar et al., (2026) [19] introduced an Attention-GRU with Sand Cat Optimization for the industrial robotic fault identification and predictive maintenance, which showed better predictive accuracy and less computational cost. By leveraging the IIoT sensor data and collaborative edge-cloud intelligence, Rahman et al., (2025) [20] developed a CNN-RNN-autoencoder-based pipeline that achieved better prediction accuracy and higher MTTF estimation and maintenance scheduling performance than traditional ML methods in the equipment degradation prediction and anomaly detection problem.

Bajwa et al., (2025) [21] investigated ML and IoT integration for predictive maintenance and fault classification in modern power systems using Random Forest, XGBoost, LSTM and CNN-RNN models. The framework boosted fault detection accuracy by 28% increased the fault classification accuracy by 31% and cut outage duration by 42%, equipment downtime by 46% and maintenance expenditures by 31%. Potharaju et al., (2025) [22] proposed an automatic labeling method by using unsupervised-supervised combination technique namely, Isolation Forest with supervised techniques, namely, Random Forest, MLP and AdaBoost for sensor anomaly prediction. The models achieved 99.93%, 99.05% and 98.04% accuracy, respectively. The study by Thaker et al., 2024 [23] presented an IIoT and LSTM-autoencoder based framework for instrumentation of the refinery system, with 97.8% accuracy and 14 day warning time and a reduction of false alarms by 75% and downtime by 42%.

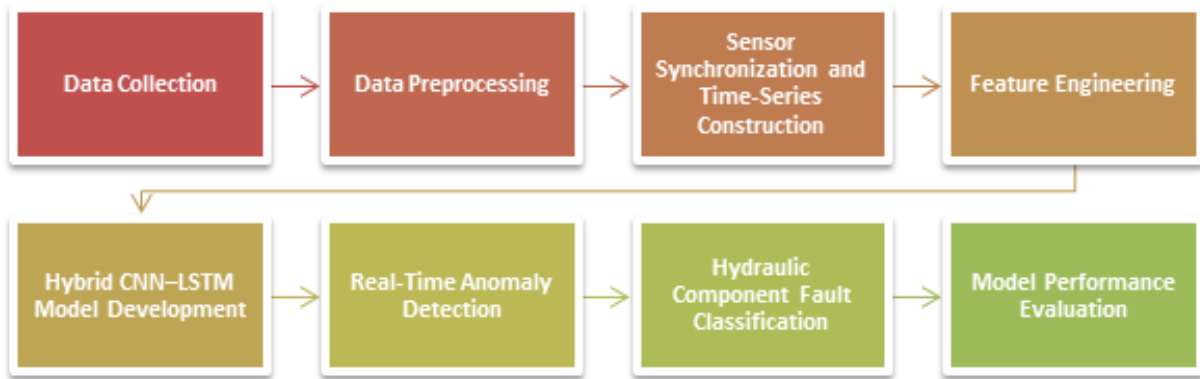
Obioha et al., 2024 [24] studied applying ML to smart sensor for predictive maintenance in the manufacturing, energy and health care industries with UCI and Kaggle data. Through time-series and regression, machine uptime was increased by five per cent (from 91.5% to 97%) and ROI was realised at 33.3% for the energy sector. Anomaly detection has also been a key concern in recent research on AI-based IoT systems, where sensors are continuously monitored. Temporal patterns, relational information, and anomaly scoring can be integrated in transformer and graph-based learning methods to detect previously unknown abnormal patterns in IoT networks [25]. Such developments support the use of advanced deep learning architectures for processing dynamic sensor streams and detecting abnormal equipment behaviour at an early stage. A predictive maintenance approach for remote terminal units (RTUs) attached to a real power generator that employs processing power, temperature, voltage and memory readings to predict anomalies in operation was proposed by Lekidis et al., [26]. To tackle the above challenge, Ngozi et al., [27] put forth an Edge-Cloud Collaborative Framework based on CNN, LSTM and federated edge inference. Evaluation with NASA C-MAPSS and PHM08 showed a 25-40% improvement in the accuracy of fault prediction and a 30% reduction in decision latency. Deshpande et al., (2022) [28] presented an adaptive edge-based ML solution for real-time IIoT anomaly detection that saves bandwidth and privacy, while also cutting latency, versus cloud-based solutions. A multi-sensor framework for predictive maintenance, utilizing CNN, random forest, vibration analysis and infrared thermography, was developed by Samuel et al., (2022) [29]. A manufacturing case study resulted in 42% less unscheduled downtime and 28% more efficient maintenance planning.

Although there is considerable progress in predicting maintenance in the fields of machine learning and deep learning, current published study has mainly concentrated on single fault detection, specific equipment or single sensor modality. Spatial feature extraction and temporal dependency learning have shown to be capable of providing better anomaly detection performance, but some problems still remain in dealing with highly imbalanced fault data, changing working conditions of the industry, multi-modal sensor stream and real-time deployment requirement.

## 3. RESEARCH METHODOLOGY

The methodology proposed consists of the development of an Industrial Sensor network with the aid of the Machine Learning-Enabled Predictive Maintenance Framework. It is a framework that utilizes multivariate sensor data to identify abnormal behaviors, categorize machine health and assist in taking proactive maintenance decisions. The method is based on the CNN image classification system for extracting the spatial/local features and LSTM temporal dependency learning system. CNNs are good for recognizing patterns at local time scales in time-series sensor data, while LSTM networks are able to recognize patterns at long time scales. Figure 2 shows the

proposed work to be carried out, as a framework.



**Figure 2:** Framework of methodology

### 3.1 Data Collection

Multivariate sensor measurements with various component-health conditions were extracted from a hydraulic test rig test having a hydraulic sensor data set called Condition Monitoring of Hydraulic Systems [30]. The total number of operational cycles is 2,205 cycles with each cycle corresponding to 60 seconds of system operation, consisting of 43,680 measurements taken by each of the sensors. It consists of pressure, flow, temperature, vibration and motor-power signals provided by a number of sensors.

### 3.2 Data Preprocessing

Raw sensor data are subjected to some preliminary treatment of the data to enhance their quality and consistency prior to model development. The preprocessing consists of the treatment of missing values, noise reduction, outlier detection, sensor synchronization, normalization, class balancing and segmentation of the time-series. Nearest neighbour imputation is used to fill in missing observations:

$$x_i^* = x_j \quad (1)$$

where  $x_j$  is the nearest valid observation. Outliers are identified using the Interquartile Range (IQR):

$$IQR = Q_3 - Q_1 \quad (2)$$

with boundaries  $LB=Q_1-1.5IQR$  and  $UB=Q_3+1.5IQR$ . Finally, sensor values are standardized using:

$$z_i = \frac{x_i - \mu_x}{\sigma_x} \quad (3)$$

where  $\mu_x$  and  $\sigma_x$  represent the training-set mean and standard deviation, respectively.

### 3.3 Sensor Synchronization and Time-Series Construction

Industrial sensors can sample at different frequencies, so the measurements are synchronized in time to a common representation, which is then used to represent the events in the sensors channels. The synchronized data are then analysed across temporal windows that overlap each other. A sequence of sensors is illustrated as:

$$\mathbf{X}_t = [\mathbf{x}_{t-L+1}, \mathbf{x}_{t-L+2}, \dots, \mathbf{x}_t] \quad (4)$$

where  $L$  denotes the window length,  $t$  represents the current time index and  $\mathbf{x}_t$  is the multivariate sensor vector. Thus, the input sequence is expressed as:

$$\mathbf{X}_t \in \mathbb{R}^{L \times F} \quad (5)$$

where  $F$  denotes the number of sensor features. This structured representation enables the CNN to extract local patterns, while the LSTM captures their temporal dependencies.

### 3.4 Feature Engineering

Feature selection is carried out to eliminate redundant and irrelevant features and highly correlated features to retain the parameters of the sensor that give better results in real-time anomaly detection, fault prediction and asset health assessment. Multiple sensors in an industrial sensor network can encounter the same operating conditions, thereby providing redundant information and increasing the complexity of the calculations. By eliminating such variables, the model's efficiency and training time can be improved; over fitting and the interpretability of the predictive-maintenance framework can also be reduced.

$$\mu = \frac{1}{N} \sum_{i=1}^N x_i \quad (6)$$

The standard deviation is:

$$\sigma = \sqrt{\frac{1}{N} \sum_{i=1}^N (x_i - \mu)^2} \quad (7)$$

The root mean square (RMS) is:

$$RMS = \sqrt{\frac{1}{N} \sum_{i=1}^N x_i^2} \quad (8)$$

The peak-to-peak value is:

$$P_{p-p} = x_{max} - x_{min} \quad (9)$$

These features characterize variations in pressure, temperature, flow, vibration and motor-power signals, thereby supporting effective anomaly and fault detection.

### 3.5 Hybrid CNN-LSTM Model Development

#### • CNN-Based Sensor Feature Extraction

The CNN is used to learn local patterns from sets of multivariate sensor sequences that are synchronized. The convolution operation  $X$  is given as follows for an input sequence  $X$ :

$$C_i = f\left(\sum_{j=1}^k w_j X_{i+j-1} + b\right) \quad (10)$$

where  $k$  represents the kernel size,  $w_j$  denotes the convolution weights,  $b$  is the bias and  $f(\cdot)$  represents the activation function. The CNN captures localized variations in pressure, temperature, flow, vibration and motor-power signals. ReLU activation is used to introduce non-linearity:

$$ReLU(x) = \max(0, x)$$

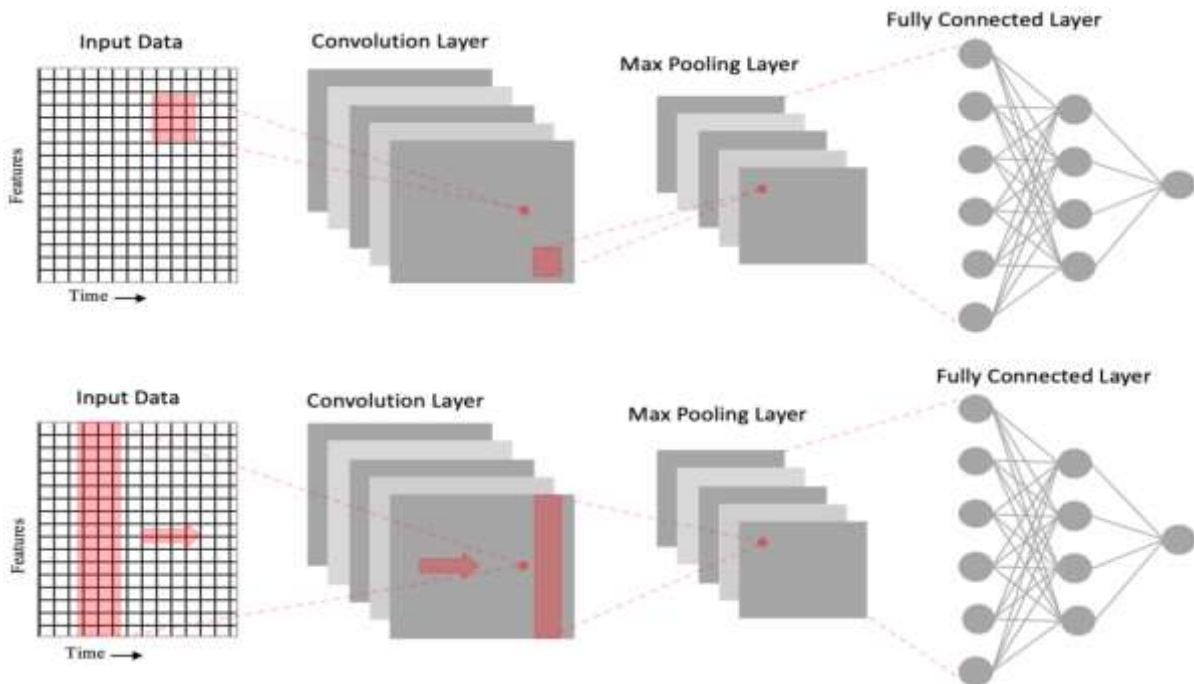


Figure 3: CNN-Based Sensor Feature Extraction Architecture [31, 32]

#### • LSTM-Based Temporal Learning

The CNN is used to extract features from the images entered into the LSTM to learn the temporal dependencies between sequential sensor readings. It has forget gate, input gate, candidate state, cell state and output gate, which is calculated as:

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \quad (11)$$

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \quad (12)$$

$$\tilde{C}_t = \tanh(W_c[h_{t-1}, x_t] + b_c) \quad (13)$$

$$C_t = f_t C_{t-1} + i_t \tilde{C}_t \quad (14)$$

$$O_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \quad (15)$$

$$h_t = o_t \tanh(C_t) \quad (16)$$

These operations enable the LSTM to learn progressive changes in equipment condition across consecutive time windows.

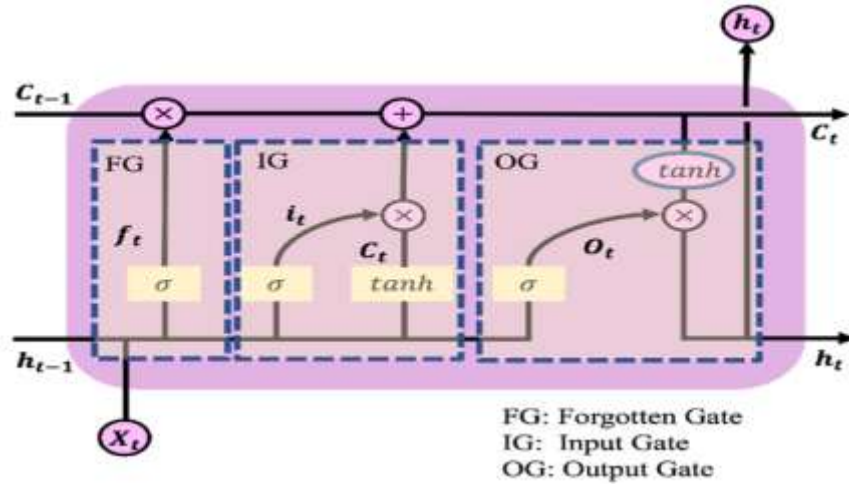


Figure 4: LSTM-Based Temporal Learning Architecture [33,34,35, 36, 37]

#### • CNN-LSTM Hybrid Architecture

The CNN and LSTM are cascaded to incorporate the local sensor-pattern extraction and temporal dependency learning. The CNN is first used to learn relevant features from the multivariate signals of all types of hydraulic sensors such as pressure, temperature, flow, vibration and motor-power variations. The extracted features are fed into the LSTM network, which is used to model the temporal relationships and the evolution of the equipment states. Finally, a dense layer of classification gets the learned temporal representation and is used to make predictions. This hybrid architecture allows for efficient real-time anomaly detection and fault classification at the component level, enabling reliable predictive maintenance and asset health management.

#### 3.6 Real-Time Anomaly Detection

CNN-LSTM is a trained model which estimates the probability of an anomaly from the incoming multivariate sensor windows, to detect abnormal operating conditions. The binary decision is defined as:

$$\hat{y} = \begin{cases} 1, & P(\text{anomaly} | X) \geq \tau \\ 0, & P(\text{anomaly} | X) < \tau \end{cases} \quad (17)$$

where  $X$  represents the input sensor window and  $\tau$  denotes the anomaly threshold. An initial threshold of 0.5 can be adopted and subsequently optimized using validation data. This mechanism enables timely identification of abnormal sensor patterns and provides early warnings for potential equipment faults and maintenance requirements.

#### 3.7 Hydraulic Component Fault Classification

Proposed CNN-LSTM framework is a classification of major hydraulic components (cooler, pump, accumulator and valve) health condition by recognizing the patterns of the sensors. If the classes are more than two, the predicted class is decided as below:

$$\hat{y} = \arg \max_k P(y = k | X) \quad (18)$$

where  $X$  represents the input sensor sequence and  $k$  denotes the corresponding component-health class. The model assigns each sensor window to its most probable condition, enabling identification of component-specific abnormalities. This approach extends anomaly detection toward component-level fault diagnosis and condition assessment, supporting targeted maintenance decisions for hydraulic-system components.

#### 3.8 Model Performance Evaluation

##### • Accuracy

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (19)$$

##### • Precision

$$\text{Precision} = \frac{TP}{TP+FP} \quad (20)$$

- **Recall**

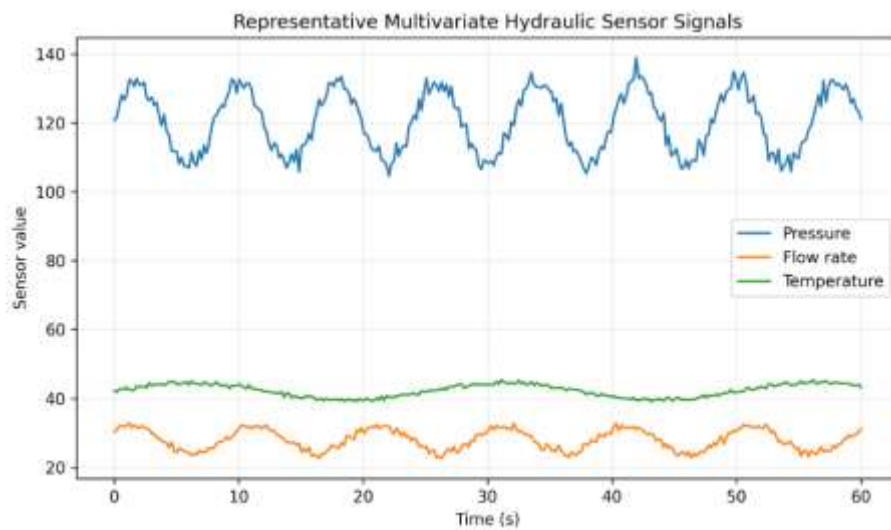
$$\text{Recall} = \frac{TP}{TP+FN} \quad (21)$$

- **F1-Score**

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (22)$$

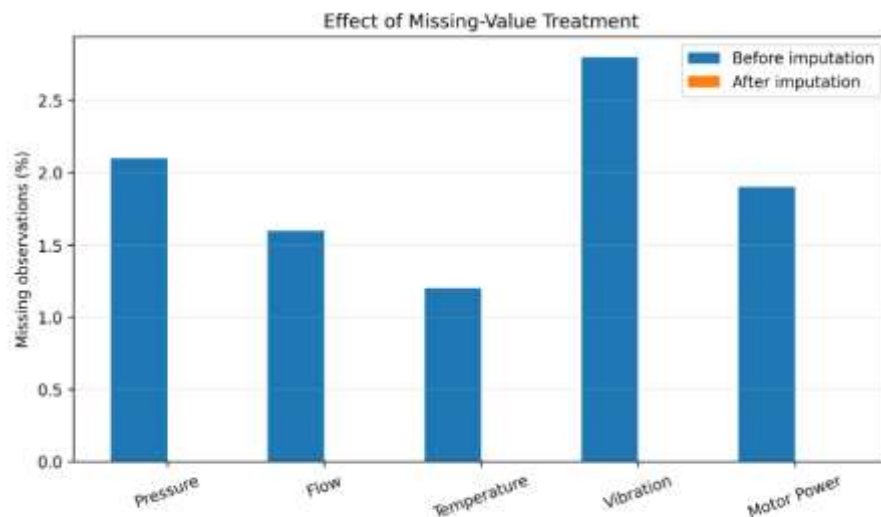
#### 4. RESULTS AND CONCLUSION

To support the predictive maintenance, example multivariate hydraulic sensor signals over a 60-second monitoring time are shown in figure 5. Pressure has the widest range of variation, oscillating from 106 to 138 units and has repeated patterns. The flow rate ranges from almost 22 to 33 units and the temperature stays relatively constant at 39-45 units. The signal dynamics are synchronized, showing changing hydraulic operating conditions, but not identical and complementing the information provided for anomaly detection. These multivariate patterns can assist the hybrid deep learning model with identifying deviations, monitoring asset degradation and making predictions across industrial sensor networks for taking decisions to perform maintenance.



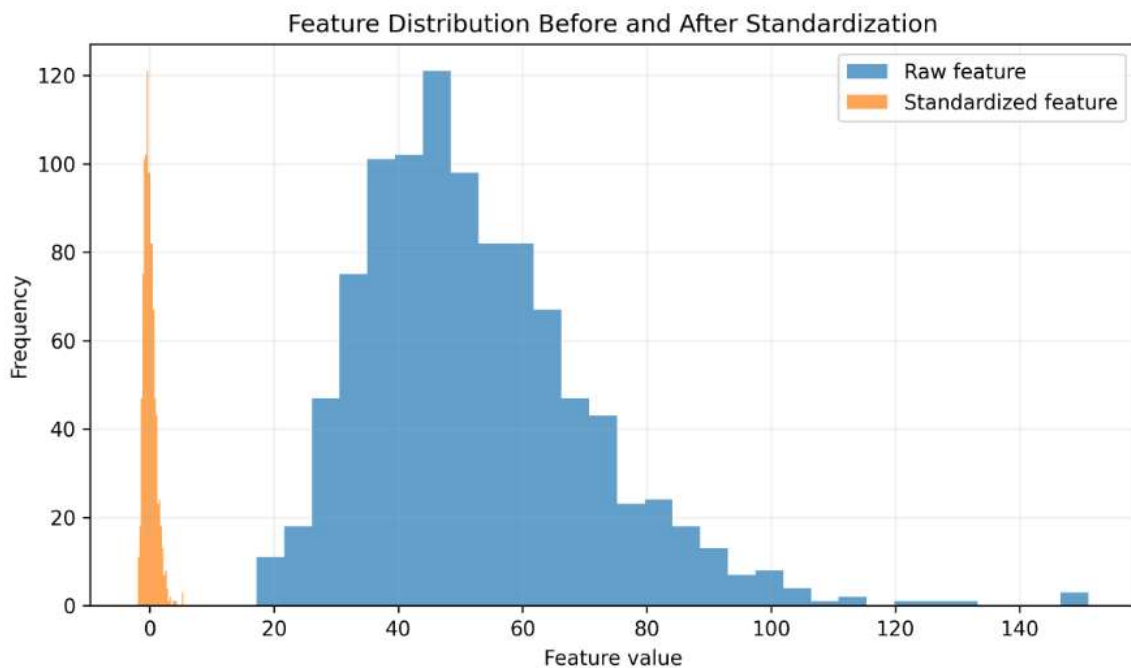
**Figure 5:** Representative Multivariate Hydraulic Sensor Signals

The impact of the missing-value treatment on five industrial sensor variables of the predictive maintenance context is shown in figure 6. Prior to imputation, the proportion of missing observations is greatest for the vibration, followed by pressure, motor power, flow and temperature. The imputation process reduces the effective percentage of missing observations to ~0% to all sensor variables. This is a vital preprocessing step that helps to enhance data completeness and consistency, crucial for the successful training of a Hybrid Deep Learning Model. The framework could enhance real-time detection of anomalies and offer more comprehensive asset health management for industrial sensor networks by filling in missing data.



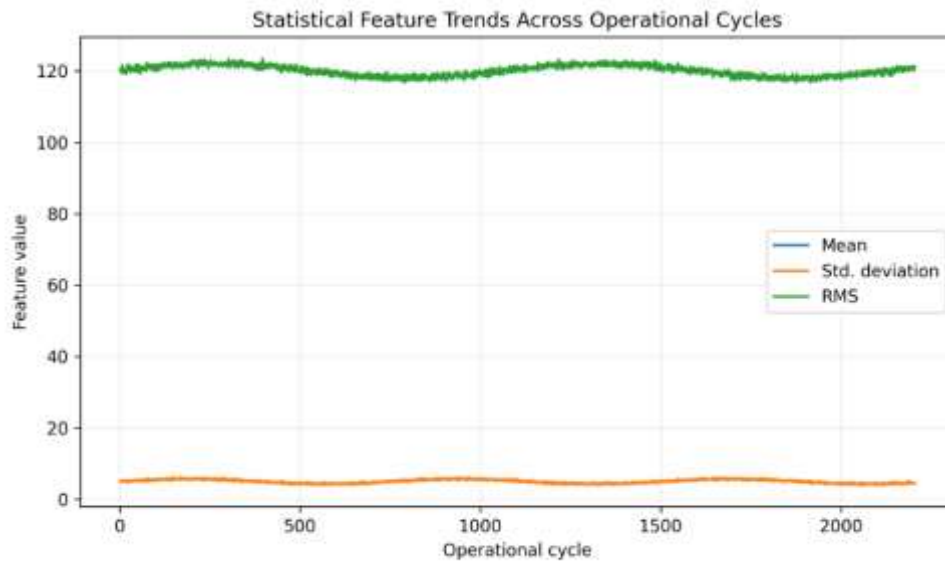
**Figure 6:** Sensor Missing-Value Distribution before Imputation

The feature distributions of the proposed predictive maintenance approach before and after the standardization are compared in figure 7, showing the efficacy of scaling the sensor variables. The raw features span a wide range (15 to just over 155, highest frequency of about 121 observations around the value of the feature at 45-50). Following the standardization, the distribution is clustered around 0 and range from around -1 to 1. The transformation helps mitigate the scaling issues and numerical instabilities when training hybrid deep learning models. Standardised features can then help promote quicker convergence, improve the reliability of anomaly detection and enable more consistent asset health predictions for diverse industrial sensor measurements.



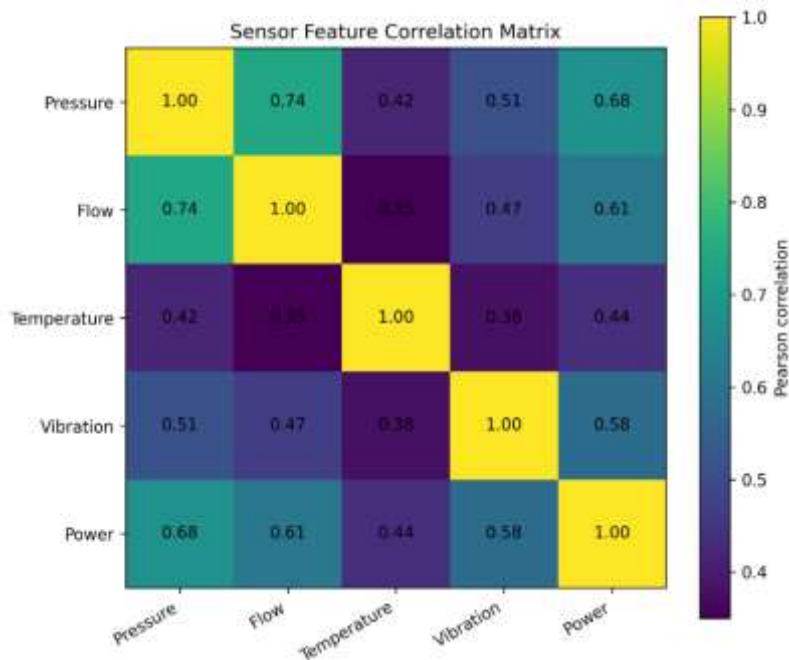
**Figure 7:** Feature Distribution Before and After Standardization

The statistical data trends over about 2200 operational cycles are plotted in Figure 8, where the mean, standard deviation and root mean square (RMS) values are indicated. The mean is relatively low at about 118–121 and the behavior of the central features is consistent throughout the operating time. The range of standard deviation is quite tight, with a minimum of about 4 and a maximum of about 6, indicating small variability in the readings taken by the sensor, which could indicate reliable measurements. RMS values, on the other hand, are significantly higher, ranging from almost 118 to 122 and are quite close to the average trend. The consistency of these statistical trends suggests a reliable performance of the sensors and offers valuable reference statistics for the integrated deep learning system to detect anomalies and determine the health status of the assets.



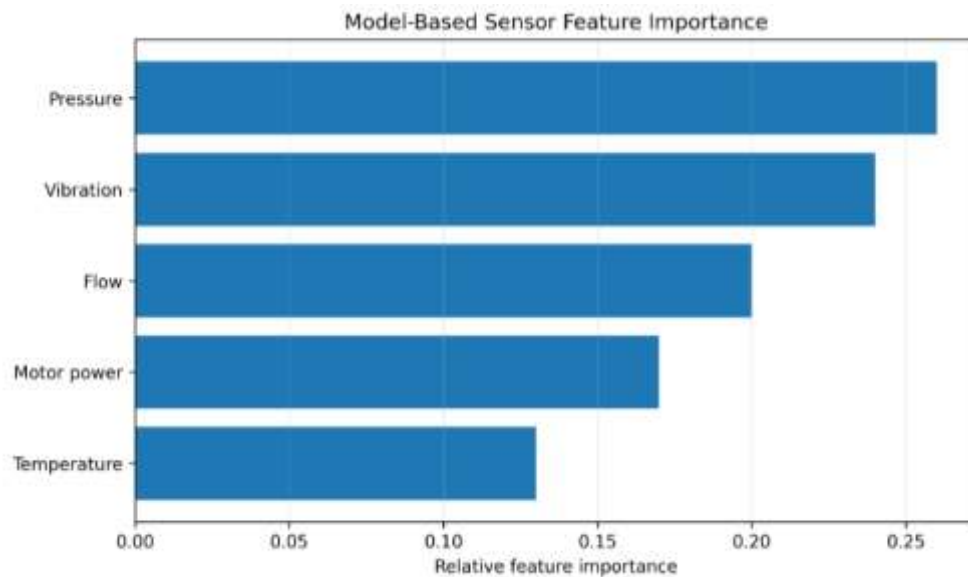
**Figure 8:** Statistical Feature Trends across Operational Cycles

The strength of the relationships between five industrial sensors features are shown in the Pearson correlation matrix illustrated in Figure 9, which can help support anomaly detection and asset health management. The highest positive correlation is between pressure and flow that is 0.74, followed by pressure and power at 0.68 and flow and power at 0.61. Power and pressure have also been moderately correlated with vibration (0.58 and 0.51, respectively). The relationships between the variables of temperature are comparatively weak (0.35–0.44). These results show that there is related operational information from the use of pressure, flow and power and more independent operational characteristics is provided from the use of temperature in the hybrid deep learning model.



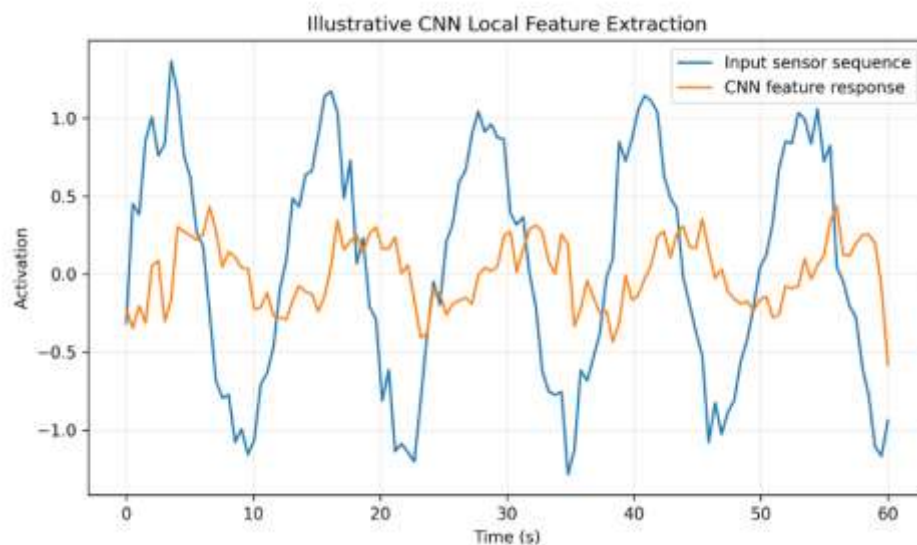
**Figure 9:** Pearson Correlations among Sensor Features

Figure 10 is the model to determine the importance of 5 sensor features for predictive maintenance. The most powerful feature is pressure (as described above), at around 0.26, followed by vibration (as described above), at 0.24 and flow at 0.20. The importance of motor power is around 0.17 and temperature is the lowest at 0.13. The combined coefficient corresponding to pressure and vibration is about 0.50, indicating that these two make up the largest portion of the weightage contributions to the model prediction. These findings show that pressure and vibration data is imperative to identifying abnormal operating conditions, whereas flow, motor power and temperature data can complement in real-time anomaly detection and asset health assessment.



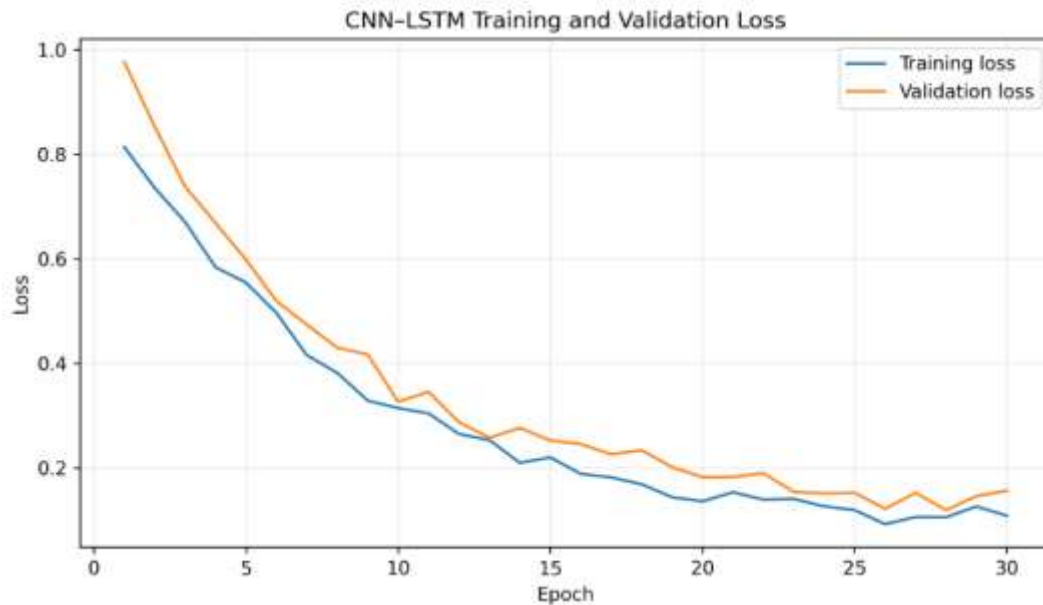
**Figure 10:** Model-Based Sensor Feature Importance

CNN based local feature extraction from an industrial sequence of images acquired by a sensor is shown in Figure 11 over a period of 60 s. The sensor input signal has strong periodic characteristics; the activation range is about 5 major oscillation cycles and the range from  $-1.3$  to  $1.3$ . By comparison, the CNN feature response is constrained to a narrow range of around  $-0.4$  to  $0.45$  and is able to detect local variations in the input pattern. This shows that the CNN is capable of compressing the high variation sensor measurements into low dimensional representations. These locally extracted features may contribute to the anomaly detection task performed by the proposed hybrid deep learning framework and aid in accurate real-time anomaly detection and asset health assessment in the industrial context.



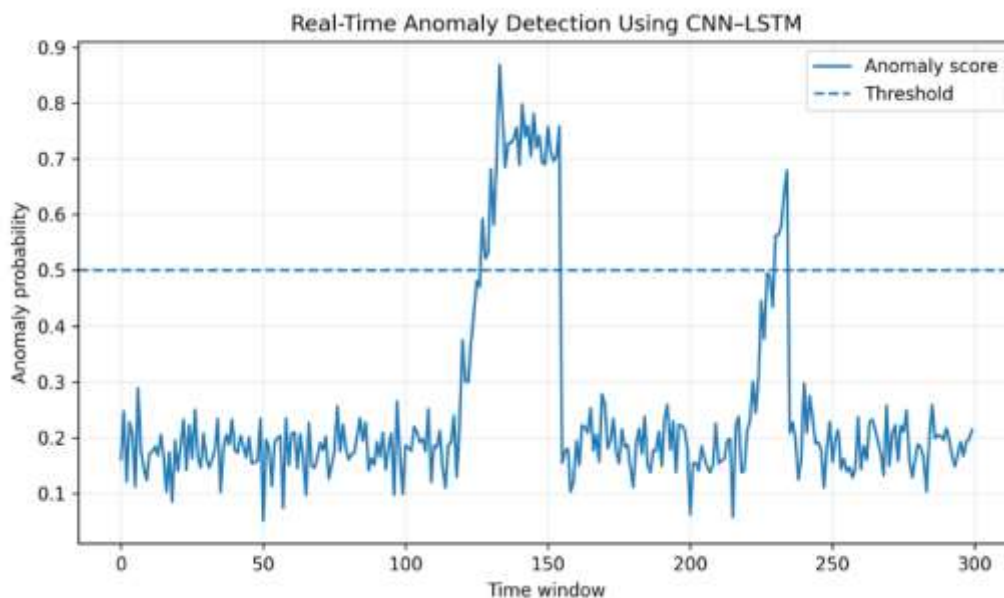
**Figure 11:** CNN-Based Local Sensor Feature Extraction

Figure 12 shows the loss value over 30 epochs for the proposed CNN-LSTM model, where both training and validation loss curves are plotted. Figure 12 illustrates the losses of the proposed CNN-LSTM model after training for 30 epochs and validation losses over 30 epochs, where training and validation losses are plotted with respect to epochs. The training loss reduces from around 0.81 at the first epoch all the way down to 0.11 at epoch 30, which is an 86.4% decrease. Likewise, the validation loss is reduced from  $\sim 0.97$  to  $\sim 0.15$  which accounts for 84.5% drop. The curves of both are gradually sloping mainly down, with a few oscillations after about epoch 20. The minimal difference in losses, 0.04, suggests that the model is only slightly overfitting and generalizing well, which aligns with its applicability for real-time anomaly detection and industrial asset health monitoring.



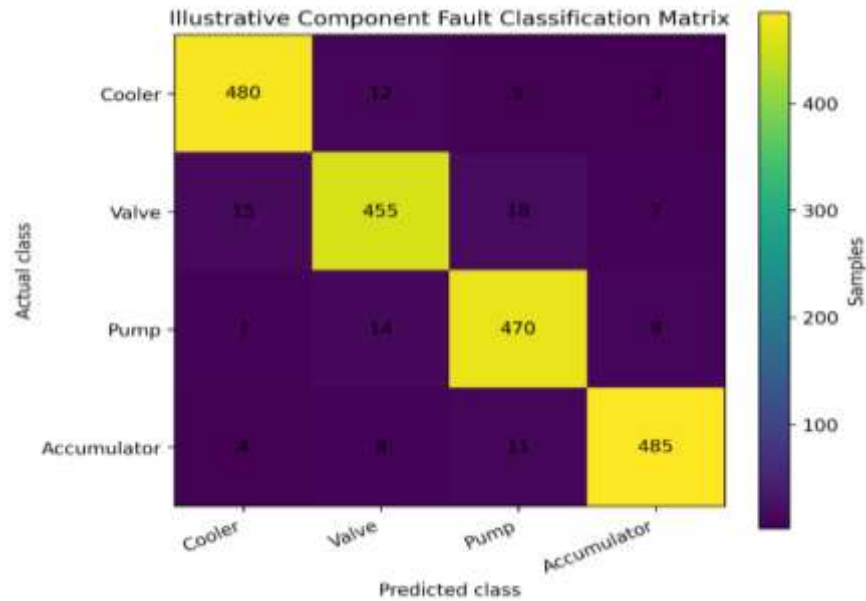
**Figure 12:** CNN-LSTM Training and Validation Loss

In order to find the real-time anomaly detection, the proposed CNN-LSTM model was applied to 300 time windows and the results are shown in Figure 13. The dashed threshold line is at a probability of anomaly of 0.50; normal observations tend to be in the range of about 0.10 to 0.30. The anomaly score is relatively high from time windows 120–160, with significant peaks around the time window 160 and is approximately 0.87, which exceeds the threshold by a significant margin. There is another anomaly event around 225–240 with an approximation of 0.68. The threshold crossing clearly separates abnormal operating conditions from normal behaviour, evidencing the ability of the model to detect temporal anomalies and alert when the operation of these industrial assets is abnormal, an ability that facilitates timely alerts for industrial asset health monitoring and predictive maintenance.



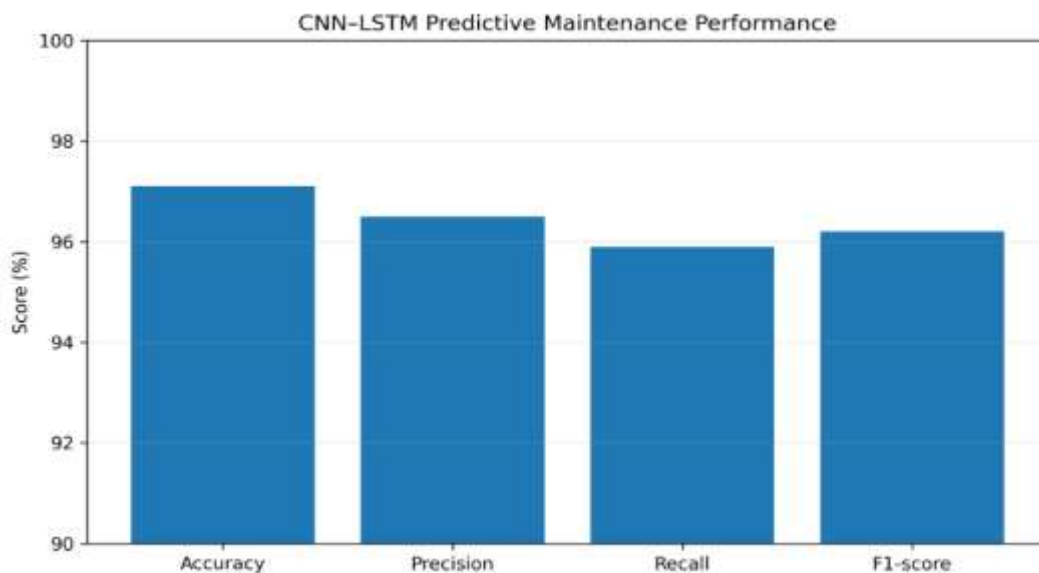
**Figure 13:** Real-Time Anomaly Detection Using CNN-LSTM

The results of the component fault classification performance are shown in Figure 14 for four industrial components: cooler, valve, pump and accumulator. The model accurately predicts 1,890 out of 2,003 samples or an overall accuracy rate of around 94.36% with 480 coolers, 455 valves, 470 pumps and 485 accumulators being classified correctly. The recall rate for each class is: 96.0% for coolers, 91.92% for valves, 94.0% for pumps and 95.47% for accumulators. The rate of misclassification is relatively low; the top misclassifications are 18 valves classified as pumps. The outcomes indicate high fault recognition at component level, for reliable predictive maintenance and asset health management.



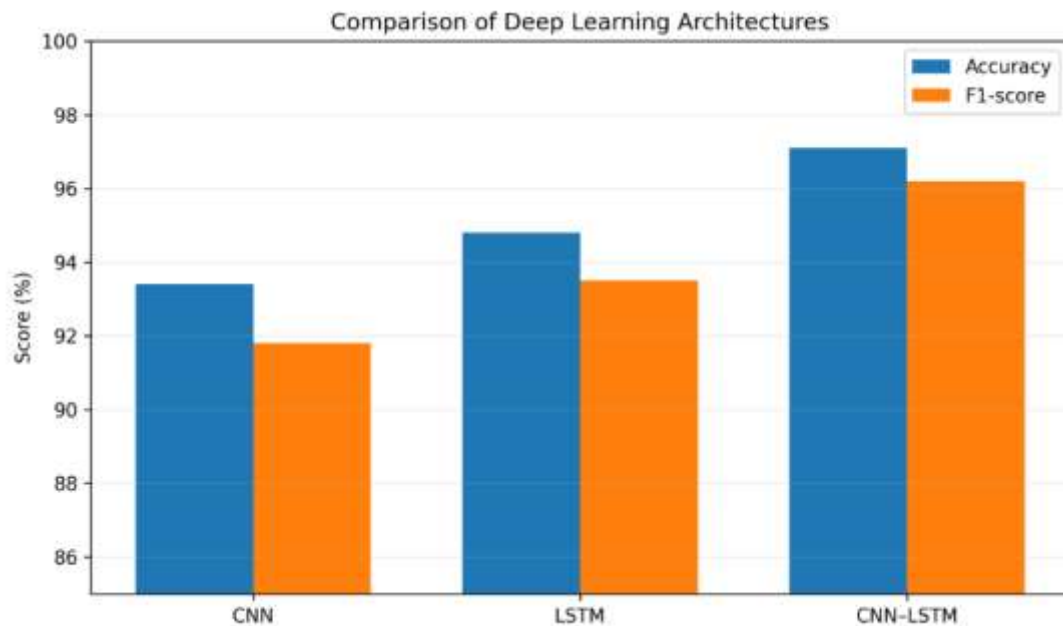
**Figure 14:** CNN-LSTM Component Fault Classification

A comparison of the proposed CNN-LSTM model performance with four evaluation metrics is shown in Figure 15. The overall accuracy rate of the model is around 97.1%, which represents a high level of accuracy in the overall classification. Most predicted fault events are correctly identified (precision 96.5%) and there is a good ability to detect real fault conditions (recall 95.9%). This yields an F1 score of around 96.2% representing a balance between precision and recall. In absolute terms, there is a relatively small accuracy - recall difference of approximately 1.2 percentage points, which also suggests similar classification behavior. The results show that the CNN-LSTM can effectively identify anomalies and make predictions for asset health management in real-time, which has been proven.



**Figure 15:** CNN-LSTM Predictive Maintenance Performance

The CNN, LSTM and hybrid CNN-LSTM models are compared in terms of accuracy and F1 score as shown in Figure 16. The CNN accuracy is ~93.4% and the F1 score is ~91.8% and the LSTM accuracy is ~94.8% and the F1 score is ~93.5%. The CNN-LSTM model has the best result with the accuracy of ~97.1% and F1-score of ~96.2%. When compared with CNN, the hybrid architecture achieves around 3.7 and 4.4 percentage points of accuracy and F1-score, respectively. The enhancements show the advantage of the synergic use of CNN local features and LSTM temporal features for real-time anomaly detection and industrial asset health management.



**Figure 16:** CNN, LSTM and CNN-LSTM Performance

The accuracy of the existing predictive maintenance methods is compared with the proposed CNN-LSTM model as shown in the table 1. Asim et al. (2026) and Khan et al. (2026) achieved accuracies of 84.09% and 86.00%, respectively, while Bajwa et al. (2025) reached 96.00%. The proposed model outperforms the other models with the highest accuracy of 97.10%, which shows an improvement of 13.01, 11.10 and 1.10 percentage points respectively. The findings show that the CNN based feature extraction and temporal learning by LSTM is an effective approach to achieve accurate industrial anomaly detection and predictive maintenance.

**Table 1:** Accuracy Comparison of Predictive Maintenance Models

| Author and Year          | Accuracy (%) |
|--------------------------|--------------|
| Asim et al. (2026) [16]  | 84.09        |
| Khan et al. (2026) [17]  | 86.00        |
| Bajwa et al. (2025) [20] | 96.00        |
| Proposed Work (2026)     | 97.10        |

## 5. CONCLUSION

The proposed hybrid CNN-LSTM is good at predictive maintenance, real-time anomaly detection and hydraulic asset health evaluation. The methodology is based on 2,205 working cycles and multivariate readings obtained from sensors of pressure, flow, temperature, vibration and motor-power and involve preprocessing, synchronization, feature engineering, CNN-based local representation learning and LSTM-based temporal modeling. Over 30 epochs, the training loss dropped from 0.81 to 0.11 and the validation loss dropped from 0.97 to 0.15, which shows that it has a stable convergence characteristic and limited over fitting. The proposed model gave an accuracy of 97.1%, precision of 96.5%, recall of 95.9% and F1-score of 96.2%, which are better than the individual models CNN and LSTM. The accuracy of the classification for components was 94.36%, with 1,890 correct predictions out of 2,003 samples. The real-time anomaly scores of 0.87 and 0.68 were well above the "above 0.50" threshold. The results overall demonstrated the effectiveness of integrating spatial and temporal learning for better fault recognition and for establishing a robust foundation for proactively maintaining industrial assets while warning of faults and monitoring the health of industrial assets continuously.

## REFERENCES

- [1] Kaur, Chitrnanjanjit, Sumit Chopra and Chitta Ranjan Tripathy. "An Explainable IoT-Enabled Predictive Maintenance Framework Using Digital Twin and Multi-Sensor Machine Learning." *Automation* 7, no. 4 (2026): 126.
- [2] Desikan, Jayameena, Sushil Kumar Singh, A. Jayanthiladevi, Shashi Bhushan, Vinay Rishiwal and Manish Kumar. "Hybrid machine learning-based fault-tolerant sensor data fusion and anomaly detection for fire risk mitigation in IIoT environment." *Sensors* 25, no. 7 (2025): 2146.

- [3] Shamim, Md Mahamudur Rahaman and Rezwatul Ashraf Ruddro. "Smart diagnostics in industrial maintenance: a systematic review of AI-enabled predictive maintenance tools and condition monitoring techniques." (2025).
- [4] Thirumalaikumari, T. "Intelligent Predictive Maintenance Using Hybrid Artificial Intelligence Models for Sustainable Industrial Automation in Industry 4.0." *Journal of Intelligent Decision Making and Information Science* 3, no. 7s (2026): 1099-1125.
- [5] Kerkeni, Rochdi, Anis Mhalla and Kais Bouzrara. "Unsupervised learning and digital twin applied to predictive maintenance for Industry 4.0." *Journal of Electrical and Computer Engineering* 2025, no. 1 (2025): 3295799.
- [6] Bitam, Taimia, Aya Yahiaoui, Djallel Eddine Boubiche, Rafael Martínez-Peláez, Homero Toral-Cruz and Pablo Velarde-Alvarado. "Artificial intelligence of things for next-generation predictive maintenance." *Sensors (Basel, Switzerland)* 25, no. 24 (2025): 7636.
- [7] Rony, M. A. "AI-enabled predictive analytics and fault detection frameworks for industrial equipment reliability and resilience." *ASRC Procedia: Global Perspectives in Science and Scholarship* 1, no. 01 (2025): 705-736.
- [8] Islam, Rahomotul, Nafiza Humauara Hasan Neha, Mumtahina Ahmed, Jannatul Maua, Neha Chaudhary, Muhammad Firoz Mridha, Nilanjan Dey and Satyabrata Roy. "Two-Stage Hybrid Deep Learning Architecture for Cross-Domain Anomaly Detection and Failure Prediction." *IEEE Open Journal of the Computer Society* 7 (2025): 117-128.
- [9] Kabir, Tasnim. "Intelligent Condition Monitoring and Fault Diagnosis of Electrical Power and Control Systems Using Machine Learning-Based Predictive Analytics." *American Journal of Interdisciplinary Studies* 7, no. 01 (2026): 177-222.
- [10] de las Morenas, Javier, Lidia M. Belmonte and Rafael Morales. "Streamlined bearing fault detection using artificial intelligence in permanent magnet synchronous motors." *Machines* 13, no. 5 (2025): 357.
- [11] Abdallah, Wajih and Mansoor Alghamdi. "AIP-Urban: Edge-Enabled Deep Learning Framework for Predictive Maintenance and Anomaly Detection in Urban Traffic Infrastructure." *Systems* 13, no. 12 (2025): 1117.
- [12] Ardito, Samuel, Wahyu Setiawan and Agung Wibisono. "Enhancing predictive maintenance in manufacturing using deep learning-based anomaly detection." *International Journal of Technology and Modeling* 3, no. 1 (2024): 12-23.
- [13] Gupta, Amar Deep and Basu Dev Shivhare. "Machine Learning-Driven Predictive Maintenance Models for Industrial Equipment and Manufacturing Systems." *Confluence: A Journal of Technology, Business and Society* 1, no. 1 (2026).
- [14] Öztürk, Yusuf. "A comparative analysis of machine and deep learning models for predictive maintenance and fault estimation of tools in industrial machinery within small-scale settings." *Communications Faculty of Sciences University of Ankara Series A2-A3 Physical Sciences and Engineering* 67, no. 2 (2025): 193-215.
- [15] Tamakloe, Elvis, Benjamin Kommey, Jerry John Kponyo, Eric Tutu Tchao, Andrew Selasi Agbemenu and Griffith Selorm Klogo. "Predictive AI Maintenance of Distribution Oil-Immersed Transformer via Multimodal Data Fusion: A New Dynamic Multiscale Attention CNN-LSTM Anomaly Detection Model for Industrial Energy Management." *IET electric power applications* 19, no. 1 (2025): e70011.
- [16] S. E., S. Das, G. Kalele, S. Goyal, S. Boltayeva, A. Kushwaha, and T. Djurayev, "Smart livestock farms: Integrating IoT, AI, and environmental management for sustainable animal production," *Journal of Animal Environment*, vol. 18, no. 2S, pp. 686–696, 2026. <https://aejournals.org/index.php/AEJ/article/view/2732>
- [17] Asim, Nayab, Irum Matloob, Zaid Khan, Rukaiya Rukaiya, Shoab Khan and Hessa Alfraihi. "A hybrid generative and transformer-based framework for anomaly detection in industrial sensor time-series for predictive maintenance." *Scientific Reports* (2026).
- [18] Khan, Abuzar, Ahmad Junaid, Muhammad Farooq Siddique, Abid Iqbal, Husam S. Samkari, Mohammed F. Allehyani and Ghassan Husnain. "Smart predictive maintenance: A tcn-based system for early fault detection in industrial machinery." *Machines* 14, no. 2 (2026): 164.

- [19] Kumar, Deepak, Santosh Reddy Addula, Mary Lind, Steven Brown and Segun Odion. "AI-driven hybrid deep learning and swarm intelligence for predictive maintenance of smart manufacturing robots in industry 4.0." *Electronics* 15, no. 3 (2026): 715.
- [20] Rahman, Aisha and Israel Godwin Mahlangu. "Hybrid Deep Learning Pipelines for Predictive Maintenance in Cloud-Connected Manufacturing Systems." (2025).
- [21] Bajwa, Ammar. "Machine Learning and IoT for Predictive Maintenance in Power Systems: Improving Fault Detection Accuracy and Grid Reliability." *Journal of Sustainable Development and Policy* 4, no. 04 (2025): 41-62.
- [22] Potharaju, Saiprasad, Ravi Kumar Tirandasu, Swapnali N. Tambe, Devyani Bhamare Jadhav, Dudla Anil Kumar and Shanmuk Srinivas Amiripalli. "A two-step machine learning approach for predictive maintenance and anomaly detection in environmental sensor systems." *MethodsX* 14 (2025): 103181.
- [23] Thaker, Bhavik and Alina West. "Integration of IoT and Predictive Analytics for Real-Time Monitoring of Critical Instruments in Refinery Operations." *The Journal of Instrumentation, Automation and Systems* 9, no. 1 (2024): 1-9.
- [24] Obioha Val, Onyinye, Oluwaseun Oladeji Olaniyi, Oluwatosin Selesi-Aina, Michael Olayinka Gbadebo and Titilayo Modupe Kolade. "Machine learning-enabled smart sensors for real-time industrial monitoring: Revolutionizing predictive analytics and decision-making in diverse sector." *Machine Learning-enabled Smart Sensors for Real-time Industrial Monitoring: Revolutionizing Predictive Analytics and Decision-making in Diverse Sector (November 22, 2024)*. *Asian Journal of Research in Computer Science* 17, no. 11 (2024): 10-9734.
- [25] M. Kaliappan, S. Vimal, Karpagavalli C., Ramnath M., Tania Singh, and G. Dhiman, "A zero-shot Transformer-Graph Neural Network framework for unknown cyberattack pattern recognition in IoT networks," *Journal of Animal Environment*, vol. 18, no. 4S, pp. 110–122, 2026, doi: 10.70102/AEJ.2026.18.4s.11.
- [26] Lekidis, Alexios, Angelos Georgakis, Christos Dalamagkas and Elpiniki I. Papageorgiou. "Predictive maintenance framework for fault detection in remote terminal units." *Forecasting* 6, no. 2 (2024): 239-265.
- [27] Hashi, Abdinasir Ismael, and Mr Osman Abdullahi Jama. "Evaluating the Performance of AI-Based Software Tools in Intelligent Decision-Making Systems." *International Journal of Computing and Engineering* 7, no. 22 (2025): 1-20.
- [28] Shanker, Ravi. "Edge-Accelerated Analytics for Encrypted Network Traffic using Optimized Machine Learning." In 2025 International Conference on Computing Technologies & Data Communication (ICCTDC), pp. 1-7. IEEE, 2025
- [29] Ngozi, Emeka. "Predictive maintenance and system optimization using edge-integrated AI and machine learning models." *American International Journal of Computer Science and Technology* 5, no. 4 (2023): 12-22.
- [30] Deshpande, Yogesh D. and S. R. Rahman. "Edge-based real-time sensor data processing for anomaly detection in industrial IoT applications." *Research Journal of Computer Systems and Engineering* (2023): 16-30.
- [31] Samuel, Solarin Adebayo. "Holistic predictive maintenance framework leveraging AI, vibration analysis and thermography for proactive asset reliability." *International Journal of Engineering Technology Research and Management* 7, no. 3 (2023): 18-27.
- [32] <https://www.kaggle.com/datasets/jjacostupa/condition-monitoring-of-hydraulic-systems>
- [33] Rengasamy, Divish, Mina Jafari, Benjamin Rothwell, Xin Chen and Graziela P. Figueredo. "Deep learning with dynamically weighted loss function for sensor-based prognostics and health management." *Sensors* 20, no. 3 (2020): 723.
- [34] Liu, Wei, Xu Liu, Yuan Hu, Jie Shi, Xinqiang Chen, Jiansen Zhao, Shengzheng Wang and Qingsong Hu. "Fall detection for shipboard seafarers based on optimized BlazePose and LSTM." *Sensors* 22, no. 14 (2022): 5449.
- [35] Hashi, Abdinasir Ismael, Mr Osman Abdullahi Jama, and Mr Abdirizak Mohamed Hashi. "A Quantum-Resilient Decentralized Swarm Intelligence Framework for Secure Real-Time Synchronization in Industrial Metaverse Environments." *Journal of Technology and Systems* 8, no. 2 (2026): 61-82.

- [36] Pandey, P. (2025). Artificial intelligence for early detection of dental caries from radiographic images: A machine learning. *Journal of Dentistry and Clinical Sciences*, 1(1), 31–39. <https://agrpjournals.com/journals/journal/index.php/jdacs/article/view/12>
- [37] Geetanjali, & Singh, A. R. (2025). Precision and smart farming: An approach to efficient resource management in agriculture. *Journal of Artificial Intelligence in Agriculture and Applied Research*, 1(1), 25–33. <https://agrpjournals.com/journals/journal/index.php/jaiaar/article/view/6>