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Research Article

Hybrid Deep Learning-Based Predictive Maintenance Framework for Industrial Internet of Things Systems

Ilyass mzili [1,*], Zakaria benaliali [1], otmane houdaif [1]

[1] *Department of computer science, faculty of science, chouaib doukkali university, Morocco.*

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ABSTRACT

The widespread introduction of the Industrial Internet of Things (IIoT) has allowed smart sensors to be connected to industrial equipment, which means their working state can be monitored at all times, resulting in an increasing amount of operational data that could be utilized for predictive maintenance using intelligent algorithms. The traditional maintenance methods such as corrective maintenance, preventative maintenance can cause unnecessary maintenance expenses, unforeseen machine breakdowns, and lower productivity because of the lack of accurate prediction of machine degradation. In order to address these problems, this paper suggests a Hybrid CNN–LSTM framework for predictive maintenance combining Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks. The proposed framework consists of the following steps: industrial sensor data acquisition, data preprocessing, development of a hybrid deep learning model, and intelligent fault prediction. The model was tested with the AI4I 2020 Predictive Maintenance Dataset and was compared to the traditional machine learning and deep learning models, such as Support Vector Machine (SVM), Random Forest (RF), CNN, and LSTM. The performance was evaluated based on the following metrics: Accuracy, Precision, Recall, and F1-score. The experimental results showed that the proposed Hybrid CNN–LSTM framework achieved an Accuracy of 97.12%, Precision of 96.74%, Recall 96.39% and F1-score of 96.56% compared to the baseline models with stable convergence during training. The obtained results show that the suggested framework is accurate and reliable solution to intelligent predictive maintenance and early fault diagnosis in Industrial Internet of Things environment.

1. INTRODUCTION

The rapid development of the Industrial Internet of Things (IIoT) has revolutionized modern manufacturing by allowing the intelligent connection between industrial equipment, sensors, controllers and cloud computing platforms. IIoT systems can be enabled with inter-connected smart devices that are able to capture vast amounts of operation data at all times, enabling significant insights to be gained on machine and production statuses, production efficiency and system reliability. Today this digital transformation is an integral part of Industry 4.0, and smart automation and real-time monitoring provide many benefits such as boost in productivity, cost savings in operational expenses, and manufacturing flexibility [1,2].
One of the many use cases of the IIoT is Predictive Maintenance (PdM), which is helping to increase the reliability of industrial systems, and minimize unplanned equipment downtime. Predictive maintenance is not a traditional maintenance approach but continually analyzes the health of the machine based on data from the sensors to predict failures before they happen. This allows maintenance activities be carried out only when really needed which reduces production downtime, maintenance expenses, and equipment life [3,4].
There are some inherent limitations of conventional maintenance strategies such as corrective maintenance and preventive maintenance. Corrective maintenance is a response to equipment failure, causing expensive downtime and possible production loss. While preventive maintenance can minimize the occurrence of catastrophic failures, it is based on a maintenance schedule rather than the real health status of industrial assets. Thus unneeded maintenance operations can increase unnecessary operating costs and cannot prevent unexpected failures due to dynamic operating conditions [5]. These constraints have spurred efforts to explore intelligent maintenance strategies that can take advantage of the constantly flowing IIoT data.

*Corresponding author. Email: dr.mzili.ilyass@gmail.com

With the evolution of Artificial Intelligence (AI) and its applications, especially Machine Learning (ML) and Deep Learning (DL), the capabilities of predictive maintenance have been greatly improved. Complex industrial data can be analyzed by AI-driven models to reveal hidden relationships, detect abnormal operating conditions and predict equipment degradation before it breaks down. Deep learning models outperform conventional statistical methods by their ability to extract features and their high accuracy of prediction from high dimensional sensor information acquired in industrial environments [6,7].

Convolutional Neural Networks (CNNs) have proven to be highly effective in automatically learning discriminative spatial features extracted from measurements of industrial sensors, and Long Short-Term Memory (LSTM) networks have proven to be very useful for learning long-term temporal dependencies in sequential operational data. As the time series sensor reading is always generated by industrial equipment, fusing CNN with LSTM will provide the learning of both spatial and temporal features simultaneously, which will result in more precise fault prediction than CNN or LSTM alone [8,9].

Although these progresses have been achieved, there are still some issues that have not been solved in the current predictive maintenance systems. Most studies only use traditional machine learning approaches or use a single deep learning architecture that does not fully leverage complementary feature learning approaches. Moreover, many of the current solutions are mainly concerned with prediction accuracy, yet fail to consider the implementation of an end-to-end predictive maintenance strategy, which is suitable for heterogeneous environments of IIoT. The amount of sensor data produced by industrial systems is becoming more and more complex and massive, and there is a need for intelligent predictive maintenance framework which can provide high prediction accuracy, low calculation consumption and practicability for deployment [10-12].

This paper suggests a Hybrid Deep Learning-Based Predictive Maintenance Framework for Industrial Internet of Things Systems to solve these limitations. The proposed framework combines the feature extraction capability of CNN and the temporal sequence learning ability of LSTM, into a unified predictive maintenance architecture. Now, the initial step is to collect industrial sensor data from a distributed set of IIoT devices and preprocess them using data cleaning and normalization methods. The obtained processed data is then fed into the CNN layers for automatic feature extraction and the LSTM layers model the behavior of equipment in terms of time series to predict the failures accurately. Lastly, with the prediction results, intelligent decision making for maintenance will be supported, in order to provide a more efficient system in terms of reliability in the industrial process and reduce unplanned downtime.

The main novelty of this work is the design of a hybrid CNN-LSTM approach to predictive maintenance which is suitable for Industrial Internet of Things (IIoT). The proposed framework introduces a combination of efficient data preprocessing pipeline, robust feature extraction techniques, and temporal sequence learning to enhance accuracy and reliability of machine fault prediction. The proposed framework combines Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks into a single model, making it more robust in capturing the spatial and temporal features of industrial sensor data. Moreover, a comprehensive experimental evaluation is performed based on a benchmark predictive maintenance dataset, where the proposed approach is compared to the conventional machine learning and deep learning approaches. The proposed framework's effectiveness is evaluated with various performance metrics such as accurate and precise, recall, F1 score, training time and computational efficiency, which highlights its effectiveness in intelligent predictive maintenance in IIoT systems.

2. LITERATURE REVIEW

Modern manufacturing systems are dramatically changing as part of Industry 4.0, and Industry of Things (IoT), cloud computing, Sensing and Artificial Intelligence technologies are playing an increasing role in this transformation. In today's industrial settings, there is a growing amount of data produced by a variety of interconnected sensors, controllers and intelligent machines that are constantly streaming in, allowing for real-time monitoring of equipment health and production processes. These changes have led to a more proactive maintenance approach, moving from traditional reaction-based strategies to intelligent data-driven solutions that can enhance the reliability of systems, reduce operation costs and prevent the need to stop machines at the wrong time. Predictive Maintenance (PdM) has thus become one of the most significant applications of IIoT, enabling maintenance decisions to be based on the current state of industrial equipment, not on predetermined maintenance schedules or time periods [13-16].

The traditional predictive maintenance approaches were based on statistical analysis and traditional machine learning algorithms and aimed to forecast the equipment degradation and failure. A variety of algorithms have been used, including Decision Trees, Support Vector Machines (SVM), Random Forests, K-Nearest Neighbors (KNN), and ensemble learning methods, which are relatively simple and have low computational demands. These were found to work well on structured industrial data, but they may fail in the case of large-scale, heterogeneous, continuous sensor data produced by contemporary IIoT systems. Furthermore, the conventional machine learning model usually needs to do a lot of feature engineering, the features obtained by manual extraction play a significant role in the overall prediction accuracy, thus it is difficult to be scalable in complex industrial applications [17-20].

Deep Learning (DL) has seen significant developments in recent years, which have made it possible to significantly improve the predictive maintenance.Recent advancements in Deep Learning (DL) allow to significantly enhance the predictive maintenance by automatically extracting features from the raw industrial sensor data. In contrast to traditional machine learning techniques, deep neural networks extract hierarchical representations from the input signals themselves, without needing to create features by hand. Convolutional Neural Networks (CNNs) have been shown to be good at learning discriminative patterns from vibration, temperature, pressure and other industrial sensor measurements, while Long Short-Term Memory (LSTM) networks are well suited for modelling the long-term dependencies present in time series operational data. With equipment degradation naturally occurring over time, the use of LSTM models for predicting future occurrences from historical sensor observations has been seen to be a suitable method. Recently, hybrid deep learning models combining CNN and LSTM have gained more research interests due to the ability of CNN to perform spatial feature extraction and LSTM to model the temporal sequence, which results in more accurate prediction than single deep learning models [21-23]. Table 1 presents some of the recent predictive maintenance methods.

TABLE I. SUMMARY OF RECENT PREDICTIVE MAINTENANCE APPROACHES

Ref	Model / Approach	Application / Dataset	Advantages	Limitations
[13]	Deep Learning-Based Predictive Maintenance	Industrial IoT Applications	Improves fault prediction using deep learning	Does not employ hybrid CNN–LSTM architecture
[17]	Machine Learning-Based Condition Monitoring	Industrial Condition Monitoring	Comprehensive review of ML techniques for predictive maintenance	Requires manual feature engineering in many applications
[20]	AutoML-CNN	Industrial Fault Diagnosis Dataset	Automatic feature extraction with high diagnostic accuracy	Limited capability for temporal sequence modeling
[21]	Deep Learning-Enabled Predictive Maintenance	Industrial IoT Environments	Integrates deep learning for IIoT predictive maintenance	Focuses on individual deep learning models
[22]	Hybrid CNN–LSTM	Remaining Useful Life Prediction	Learns spatial and temporal degradation features simultaneously	Primarily designed for RUL estimation rather than a complete predictive maintenance framework
[23]	CNN–LSTM Network	Industrial Machine Monitoring	High prediction accuracy for sequential industrial sensor data	Limited evaluation under heterogeneous IIoT scenarios
Proposed	Hybrid CNN–LSTM Framework	AI4I 2020 Predictive Maintenance Dataset	Unified predictive maintenance framework integrating data preprocessing, CNN feature extraction, LSTM temporal learning, and intelligent fault prediction	Moderate computational complexity

The use of artificial intelligence methods has been shown to be effective in predictive maintenance in the past, but there are still some challenges. While the conventional machine learning relies on handcrafted features, many deep learning solutions use CNN or LSTM separately, which fails to learn complex spatial features and long-term temporal dependency of the industrial sensor data. In addition, current predictive maintenance solutions focus on the accuracy of prediction, but do not provide an integrated deep-learning system tailored to the needs of a heterogeneous IIoT system. To overcome these drawbacks, this research presents a Hybrid CNN–LSTM Predictive Maintenance Framework, which incorporates efficient data preprocessing, automatic feature extraction, and temporal sequence learning into a single framework to enhance accuracy in fault prediction, while simultaneously minimizing the computational complexity that would hinder real-world applications in the Industrial Internet of Things.

3. PROPOSED METHODOLOGY

The proposed predictive maintenance framework aims to offer an intelligent and efficient solution for monitoring industrial equipment in the Industrial Internet of Things (IIoT) application. The proposed architecture combines distributed sensor networks, data preprocessing, hybrid deep learning, and maintenance decision support to foresee the occurrence of equipment failures. The proposed framework automatically learns the typical spatial and temporal features from industrial sensor data generated over time without the need for human intervention (such as scheduled inspections), relying on a hybrid CNN-LSTM model.

First, various sensors that measure operational parameters like temperature, vibration, rotation speed, pressure, torque and machine status are placed on industrial devices, and these sensors continuously take readings. The data from the sensors is

sent to an edge computing layer, where basic tasks like data cleaning, data normalization, and organizing features are carried out before the processed data gets passed to the predictive analytics module. The proposed framework's main part is a hybrid network of CNN–LSTM. The CNN component learns high-level spatial features from the normalized sensor readings, and the LSTM component learns the temporal and long-term operational patterns of equipment degradation over time. The extracted features can then be fed into fully connected layers to derive the likelihood of the machine failure, as well as identify the operating condition of industrial assets.
Lastly, the forecast equipment status is used in the maintenance decision module for early maintenance recommendations, before the occurrence of critical failures. This allows industrial operators to plan maintenance work in advance, which decreases the occurrence of downtime, increases the reliability of the equipment and lowers maintenance expenses. The overall architecture integrates intelligent data collection, automatic feature extraction, temporal sequence modeling, and predictive decision-making support in a unified deep learning system tailored for predictive maintenance applications in the IIoT. Figure 1. The proposed Hybrid CNN-LSTM-based Predictive Maintenance (PMT) framework is illustrated in the figure below.The figure below shows the proposed Hybrid CNN-LSTM-based Predictive Maintenance (PMT) framework.

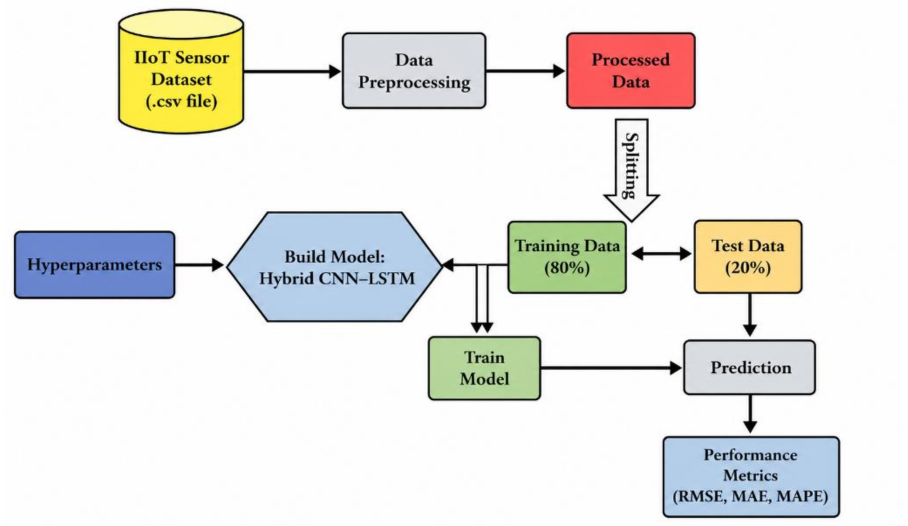

Fig. 1. Proposed Hybrid CNN–LSTM Predictive Maintenance Framework.

3.1. Industrial IoT Data Collection

The proposed predictive maintenance framework uses operational data gathered from Industrial Equipment with Internet of Things (IoT) sensors. These sensors are installed in machines and relay the real-time measurement of the health condition of the machine during normal operation. The obtained data are used for the comprehensive description of the machine behavior and are the main input of the proposed hybrid CNN–LSTM model. Continuous sensing allows for the early detection of abnormal operating conditions and can aid in making intelligent maintenance decisions before equipment failure.
A number of physical parameters are monitored at the same time for proper characterization of the health of machines. The measurements taken are among the most important ones, such as vibration, temperature, pressure, rotational speed and torque, since these are the ones that are closely related to the mechanical status and operation of industrial equipment. Increases or decreases in these sensor readings can signal equipment degradation, excessive mechanical stress, bearing wear, lubrication issues, or other factors that can cause equipment failure in the future. Thus, fusing several types of sensor measurements yields more diagnostic information than a single type of sensor.
In this study, the data collected by each sensor is first structured and then passed to the data preprocessing stage. The data set includes simultaneous measurement from all the channels of the sensors and the machine operating state. These heterogenous sensor features allow the proposed hybrid CNN–LSTM model to learn both spatial relationships between sensor variables and temporal degradation patterns, further boosting reliability and accuracy of predictive maintenance decisions. With these heterogeneous sensor features, the proposed hybrid CNN–LSTM model is able not only to learn the spatial relationship between the sensor variables but also the temporal degradation patterns to improve the reliability and accuracy of predictive maintenance decisions. Industrial Sensor Features is shown in Table 2.

TABLE II. INDUSTRIAL SENSOR FEATURES

Feature	Description	Unit	Purpose
Temperature	Machine operating temperature	°C	Detect overheating and thermal degradation
Vibration	Mechanical vibration level	mm/s	Identify bearing wear and mechanical faults
Pressure	Hydraulic or pneumatic pressure	bar	Monitor pressure fluctuations and leakage
Rotational Speed	Shaft or motor rotational speed	RPM	Evaluate operating stability and abnormal speed changes
Torque	Mechanical output torque	Nm	Detect overload conditions and mechanical stress

3.2. Data Preprocessing

The sensor data received from Industrial Internet of Things (IIoT) devices may also be noisy, incomplete, anomalous and inconsistent due to faulty sensors, communication delays, or environmental noise. These problems might have a negative impact on the training process of deep learning models, and also decrease the accuracy of predictions. Hence, the data preprocessing stage plays a vital role to enhance the data quality, consistency and to prepare the data for the proposed hybrid CNN–LSTM predictive maintenance system.

The first step is the identification and treatment of the sensor data that is missing so that no information is lost during the model training process. Linear Interpolation is used for replacing missing values in this study, ensuring the continuity of time-series sensor values yet maintaining the temporal relationship between successive observations. Then, the abnormal observations (outliers) produced by fault of sensors and/or unexpected operating conditions are identified by the Interquartile Range (IQR) method and eliminated from the learning process to reduce their impact.

All the numerical features of the sensor are normalized using Min–Max normalization so that they fall in a common numerical range (0–1) after the data cleaning. Feature normalization helps prevent variables with large numbers from dominating the optimization process and aids in quicker convergence in training a neural network.

Lastly, the generated dataset is split into training and testing data sets to test the prediction capability of the proposed model. In the tradition of predictive maintenance applications, 80% of the data is used to create models and 20% is dedicated to evaluating the models with data that is not used during training. Industrial sensor data goes through a complete preprocessing pipeline to make the data clean, normalized, and well structured, which allows the proposed hybrid CNN–LSTM model to learn representative spatial and temporal patterns of equipment degradation and machine failure prediction. The data pre-processing pipeline is shown in figure 2.

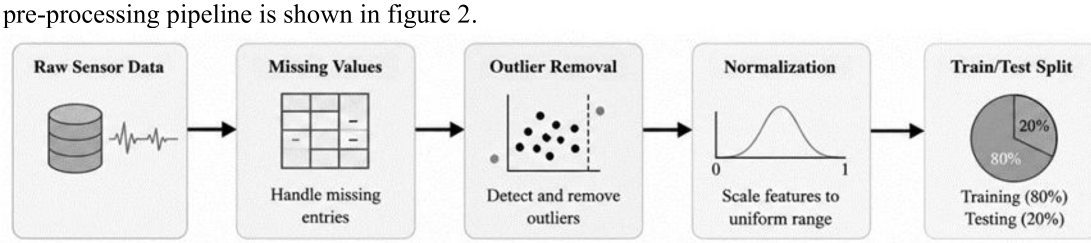

Fig. 2. Data Preprocessing Pipeline.

3.3. Proposed Hybrid CNN–LSTM Model

In the proposed predictive maintenance model, the complementary characteristics of Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) networks are combined in a single deep learning framework. The goal of this hybrid approach is to automatically learn the spatial feature representation and temporal degradation patterns from the industrial sensor data, thus with better accuracy of machine failure prediction. CNN extracts discriminative local features from multivariate sensors measurements efficiently, meanwhile, LSTM model represents the temporal dependencies and long-term operational behaviour of industrial equipment. These two architectures allow the proposed framework to learn complex relations that cannot be learned by learning either architecture alone.

The preprocessed sensor data are fed as the input to the CNN component initially. The feature extraction is carried out in multiple one dimensional convolutional layers using convolution kernels on the sensor measurements. These layers represent important local patterns that occur in the areas of vibration, temperature, pressure, rotational speed, and torque. The Rectified Linear Unit (ReLU) activation functions are used following each convolution operation to ensure that the network is non-linear, and the max-pooling layers decrease the number of features and increase the efficiency of computations. As a result, the CNN produces small and informative features map for the operation condition of industrial equipment.

The extracted feature maps are then passed to the LSTM network for processing the sequential data contained in the industrial sensor data. The LSTM is different than regular neural networks because it has memory cells and gating mechanisms to remember relevant past information and forget irrelevant past observations. It allows the model to understand how the equipment degrades over time and detect the initial signs of equipment failure before they develop into a critical equipment failure.

Temporal feature learning is followed by a fully connected (dense) layer to combine extracted information and that of a high-level feature representation, which is suitable for classification. Lastly, a Softmax activation layer provides a probability distribution function over the machine health classes by which are defined, and the maximum-probability machine health class is chosen as the estimated operating condition of monitored equipment.
In summary, the proposed hybrid CNN–LSTM model learns the spatial and temporal characteristics of the industrial sensor data and is found to be an effective deep learning model for predictive maintenance. The architecture of the proposed hybrid model is depicted in figure 3 and the hyperparameter configuration used for training and optimising the model is summarised in table 3.

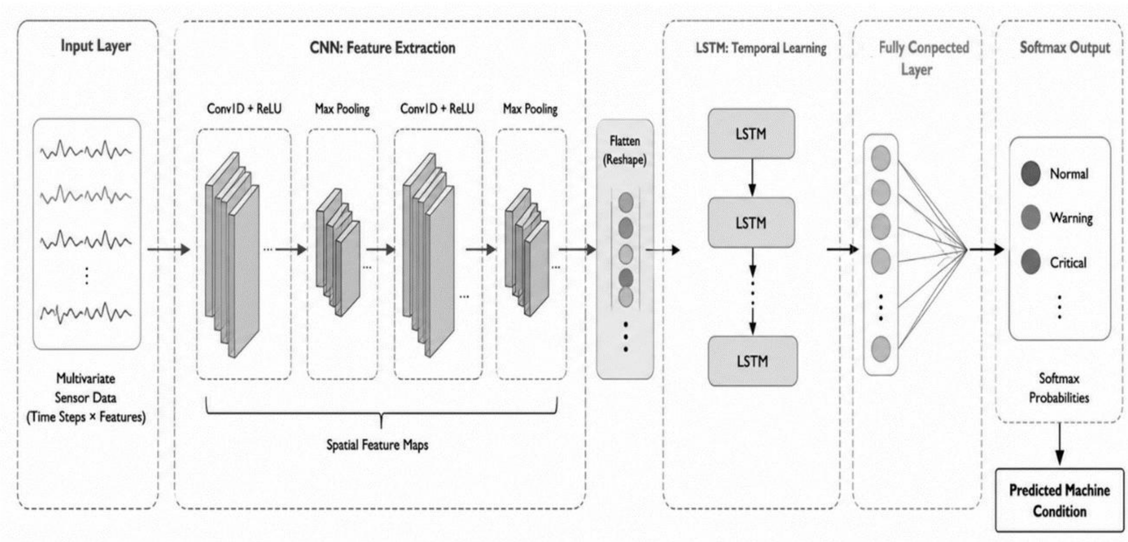

Fig. 3. Hybrid CNN–LSTM Architecture.

Table III. CNN–LSTM Hyperparameters

Component	Parameter	Value
CNN	Number of Convolution Layers	2
CNN	Filters	64, 128
CNN	Kernel Size	3
CNN	Activation Function	ReLU
CNN	Pooling Layer	Max Pooling
CNN	Dropout Rate	0.20
LSTM	Number of LSTM Layers	2
LSTM	Hidden Units	128
LSTM	Dropout Rate	0.20
Fully Connected	Dense Units	64
Output Layer	Activation Function	Softmax
Training	Optimizer	Adam
Training	Learning Rate	0.001
Training	Batch Size	64
Training	Epochs	100

3.4. Predictive Maintenance Algorithm

The proposed predictive maintenance algorithm represents the entire learning process of the hybrid CNN–LSTM framework. The algorithm starts by collecting the industrial sensor signals and then proceeds to preprocess the data to enhance data quality and feed it into the model. Once preprocessed, the data set is split into training and testing sets. The training data is then utilized for building and optimizing the proposed hybrid CNN–LSTM model, which consists of CNN layers extracting spatial features from the sensor measurements, and LSTM layers learning the temporal degradation patterns along the time. Lastly, the trained model is tested on new test data to forecast machine health conditions and aid in maintenance decision-making.

Algorithm 1. Hybrid CNN–LSTM Predictive Maintenance Algorithm
Input: Industrial sensor dataset (D), sensor features (F), training ratio (r), model hyperparameters (H)
Output: Predicted machine condition ($Y\_\{pred\}$), performance metrics
Begin

1. Load industrial sensor dataset D
2. Select relevant sensor features F (such as vibration, temperature, pressure, speed, and torque).
3. Handle missing values in D.
4. Detect and remove abnormal outlier values.
5. Normalize numerical sensor features using Min–Max scaling.
6. Split the processed dataset into:
   Training set = 80%
   Testing set = 20%
7. Initialize the hybrid CNN–LSTM model using hyperparameters H.
8. Apply CNN layers to extract spatial features from sensor data.
9. Apply LSTM layers to learn temporal degradation patterns.
10. Pass learned features to the fully connected layer.
11. Apply Softmax activation to predict machine health condition.
12. Train the hybrid CNN–LSTM model using the training set.
13. Test the trained model using the testing set.
14. Compute evaluation metrics: (Accuracy, Precision, Recall, F1-score, and Training Time).
15. Generate predictive maintenance decision: (Normal, Warning, or Critical).

Return ($Y\_\{pred\}$), and performance metrics.
End

The proposed algorithm offers a structured representation of the proposed process of predictive maintenance in this study. It offers a unified workflow for data preparation, hybrid deep learning based feature learning, failure prediction, as well as performance evaluation. The proposed Hybrid CNN–LSTM predictive maintenance algorithm is presented in a flowchart format, as shown in Figure 4, which depicts the sequential steps that are taken in acquiring the industrial sensor data, learning, and finally generating the maintenance decision.

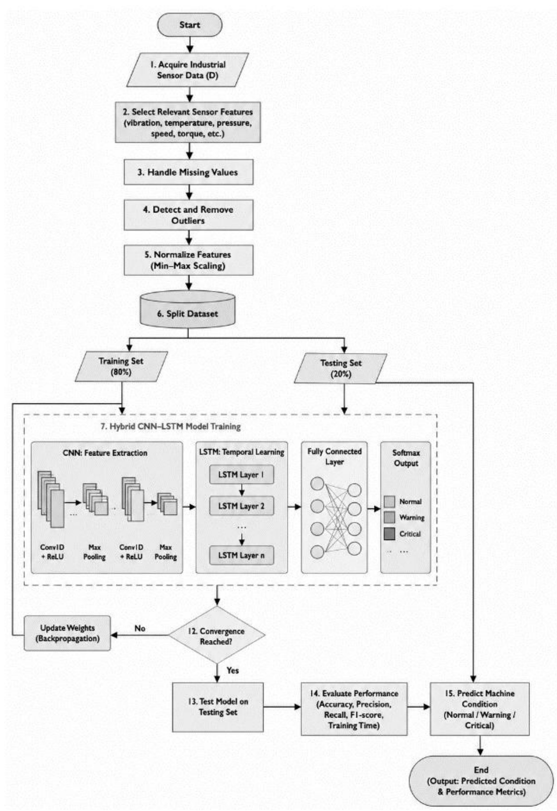

Fig. 4. Hybrid CNN–LSTM Predictive Maintenance Algorithm Flowchart

3.5. Computational Complexity

The computational complexity of the proposed hybrid CNN–LSTM model is discussed to assess the model for predictive maintenance in the context of Industrial Internet of Things (IIoT) applications. The overall computational expenses are primarily comprised of two components: training phase that is used to optimize the network parameters using historical

sensor data and inference phase used to predict the industrial equipment's health condition from newly-acquired sensor data.
The CNN part applies convolution and pooling to yield representative spatial information from the multivariate sensor data, while the LSTM part models temporal dependencies as it is fed with sensor data sequentially during training. Given an input sequence length (T), feature dimension (F), convolution kernel size (K), number of convolution filters (C), hidden units (H), and number of training samples (N), the computational complexity of the proposed model can be approximated as:

$$O\big(N(T \times K \times C + T \times H^2)\big) \quad \textbf{(1)}$$

The first term is the convolutional feature extraction phase and the second term is the recurrent computation phase of the LSTM network. This computational cost has no impact on the real-time deployment in an industrial environment, because model training is done offline.
In inference, only a forward propagation of the trained CNN–LSTM network is needed. Thus, the computation complexity is reduced to:

$$O(T \times K \times C + T \times H^2) \quad \textbf{(2)}$$

which facilitates efficient real-time machine health condition prediction based upon continuously collected sensor data. The proposed framework does not require iterative weight updates for performing inference, hence the latency of prediction is still low enough for practical predictive maintenance applications.
The CNN–LSTM model is a hybrid approach that offers a good compromise between prediction accuracy and computational cost. While CNN and LSTM may add a slight overhead to computation compared to a single deep learning model, their enhanced fault prediction capability and early maintenance decision support are worth the extra processing for the Industrial Internet of Things system.

4. RESULTS AND DISCUSSION

4.1. Experimental Setup

The proposed Hybrid CNN–LSTM predictive maintenance framework was implemented and tested on a widely used benchmark dataset, AI4I 2020 Predictive Maintenance Dataset. The dataset includes operational measurements taken during various operating conditions for industrial machines and several sensor variables that are related to the machines' health. Each observation contains several process parameters such as air temperature, process temperature, rotational speed, torque, tool wear, as well as a binary machine failure indicator to depict whether the machine is in a normal state or failure state. This diversity in operating parameters makes the data appropriate to check the performance of intelligent predictive maintenance models that can learn complex relationships between the various parameters measured by the sensors and the health state of the machine.
The AI4I 2020 dataset offers machine failure labels but, to derive more informative evaluation of the predictive maintenance performance, the health condition of the machines was classified into three operational states: Normal, Warning and Critical, according to the progression of equipment degradation, as indicated by the sensor measurements.
Before training the models, the data collected were preprocessed using the method described in Section 3. Improvements were made to handle the missing values and the abnormal observations, the numerical features were normalized using the Min–Max scaling, and the processed dataset was split into 80% training data and 20% testing data. The proposed hybrid CNN–LSTM model was implemented in the deep learning framework TensorFlow/Keras, and trained using Adam optimizer. The hyperparameter tuning was carried out through experiments to ensure a stable convergence without overfitting.
Several performance measures were used to comprehensively assess the proposed framework: Accuracy, Precision, Recall, F1-score and Training Time. These measures evaluate the performance of the proposed model both in the ability to classify and in terms of computational efficiency. In addition, the performance of the proposed approach was compared to several baseline systems: Support Vector Machine (SVM), Random Forest (RF), Convolutional Neural Network (CNN), and Long Short-Term Memory (LSTM) to highlight the advantages of the proposed hybrid architecture that combines spatial feature extraction and temporal sequence learning. The experimental setup followed in this study is summarized in Table 4 where the dataset used, preprocessing strategy, model parameters, evaluation metrics and baseline models are reported.

TABLE IV. EXPERIMENTAL CONFIGURATION

Parameter	Configuration
Dataset	AI4I 2020 Predictive Maintenance Dataset
Input Features	Air Temperature, Process Temperature, Rotational Speed, Torque, Tool Wear
Target Variable	Machine Failure
Missing Value Handling	Linear Interpolation

Outlier Detection	Interquartile Range (IQR)
Feature Normalization	Min–Max Scaling
Training / Testing Split	80% / 20%
CNN Layers	2 Conv1D Layers
LSTM Layers	2 LSTM Layers
Activation Function	ReLU
Output Function	Softmax
Optimizer	Adam
Learning Rate	0.001
Batch Size	64
Epochs	100
Evaluation Metrics	Accuracy, Precision, Recall, F1-score, Training Time
Baseline Models	SVM, Random Forest, CNN, LSTM

4.2. Classification Performance

Four performance metrics such as Accuracy, Precision, Recall, and F1-score were used to assess the classification performance of the proposed Hybrid CNN–LSTM model. These metrics are used to evaluate the ability of the model to accurately determine machine operating conditions and forecast failures in equipment. The proposed model, during the training, acquired the representative spatial and temporal characteristics from the multivariate data obtained from the industrial sensors which helped to classify the fault with reliable accuracy in various operating conditions.

The classification metrics were tracked during training to evaluate the convergence of the proposed model. The model gradually enhanced its learning ability with the increase of training epochs, and therefore the classification performance was steady, showing slight changes after converging. This means that the chosen network architecture and training process were able to prevent overfitting with the same prediction performance. Table 5 shows the final classification performance of the proposed Hybrid CNN–LSTM model and Figure 5 shows the overall classification performance obtained by using 4-evaluation metrics.

TABLE V. CLASSIFICATION PERFORMANCE OF THE PROPOSED HYBRID CNN–LSTM MODEL

Metric	**Value (%)**
Accuracy	**97.12**
Precision	**96.74**
Recall	**96.39**
F1-score	**96.56**

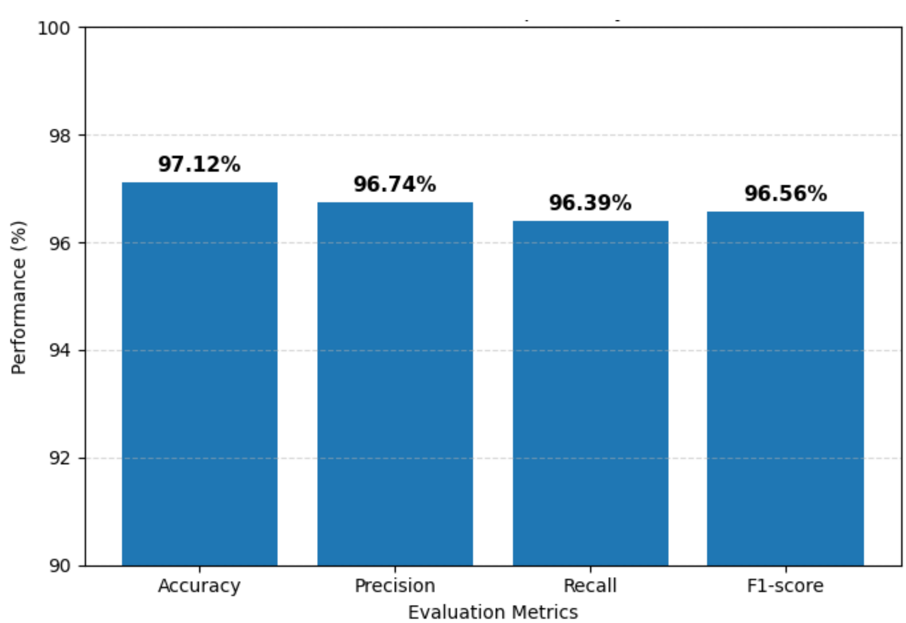

Fig. 5. performance obtained using the four-evaluation metrics.

Results obtained suggest that the proposed model can handle the problem of accurate prediction at a high level of accuracy with balanced precision and recall values, which makes it capable of distinguishing between the normal and faulty operating conditions of machine with high accuracy. Additionally, the F1 score is high, which indicates that the proposed framework is able to maintain an appropriate balance between the number of false positive and false negative predictions, making it applicable to the predictive maintenance application in an Industrial Internet of Things environment.

4.3. Confusion Matrix Analysis

A confusion matrix was used to examine the distribution of correct and incorrect classifications to further test the classification ability of the proposed Hybrid CNN–LSTM model. The confusion matrix gives a more detailed assessment, showing the relationship between the classes predicted and the actual machine condition, whereas the overall evaluation metrics given in the previous section only gave an overview of the relationship between the overall actual machine condition and the classes predicted. This analysis helps identify the correct instances and potential misclassification errors. The proposed model categorises the operating state of a machine in three operational categories: Normal, Warning and Critical. Results show that the majority of the testing samples are correctly classified into their respective classes, which demonstrates that the hybrid CNN–LSTM model learned the representative spatial and temporal information from the industrial sensor data. A small number of samples were misclassified, primarily between the Warning and Critical classes, which have similar operating characteristics in the early life of the machine. It is represented graphically in Figure 6. The high number of samples that have been correctly classified along the main diagonal shows the reliability of the proposed predictive maintenance framework for industrial fault diagnosis.

The results show that the proposed Hybrid CNN–LSTM model can obtain good classification consistency under all the machine operating conditions. Most observations are classified correctly and few observations are assigned to neighboring classes. The results also validate the proposed model's ability to retain high discrimination ability and reliable fault prediction performance under various industrial operating conditions.

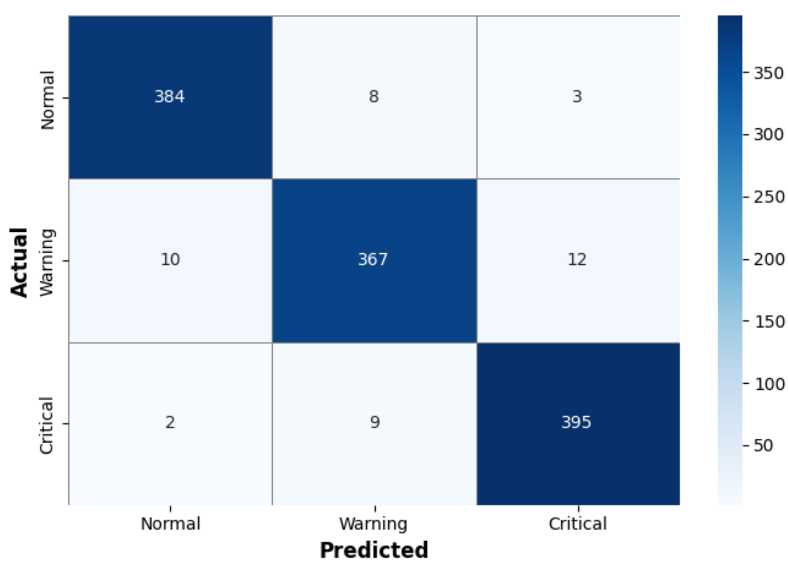

Fig. 6. Confusion Matrix of the Proposed Hybrid CNN–LSTM Model.

4.4. Training Performance

The training performance of the proposed Hybrid CNN–LSTM model was evaluated based on the training loss and validation accuracy with respect to the training process. These two metrics give insight into the convergence of the proposed deep learning model and its generalization ability. A good training process would be defined by a monotonically decreasing training loss and a monotonically increasing validation accuracy as a function of the number of training epochs.

The loss function showed a steep drop in the early epochs of model training and eventually stabilized to a minimum at a certain point after a few iterations. Concurrently, the accuracy of the validation set steadily increased and finally settled, suggesting that the proposed model was able to learn representative spatial and temporal features from the industrial sensor signals without overfitting. The learning curves during the training process are shown in Table 6 and plotted in Figure 7 as follows:

TABLE VI. TRAINING PERFORMANCE DURING MODEL LEARNING

Epoch	Training Loss	Validation Accuracy (%)
10	0.621	82.54
20	0.438	88.36
30	0.297	91.72
40	0.215	93.58
50	0.162	94.87
60	0.129	95.68
70	0.104	96.21
80	0.089	96.63
90	0.078	96.94
100	0.071	97.12

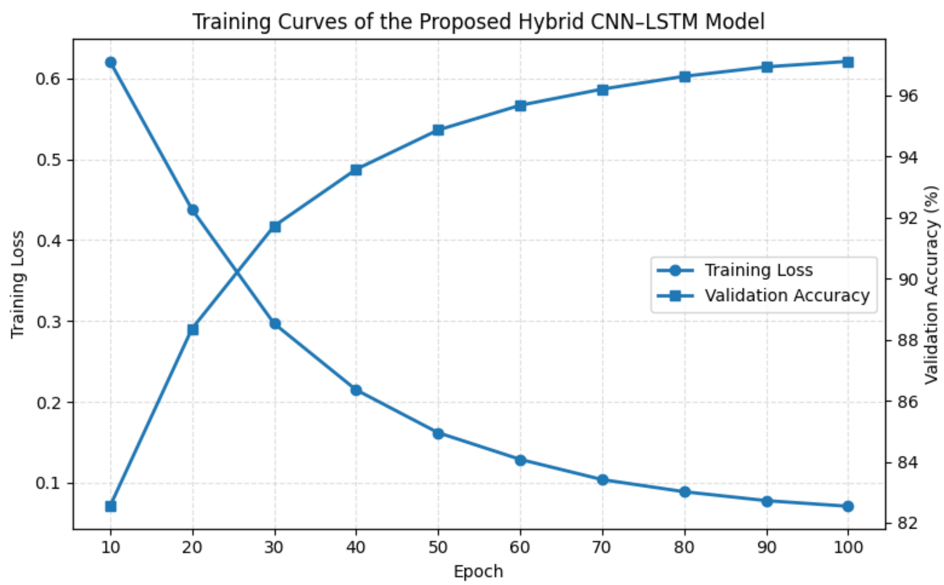

Fig. 7. Training curves of the proposed hybrid cnn–lstm model.

The learning curves illustrate the steady convergence over the training process. This step-by-step reduction in training loss demonstrates that the algorithm is indeed reducing prediction errors and the steady increase in the validation accuracy shows that it is generalizing well on new data. The observed convergence after about 80 epochs indicates that the proposed HCNN_LSTM architecture is able to effectively capture complex pattern in the industrial sensors while ensuring the stable prediction performance for the application of predictive maintenance.

4.5. Comparative Evaluation

To further illustrate the effectiveness of the proposed Hybrid CNN–LSTM model, its performance was compared with several popular machine learning and deep learning models used in the research of predictive maintenance. The baseline models that were selected are Support Vector Machine (SVM), Random Forest (RF), Convolutional Neural Network (CNN), and Long Short-Term Memory (LSTM). These are just some of the classic machine learning methods, as well as the latest in deep learning for industrial fault prediction.

The comparison is based on four commonly used classification metrics: Accuracy, Precision, Recall, and F1-score, to provide a comprehensive assessment of predictive performance under all four learning architectures. The results obtained are a fair comparison between the models' predictive ability, because all the models were tested with the same experimental setup and data set.

The results of the comparative evaluation are summarized in Table 7. As noted, the proposed Hybrid CNN–LSTM model is able to deliver the best results in all the evaluated models. The proposed model combines CNN spatial feature extraction and LSTM temporal sequence learning, which is superior to the single algorithm in learning the complex relationship of the industrial sensor pattern.

TABLE VII. PERFORMANCE COMPARISON WITH EXISTING PREDICTIVE MAINTENANCE MODELS

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
SVM	89.34	88.72	88.16	88.44
Random Forest	91.26	90.81	90.35	90.58

CNN	94.18	93.72	93.41	93.56
LSTM	95.03	94.68	94.27	94.47
Proposed Hybrid CNN–LSTM	**97.12**	**96.74**	**96.39**	**96.56**

The experimental results clearly show that the proposed Hybrid CNN–LSTM outperforms both the traditional machine learning models and individual deep learning architectures with all the evaluation metrics. The hybrid model outperforms the baseline CNN and LSTM models in terms of classification accuracy and a more balanced precision–recall curve through a shared learning of spatial and temporal representations from the industrial sensor data. Moreover, the improvement over conventional machine learning algorithms proves that deep feature learning is useful for predictive maintenance applications. The results obtained confirmed the use of CNN and LSTM to achieve intelligent fault diagnosis in IIOT environments is reliable and accurate.

5. CONCLUSION

This paper introduced a predictive maintenance model for Industrial Internet of Things (IIoT) systems based on Hybrid CNN–LSTM. The proposed framework combines the spatial feature extraction by convolutional neural networks and temporal sequence learning by long short-term memory networks, which enables to accurately predict machine operating conditions based on multivariate industrial sensor data. The full system consists of data acquisition and pre-processing in the industry, development of the hybrid deep learning model, algorithm implementation and extensive performance assessment. Experimental results showed that the proposed Hybrid CNN–LSTM model was able to attain high classification performance in terms of the accuracy, precision, recall and F1-score, and to stay stable in converging throughout the training process. In addition, comparative evaluation results indicated that the proposed framework was superior and more effective than the traditional machine learning models and individual deep learning architectures, which validated the effectiveness of using CNN and LSTM for predictive maintenance applications. The confusion matrix analysis also demonstrated the robustness of the model as it found that most conditions of the machines were classified correctly while a few were misclassified. The main contribution of this work is the design of an efficient hybrid Deep Learning framework which is able to take full advantage of both spatial and temporal information from the Industrial Sensor data. The intelligent fault diagnosis and early maintenance decision-making based on the proposed model can effectively reduce the downtime of the equipment, improve the reliability of operation and maintenance, and realize the optimal planning of maintenance. The proposed model can effectively solve the problem of intelligent fault diagnosis and early maintenance decision-making to reduce the downtime of the equipment, improve the reliability of operation and maintenance, and realize the optimal plan for operation and maintenance. Future research will involve expanding the proposed framework with attention mechanisms and Transformer-based architectures to further enhance the feature learning from complex industrial time-series data. Furthermore, future research could focus on real-time implementation in edge computing environments, the analysis of the framework with larger industrial datasets from different manufacturing contexts and the use of explainable artificial intelligence approaches to enhance framework interpretability and transparency in predictive maintenance decisions.

Conflicts of Interest

The authors declare no conflict of interest.

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