An Effective Machine Failure Diagnosis Model Using Artificial Intelligence Algorithms

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ABSTRACT

This study examines the feasibility of machine failure detection using deep learning approaches in a bid to improve predictive maintenance approaches. A deep-learning model has been created using the AI4I 2020 Predictive Maintenance dataset in order to effectively predict equipment failures. The model is built using two deep learning algorithms Long – Short Term Memory (LSTM), and Convolutional Neural Networks (CNNs). The preprocessing of the data that encompasses data cleaning, feature engineering, and normalization is applied to guarantee data quality. The metrics used to evaluate model performance are accuracy, ROC and AUC. Empirical findings show that the proposed LSTM-CNN model has a high predictive accuracy and significantly better results compared to the other traditional Support Vector Machine (SVM) models, especially when it comes to predicting complex patterns and dependence of operational data. In spite of the benefits, there are still issues of data quality, architecture, hyperparameter choice, and model interpretability. In general, the research validates the high potential of deep learning in reliable machine failure detection and specifies the main directions of future studies.

Keywords: Machine failure diagnosis; LSTM; CNN; SVM; Data preprocessing.

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1- Introduction

The swift merger of smart manufacturing, industrial big data, and Industry 4.0 has catalyzed the complete transformation of the traditional manufacturing systems to the smart and data-driven manufacturing environments [1]. A major part of this change is mechanical equipment, but the nonstop working process inevitably causes degradation of the machine and its breakdowns that may cause unexpected shutdowns, loss of considerable revenue and pose serious safety risks [2]. At the same time, the current industrial systems produce high amounts of working data, providing unprecedented chances to track the state of machines and enhance the maintenance plans. Utilizing this data most effectively has thus become a major concern in the provision of reliable, safe, and cost-effective industrial processes [1].

Predictive maintenance has become one of the most advanced maintenance techniques, which tries to predict the failure of equipment in advance with constant observation of the working states with the help of sensors [3]. The vibration, temperature, pressure, and other process variables are monitored to determine when they are going to degrade. Conventional machine learning methods, such as support vector machines, statistical time-series models, and regression-based methods, have also been extensively implemented in this regard, and they have shown encouraging outcomes. However, such techniques are frequently based on handcrafted properties and can have difficulties solving complex nonlinear properties of the data in industry [4, 5].

Deep learning has received more and more interest in predictive maintenance in recent years because it has a high potential for automatic feature extraction and nonlinear modelling. Autoencoders, recurrent neural networks, and convolutional neural network deep learning structures have been found superior in fault diagnosis and failure forecasting tasks [6]. In spite of these developments, the literature is often concerned with either single-model architectures or deeply complicated frameworks of deep learning that need significant computational capabilities. Also, most methods do not have a formal data analysis flow and strict validation steps, which restricts their generalizability and practical use in a real industrial setup [2], [3], [7].

To overcome these shortcomings, this work suggests a hybrid predictive maintenance model, which uses Convolutional Neural Networks (CNN) [8] and Long Short-Term Memory (LSTM) [9]. The suggested solution is created through a systematic methodology that involves the stages of extensive data pre-processing, exploratory data analysis, model training, cross-validation, and evaluation of the results. The AI4I 2020 Predictive Maintenance data is used to carry out the experiments, and the model performance is evaluated by accuracy and ROC-based measures. This study will offer a dependable and viable predictive system to predict failure of machines in a contemporary manufacturing facility by balancing predictive accuracy and strong and efficient execution.

The rest of this paper is structured in the following way: Section 2 explains the proposed methodology. In Section 3, the data from the experiment are discussed and presented. Lastly, there is the conclusion of the paper in Section 4.

2- The Proposed Methodology

This section presents a systematic research process of building a machine fault predictive maintenance model, which will start its development process with the identification of the problem and the collection of data and proceed to model development, validation, and performance optimization with the objective of having an accurate prediction of machine failures in the future. The key activities of the proposed LSTM-CNN based accurate machine failure prediction model are listed in the section below.

- **i.** ***Collection of datasets***: Obtain the dataset of the experiments, i.e. AI4I 2020 Predictive Maintenance dataset offering the necessary operational and failure-related variables.
- **ii.** ***Data preprocessing/cleaning***: Clean the gathered data, fill in the missing data, identify and remove outliers and eliminate noise to guarantee the quality of data.
- **iii.** ***Exploratory data analysis (EDA)***: Conduct exploratory analysis to understand the distribution of data, patterns and relationships among variables [10].
- **iv.** ***Model selection and development***: Train the prediction model with a deep learning LSTM-CNN architecture that is appropriate for non-linear failure prediction.
- **v.** ***Model training***: Train the LSTM-CNN model on the preprocessed data to obtain underlying trends that are related to machine failures.
- **vi.** ***Parameter tuning and validation***: Find the best model parameters and use cross-validation methods to better generalize the model and avoid overfitting.
- **vii.** ***Model assessment***: Test the model based on suitable metrics, such as accuracy, Receiver Operating Characteristic (ROC) curves, and Area Under ROC Curve (AUC).
- **viii.** ***Optimization and refinement***: In case needed, optimize and further refine model parameters based on the results of validation to give better predictive performance on unseen data.
- **ix.** To get a deeper insight, Figure 1 shows the proposed the LSTM-CNN based machine failure prediction model and Algorithm 1 shows the sequence of the steps of the actions followed to attain the proposed model.

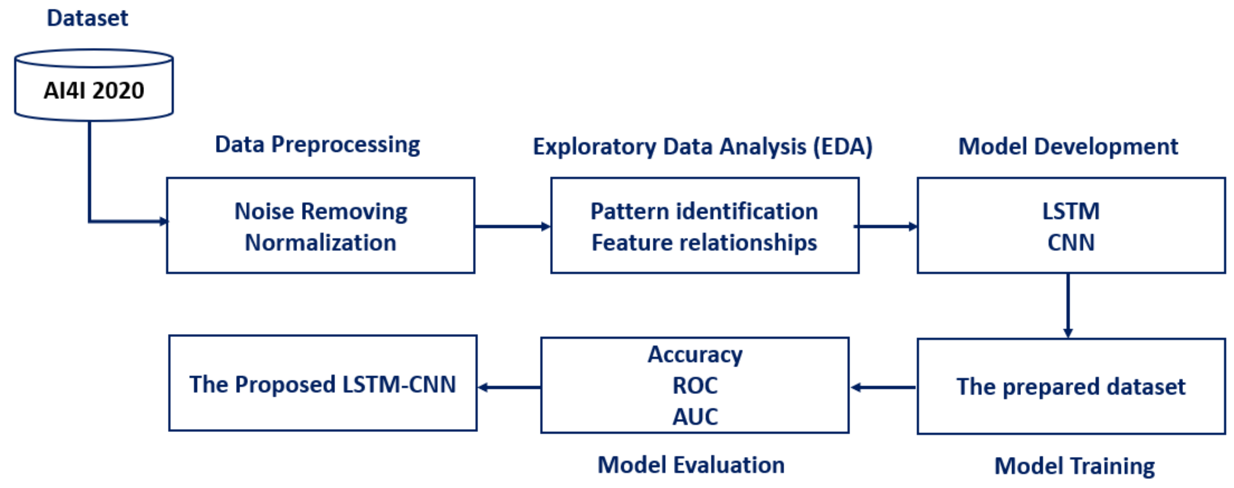


Figure 1. The methodology of the proposed LSTM-CNN Machine Predictive Maintenance model

Algorithm 1. LSTM-CNN Machine Failure Prediction (Pseudocode)

Input: AI4I 2020 Predictive Maintenance dataset D
Output: Trained LSTM-CNN model M and evaluation results R
i. *Collection of datasets*
D ← Load AI4I 2020 dataset (operational variables + failure-related variables)
ii. *Data preprocessing/cleaning*
D ← Clean(D)
- Fill Missing Values(D)
- Detect and Remove Outliers(D)
- Remove Noise(D)
iii. *Exploratory data analysis (EDA)*
Perform EDA on D to examine:
- Distributions
- Patterns
- Relationships among variables
iv. *Model selection and development*
M ← Build Model (type = "LSTM-CNN", purpose = "non-linear failure prediction")
v. *Model training*
Train M using D
vi. *Parameter tuning and validation*
Tune Parameters (M)
Validate M using Cross Validation to improve generalization and avoid overfitting
vii. ***Model assessment***
R ← Evaluate(M) using:
- Accuracy
- ROC Curve
- AUC
viii. *Optimization and refinement*
Optimize And Refine(M) based on validation results
Endif
Return M, R

2.1. Data Set

This experiment relies on the AI4I 2020 Predictive Maintenance Dataset [11] as a reference industrial dataset to test machine failure prediction using a LSTM-CNN algorithm. The dataset gives a realistic view of the industrial working conditions in a fusion of sensor and operational variables, the product ID, ambient (air) temperature, process temperature, rotational speed, torque, and tool wear that are all used to define the mechanical, thermal, and wear state of the machine.

The target variable is a nominal failure label of which one of the particular types of failure (tool wear, heat dissipation, power, overstrain or random failure) will be taken as a failure. The data is very lopsided, and it represents the real-life industrial conditions, whereby there are around 96 per cent instances of normal operation, and 4 per cent failure. To ensure this imbalance is corrected and the model can be more robust, the preprocessing stage undertaken ensured that the dataset was under sampled and normalized before training the model.

To evaluate the stability of the models and the level of model generalization, the processed dataset was split into several training-testing splits to evaluate them experimentally. It was taken into account three data compositions; 90-10, 80-20 and 70-30 training and testing data, respectively. This experimental design allows for testing the predictive ability of the LSTM-CNN algorithms model in conditions of different data availability in a systematic way, and it is also consistent with the common practice in the research of predictive maintenance.

2.2. Data Preprocessing

Data processing was conducted as an essential pre-processing phase prior to model training. The raw AI4I 2020 Predictive Maintenance Dataset contains sensor measurements that may be affected by noise due to measurement inaccuracies, operational disturbances, or transient machine conditions. Such noise can negatively influence the learning process and reduce prediction accuracy. Therefore, noise removing [12], [13] was applied to smooth the sensor signals and suppress abnormal fluctuations while preserving the intrinsic characteristics of the data. This was achieved by applying statistical filtering over local data windows, where each data point was replaced by a representative value computed from its neighboring samples. The smoothing operation is mathematically expressed as

$$\tilde{x}_i = \frac{1}{N}\sum_{j=i-k}^{i+k} x_j, \qquad (1)$$

where $\tilde{x}_i$ denotes the filtered signal, x_j represents the original data samples, and $N = 2k + 1$ is the window length. In addition, median-based filtering was employed to further reduce the influence of extreme values, defined as

$$\tilde{x}_i = \text{median}\{x_{i-k}, \dots, x_{i+k}\} \qquad (2)$$

These operations effectively reduced noise and outliers, resulting in smoother and more reliable feature distributions.

After noise removing, data normalization [14], [15] was applied to rescale all features into a unified numerical range. The dataset includes multiple variables with different units and magnitudes, and without normalization, features with larger scales could dominate the learning process. To overcome this issue, min–max normalization was applied to map each feature into a bounded range according to

$$x_i' = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \qquad (3)$$

Additionally, standardization using z-score normalization was performed to ensure zero mean and unit variance, given by

$$x_i' = \frac{x_i - \mu}{\sigma} \qquad (4)$$

where μ and σ represent the mean and standard deviation of each feature, respectively. This normalization process improved numerical stability, accelerated convergence, and ensured balanced feature contribution during model training.

2.3. Research Evaluation Metrics

The accuracy metrics, the Receiver Operating Characteristic (RoC) [16] and Area Under the Curve (AUC) [17], are used in the measurement of the performance of the model in this study. One of the measures of the performance of a classification model is accuracy. Accuracy [6] is a measure of the accuracy of the model in making the correct predictions of all the predictions. Accuracy is determined based on the number of correct predictions to the total number of predictions. When the model is right in its prediction, that is, when a data sample is rightfully classified based on the actual label or class, we say that the model has made the right prediction. The results of the accuracy are in the form of a percentage, where an accuracy of 100% implies that the model had all predictions right. Accuracy is calculated using the formula below [6]:

$$Accuracy = \frac{Number\ of\ correct\ predictions}{otal\ number\ of\ predictions} \times 100 \qquad (5)$$

In the meantime, ROC (Receiver Operating Characteristic) is a curve that explains the behavior of the classification model at various thresholds. The ROC graph gives the True Positive Rate (TPR) on the Y-axis and the False Positive rate (FPR) on the X-axis. ROC gives an insight into the discriminating capability of the model between the positive and negative classes. True Positive Rate (TPR), also referred to as sensitivity or recall, is the percentage of true positives of all true positive samples. The formula used to compute TPR is:

$$TPR = \frac{TP}{TP+FN} \qquad (6)$$

Where

TP = True Positive predictions;

FN = False Negative predictions

False Positive Rate (FPR) is the percentage of false negatives that are falsely detected from all false negative samples. FPR can be calculated by the formula:

$$FPR = \frac{FP}{FP+TN} \qquad (7)$$

Where:

FP = False Positive predictions;

TN = True Negative predictions.

The Area of the ROC curve is known as AUC (Area Under the Curve); AUC is taken as a performance measurement of the classification model. The range of AUC is between 0 and 1, whereby a score of 1 means an ideal classification, whereas a score of 0.5 means a random classification. The larger the AUC value, the better a good model the model works to distinguish between negative and positive classes.

3- Results and Discussions

This paper presents a hybrid LSTM-CNN model, which can be applied to predict machine failures in a predictive maintenance setting. The data of the AI4I 2020 Predictive Maintenance was initially processed and ready to be developed into models, which included the initial division into training and testing subsets with different proportions. The feature scaling was done by means of normalization or standardization to guarantee compatibility of the heterogeneous input variables.

The proposed LSTM-CNN model was subsequently developed with the well-specified input, hidden, and output layers. The hidden layers and the number of neurons in each layer were chosen empirically by means of experimental testing and adjusted to the needs of the task at hand, which is failure prediction. The processed training data was used to model train with parameters being optimized through the backpropagation algorithm to minimize the predictive error.

After training, a confusion matrix was used to assess the performance of the models, where accuracy, Receiver Operating Characteristic (ROC) curves, and the Area Under the Curve (AUC) were calculated. The experimental findings support the existence of a positive correlation between the proportion of training data and the predictive performance. Figure 2 shows that the maximum testing accuracy of 96% was obtained in the case of a 90 per cent training split, whereas 94 per cent accuracy was seen in the case of a 70 per cent training split.

There were consistent patterns in terms of ROC and AUC. Figure 3 shows the ROC curves of all experimental settings, and Figure 4 shows the corresponding values of AUC. Testing AUC was high at 0.99 in 90:10 and 80:20 training testing splits with almost perfect classification performance, and a 70:30 split gave an AUC of 0.97.

In comparison to the previously used Support Vector Machines (SVM) that achieved a testing accuracy of 88, the proposed model based on LSTM-CNN proves to be better in all evaluation measures. The results indicate that the hybrid LSTM-CNN model has high accuracy (96) and AUC (0.99), making it an accurate and reliable algorithm to detect machine failures during the predictive maintenance process.

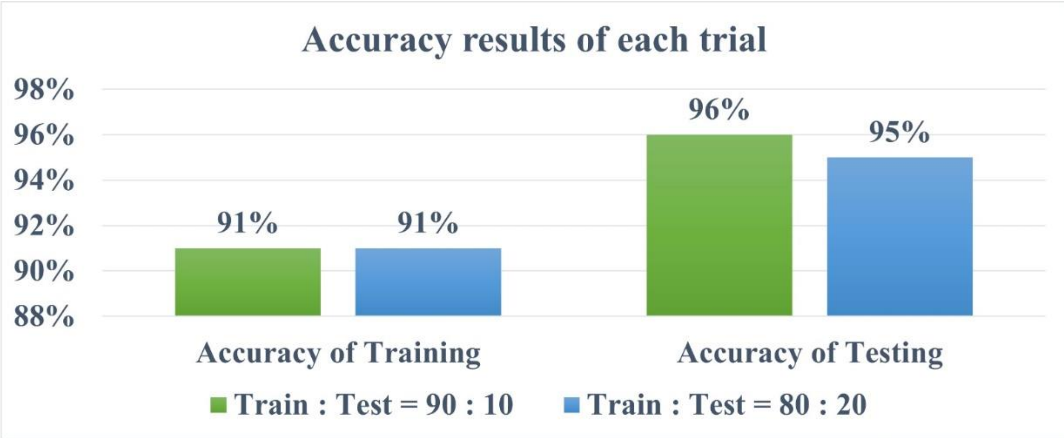
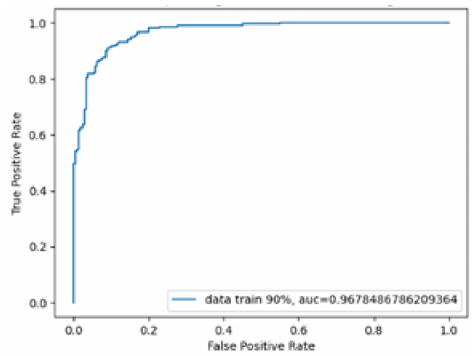
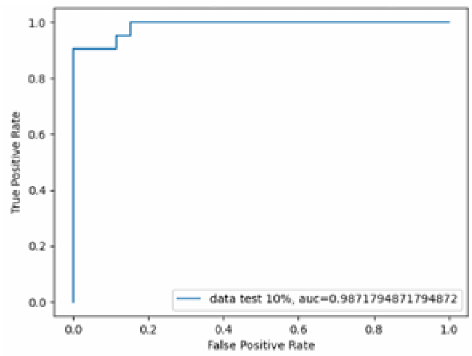


Figure 2. The accuracy results of each trial in the proposed model



(a)



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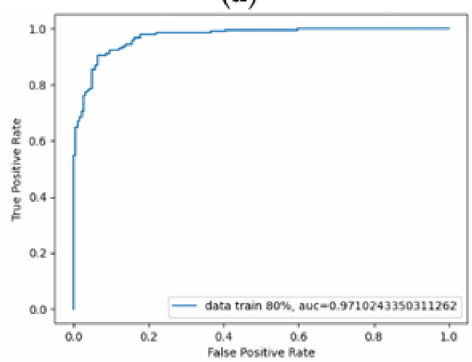

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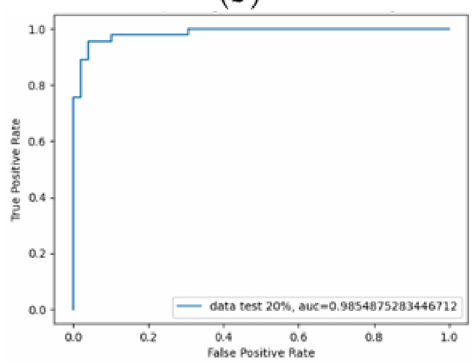

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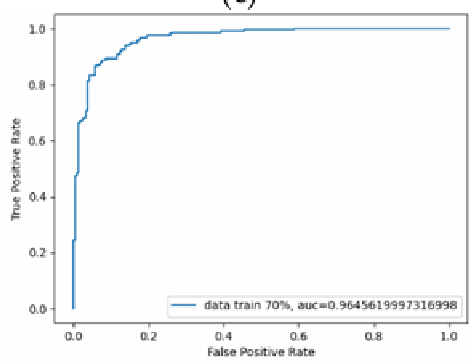

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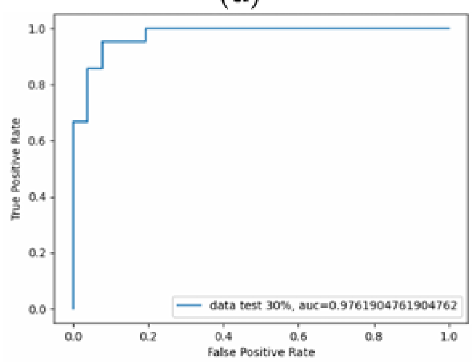

(f)

Figure 3: RoC evaluation metrics using several results: a) RoC 90 % of the training dataset; b) RoC 10 % of the training dataset; c) RoC 80 % of the training dataset; d) RoC 20 % of the training dataset; e) RoC 70 % of the training dataset; f) RoC 30 % of the training dataset.

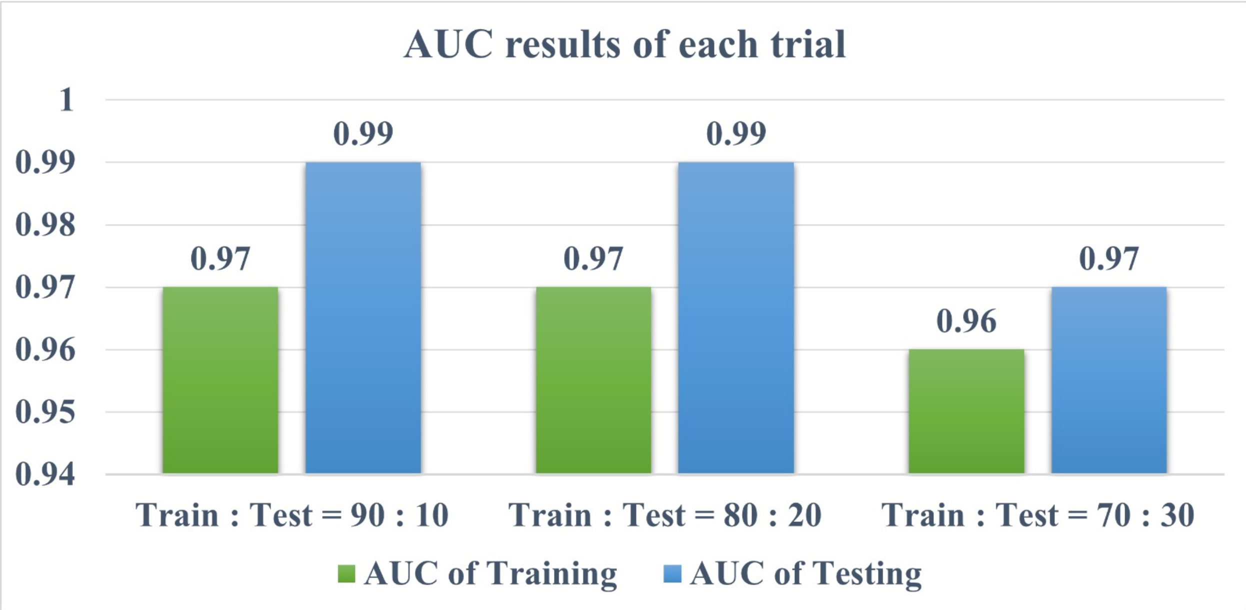

Figure 4. The AUC results of each trial in the proposed model

It is anticipated that the implementation of the LSTM-CNN model will increase the efficiency of predictive maintenance as it will allow predicting the breakdown of a machine in advance. This model can learn and derive non-linear, complicated and intricate patterns on sensor data, hence giving precise and dependable predictions of failure. However, there are a number of limitations that need to be taken into account. The proposed LSTM-CNN model has several limitations, such as the need to work with large volumes of high-quality labelled data to use all the computational capabilities to the full extent and can only be deployed by consuming a lot of computer resources. In addition, the interpretability of deep learning models is not an easy task since their decisions are more complex and less clear than the decision-making processes of conventional statistical or rule-based decision-making methods.

4- Conclusion and Future Works

4.1. Conclusion

This paper examined the predictive maintenance system in terms of predicting machine failures using deep learning methods, which are specifically the LSTM-CNN model. The entire framework incorporated the predictive performance evaluation, which used the AI4I 2020 Predictive Maintenance data to perform methods of preprocessing the data, training the model, and evaluating the model. The results of the experiment indicate that the proposed LSTM-CNN solution has a very high predictive accuracy and reliability in machine failure detection. In particular, its model achieved an accuracy of 96 and an Area Under the ROC Curve (AUC) of 0.99, which is a great ability to discriminate. These findings validate the capabilities of MLP models to dynamic and non-linear operational and sensor data relationships.

Moreover, it has been demonstrated, using comparative analysis, that the LSTM-CNN model is superior to the conventional machine learning approaches, including Support Vector Machines (SVM), in the modelling of complex trends and relationships within industrial data. This performance benefit accentuates the appropriateness of deep learning techniques in predictive maintenance cases where both failure modes are multifaceted, as well as data-motivated knowledge is imperative.

Although these outcomes are encouraging, the paper does not ignore the inherent difficulties of the deep learning methods, such as the complexity of models, computational costs, sensitivity to hyperparameter choices, and low interpretability because of the black-box nature of neural networks. These are some of the factors that should be put into serious consideration during the implementation of such models in a real-world industrial setting.

All in all, the results confirm that the proposed LSTM-CNN models are a sound and efficient choice in machine failure prediction and can be used to a great extent to improve the predictive maintenance strategies by decreasing the cases of unexpected downtime and enhancing the decision-making process.

4.2. Future Work

Future studies can build upon this study by investigating more complex and hybrid deep learning designs, including CNN and recurrent neural networks RNN, to further enrich the representation of both temporal and non-linear relationships in sensor data in industry. Moreover, enhancing model interpretability is also one of the directions because the black-box character of deep learning models restricts their clarity and applicability. The explainable artificial intelligence methodologies might be combined to give insights into the importance of features and the decision process. In addition to that, the model would be strengthened and generalized to more realistic real-world environments by using bigger and more diverse datasets gathered in various industries. More automated methods in hyperparameter optimization and model efficiency should also be explored in the future to make processing a computer-constrained, efficient deployment of models. Lastly, combining the proposed model with actual real-time predictive maintenance systems and assessing its performance in practical settings would provide a useful indication of its usefulness in minimizing downtime and maximizing maintenance plans.

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BIOGRAPHY

Yaqoob Fadhil Hussein is an Iraqi mechanical engineer who earned his Bachelor's degree in Mechanical Engineering from the College of Engineering at Wasit University between 2015 and 2019. Following his graduation, he gained valuable industrial experience by working at the Missan Oil Company in the Al-Halfaya Division, where he was involved in operational and engineering activities within the oil and gas sector.

In addition to his role at Missan Oil Company, Yaqoob worked for two years at the State Organization for Marketing of Oil (SOMO), further strengthening his expertise in energy-related operations and industrial systems. His professional background bridges mechanical engineering practice with modern data-driven technologies.

Yaqoob's research interests focus on the Industrial Internet of Things (IIoT), artificial intelligence, and AI-based machine failure diagnosis models. He is particularly interested in applying intelligent systems to enhance industrial reliability, predictive maintenance, and fault detection. He welcomes collaboration with researchers and professionals working in these domains.