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A Predictive Maintenance Approach in Manufacturing Systems via AI-based Early Failure Detection

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Abstract

To prevent idle time caused on by unpredictable tool wear or poor workpiece quality, manufacturers can identify potential problem scenarios in operations with the accurate identification of probable machine failure. It may be possible to prevent future failures and reduce downtime by predicting potential system failures relying on specific characteristics or system settings (input variables). The evaluation of various defect detection models employing machine learning (ML), deep learning (DL), and deep hybrid learning (DHL) is the focus of this paper. A synthetic predictive maintenance dataset generated by the School of Engineering at the University of Applied Sciences in Berlin, Germany, was used to test the performance of the suggested algorithms. Final results revealed that Deep Forest and Gradient Boosting algorithms have achieved relatively high accurate results (higher than 90%).

Keywords: Machine Learning; Waste Reduction; Big Data; Industry 4.0; Lean Manufacturing

1. Introduction

Lean manufacturing refers to the effective utilization of the existing resources by reducing non-value-added operations or wastes [1]. The Lean approach has been broadly embraced by several manufacturing industries over the last few decades. It originally began as the Toyota production system, which described the business's manufacturing philosophy [2]. Numerous studies have shown that the Lean approach has substantial advantages in the service sectors, including healthcare, food and beverage, education, government, retail banking, and others. Womack and Jones [3] made it abundantly evident that applying Lean thinking to the implementation of the fundamental principles of Toyota's production system in numerous industries has been successful. Lean manufacturing primarily seeks to reduce waste by making optimum utilization of resources. An operation that raises the price of a service or item without improving it for the client is referred to as a waste in lean manufacturing [4]. The waste caused by defects results in rework or scrap. Typically, such defective work is put back into production, which increases expenses that, in accordance with the Lean principle, might have been reduced [3,5]. In this paper, we propose an array of machine learning (ML), deep learning (DL), and deep hybrid learning (DHL) algorithms that have the potential to perform early failure detection that would lead to future machine failure. Furthermore, the connection between Preventive Maintenance (PM) and Lean manufacturing has been discussed, along with the role of industry 4.0 in PM.

1.1. Preventive maintenance

A successful manufacturing system mainly depends on high design quality and an adequate maintenance plan to prevent system failure. The expenses of maintenance are quite high and significant for the companies which is a significant percentage of the overall production cost [6]. Moreover, this cost has greatly increased over the last several years as a result of technical improvements. Accordingly, a scientific maintenance approach encourages lowering equipment failure rates and avoiding the need to stop costly production operations [7].

Significant focus has been placed on maintenance plans in industries for this reason. This focus depends on improving the system's availability and reliability while increasing the tools' service life. Preventive Maintenance (PM), Corrective Maintenance (CM), and predictive maintenance are the three categories into which maintenance strategies are often classified [8]. Without getting into further details on the three types of maintenance, it is important to note that CM, PM, and predictive maintenance are inconsistently categorized and described in the literature [9–12]. To boost uptime and decrease downtime, manufacturers should train, plan, and optimize utilizing all maintenance methods (CM, PM, predictive, and prescriptive maintenance), as there is no one maintenance strategy that offers the best overall solution. The relationship between the different categories of maintenance strategies is presented in Fig. 1.

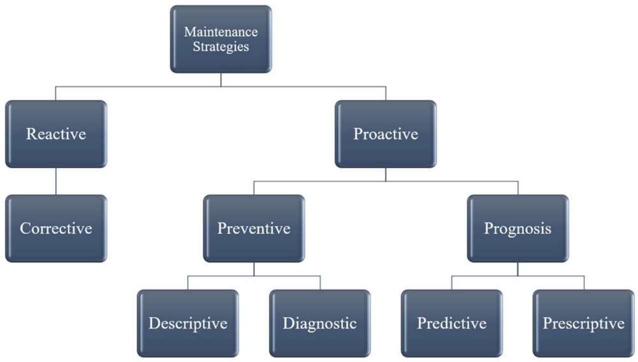

Fig. 1. An overview of the connections between the various maintenance strategy categories.

By implementing Lean manufacturing, a company attempts to improve the effectiveness of its processes by optimizing resource usage, eliminating extra expenses, and minimizing lead times by avoiding equipment failure [13]. The prescriptive maintenance approach might be used for this purpose. For example, if a business wants to be more efficient, it will aim to implement a prescriptive maintenance strategy to find the equipment that could breakdown and cut down on the amount of time lost while the equipment is being repaired [14]. In other words, a prescriptive maintenance system enables businesses to forecast when a problem may arise and makes machines more predictable and trustworthy by monitoring their performance. After that, they may arrange for spares and repairs before any more problems happen.

1.2 Industry 4.0 and prescriptive maintenance

Nowadays, Industry 4.0 not only enables a creative and effective work environment but also supports Real-time prescriptive maintenance providing Internet of Things (IoT) devices to monitor the system. Nine technologies including simulation, industrial internet, vertical and horizontal system integration, cybersecurity, cloud computing, big data and analytics, augmented reality, advanced robotics, and additive manufacturing are the foundation of industry 4.0. Such networked systems can facilitate communication and evaluate the data to forecast a company's operational success levels. As a result, many businesses have developed maintenance strategies as they transition to Industry 4.0 since it increases productivity and lowers the chance of equipment failure or imprecision. To do this, prescriptive maintenance can be utilized to detect the potential sources (variables) of the failures of each machine in the future [15].

1.3 Big Data in prescriptive maintenance

Big data, enhanced processing capabilities, and sensor technology advancements have made it possible for manufacturers to switch from "reactive" to "proactive" maintenance strategies [16]. Implementation of different artificial intelligence (AI) models such as ML and DL have facilitated the conduction of proactive maintenance in industry [17,18]. The key tactic is to predict how long it takes a tool to degrade and schedule maintenance in accordance with that prediction, as opposed to merely performing maintenance after the failure has already happened. Consequently, predictive maintenance is able to avoid employing conventional mathematical and physics-based tool life models in preference of ML algorithms to identify failure. The structure of an AI-based predictive maintenance system is depicted in Fig. 2. The dataset and the data analytics methods that were employed to obtain our results will be covered in the next section.

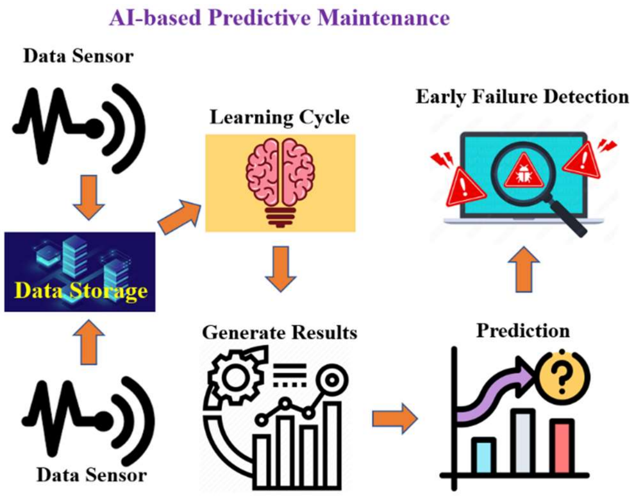

Fig. 2. The framework of an AI-based predictive maintenance.

2. Dataset and Methodology

2.1 Dataset

The "AI4I 2020 Predictive Maintenance Dataset" synthetic dataset is used since real predictive maintenance datasets are typically difficult to get in general and considerably more difficult to disclose [19]. The University of Applied Sciences' School of Engineering in Berlin, Germany, released the dataset. There are 14 features in columns and 10,000 record rows in the dataset obtained from [19]. The key features of the dataset are described in Table 1. Also, a statistical breakdown of the failure features is shown in Fig. 3.

Table 1. Description of the key features of dataset [20].

Feature	Description
UID	Unique identifier with a range of 1 to 10000.
Product ID	Including a letter L, M, or H for low (50% of all products), medium (30%), and high (20%) as product quality variants followed by a variant-specific serial number.
Type	A letter L, M, or H for low (50% of all products), medium (30%), and high (20%).
Air temperature	Generated by conducting a random walk process later normalized to a standard deviation of 2 K around 300 K.
Process temperature	Generated using a random walk process normalized to a standard deviation of 1 K, added to the air temperature plus 10 K.
Rotational speed	Calculated from the power of 2860 W, overlaid with a normally distributed noise and measured in rpm.
Torque	torque values are distributed around 40 Nm with a σ = 10 Nm and no negative values.
Output Feature	Description
Tool wear (min)	The quality variants H/M/L add 5/3/2 minutes of tool wear to the used tool in the process, and a machine failure' label that indicates whether the machine has failed in this particular data point for any of the following failure modes is true.
Tool wear failure (TWF)	The tool will be replaced or fail at a randomly selected tool wear time between 200 – 240 mins (120 times in our dataset). At this point, the tool is replaced 74 times and fails 46 times (randomly assigned).
Heat dissipation failure (HDF)	The heat dissipation causes a process failure if the difference between air- and process temperature is below 8.6 K, and the tool's rotational speed is below 1380 rpm. This is the case for 115 data points.
Power failure (PWF)	The product of torque and rotational speed (in rad/s) equals the power required for the process. If this power is below 3500 W or above 9000 W, the process fails, which is the case 95 times in our dataset.
Overstrain failure (OSF)	If the product of tool wear and torque exceeds 11,000 min Nm for the L product variant (12,000 for M, 13,000 for H), the process fails due to overstrain. This is true for 98 data points.
Random failures (RNF)	Each process has a chance of 0,1 % to fail regardless of its process parameters. This is the case for 19 data points, more frequent than could be expected for 10,000 data points in our dataset.
Predicted machine failure	If at least one of the above failure modes is true, the process fails, and the machine failure label is set to 1, which is the case for 339 data points.

Derived from Fig. 3, the dataset is severely unbalanced, with just 339 rows designated as machine failure. At the same time, a failure rate of 3.39% would typically make the system as comparable to actual industrial control systems as practicable; in addition, this percentage might be regarded as worrying in situations of mass production. However, the majority of maintenance-related datasets have this issue by default.

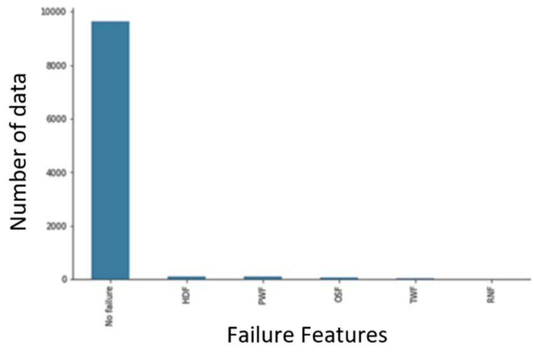

Fig. 3. Statistical description of the failure features.

The estimated relative predictive relevance of the features utilized in machine learning techniques is depicted in Fig. 4. It is interesting that the dataset for the current study was intentionally maintained unbalanced since this is a realistic circumstance that may occur in real-world situations.

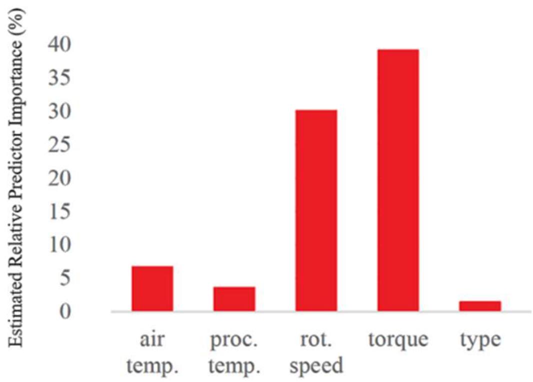

Fig. 4. The five most critical input features for ML models.

2.2 Models and algorithms

ML uses algorithms to analyze data to make informed decisions [21]. Contrarily, DL is a subdivision of ML that assembles algorithms in layers to produce an Artificial Neural Network (ANN) that is capable of self-learning and reasoning [22]. The main difference is that ML models need human intervention when their AI system produces an incorrect prediction. This intervention, known as feature engineering, raises the ultimate accuracy and effectiveness of the AI algorithm. With DL models, the AI algorithm's neural network can evaluate the accuracy of a prediction, needing additional processing power. When DL receives inadequate data, an over-fitting issue might arise. A DHL achieves excellent accuracy without over-fitting and without consuming an excessive amount of processing resources by employing a neural network of DL algorithm to extract features and traditional ML method for classification [23–25].

In this research, a variety of models were used to identify machine failure. A list of all the deployed models is presented in Table 2.

Table 2. List of utilized models.

ML models	DL models
Decision Tree (DT)	Multilayer Perceptron (MLP)
Light Gradient Boosted Machine (LightGBM)	Convolutional Neural Network (CNN)
DHL models	
ALSTM-FCN with AdaBoost	
CNN with XGBoost	

The integer encoding (assigning an integer to each category) might be deceptive for models that need several or all features to be numeric, categorical features when no ordinal connection exists. Additionally, enabling the model to consider a natural ordering across categories might increase the probability of weak performance or unexpected results, such as predictions that fall midway between classes. A one-hot encoding was used to binarize categorical inputs for a better representation in order to solve this issue [26]. All ML, DL, and DHL models' categorical features were encoded using the One-Hot Encoder. Also, the features were scaled and made robust to outliers using SKlearn Robust Scaler [27]. Worth noting that in this study for training and testing, there was a split of 90/10.

2.2.1 ML Models

Principal Component Analysis (PCA) was used in the training of all ML models. A dataset with several associated variables can have its dimensionality reduced using PCA while still keeping the majority of its variance. To estimate the dimension reduction, PCA was combined with a Maximum Likelihood Estimator (MLE) with a n component [28]. Also, Cross-Validation (CV) has been conducted on ML models. A k value of 5 was chosen, which is very common in ML [29]. ML models used in this paper are briefly explained as follows:

- Decision Tree (DT)

DT is one of the most extensively used Data Mining (DM) algorithms for regression and classification. Binary trees, which always output two categories (binary-split) at any level of the tree-like CART and QUEST, are one type of DT decision method. Other non-binary trees, like CHAID and C5.0, frequently grow more than two categories at any level in the tree. These four primary DT algorithms also differ slightly in how they handle missing data, how they choose variables, how many classes of variables they can manage, and how they use pruning [30].

- Light Gradient Boosted Machine (LightGBM)

Gradient boosting decision trees paired with Exclusive Feature Bundling (EFB), Gradient-based One-Side Sampling (GOSS), and LightGBM are yet another effective method any arbitrary differentiable loss function and the gradient descent optimization technique are used to fit the LightGBM iterations [31].

2.2.2 DL Models

Dense layers with the Softmax activation function were employed for all models, and hidden layers with Rectified Linear Activation (ReLU). LSTM and ALSTM were made up of 8 units. All DL and DHL models were trained for more than 14 epochs.

- Multilayer Perceptron (MLP)

MLP is a feedforward Artificial Neural network (ANN) that has been widely used in deep learning applications in all aspects of science [32]. Both supervised and unsupervised learning techniques can make use of MLP. It has an initial structure consisting of a network of nodes (neurons or perceptron) arranged in three layers: input, hidden, and output. By building layers upon layers of neurons with random weights, the MLP model learns how to turn input variables into output variables either linearly or nonlinearly [33]. The architecture of MLP model is demonstrated in Fig. 5.

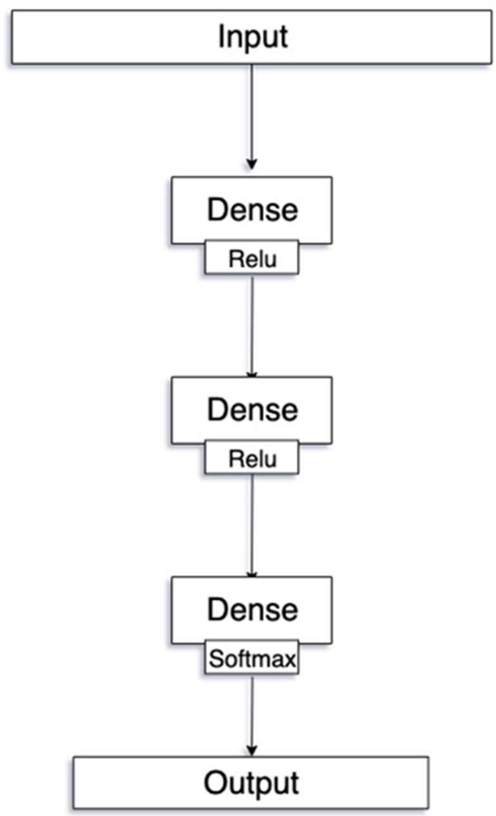

Fig. 5. The architecture of the MLP model.

- Convolutional Neural Network (CNN)

In classification and computer vision recognition applications, CNN has been widely employed [34]. The suggested Two layers CNN model is shown in Fig. 6 along with its architectures.

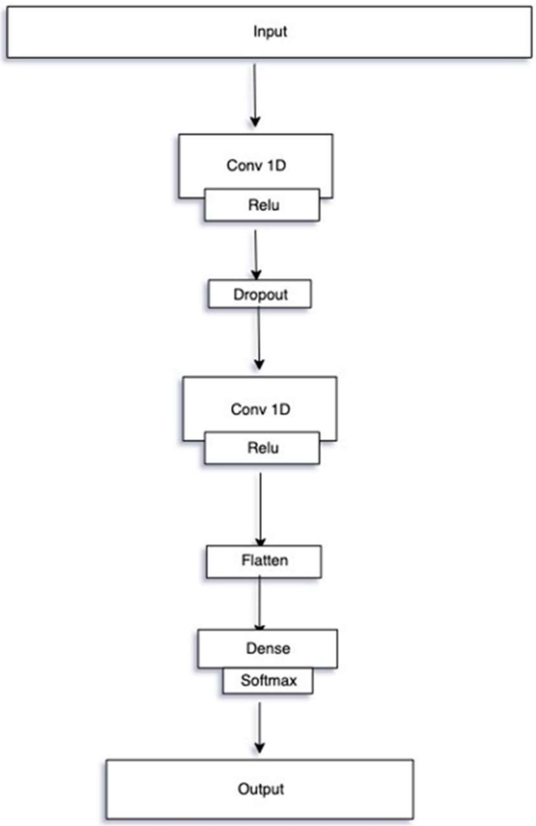

Fig. 6. The architecture of Two layers CNN model.

2.2.3 DHL Models

To extract features using its DL algorithm and to conduct detection using its ML algorithm, DHL models were deployed to the training and testing datasets. On our dataset, two different models were suggested and used.

An Attention-based Long Short-Term Memory Fully Convolutional Neural Network with Adaptive Boost is the second model (ALSTM-FCN with AdaBoost). Both are made up of two 1D convolutional hidden layers that each have 32 kernel collections (filters) of size 2 and operate on a 1D sequence. The values learnt throughout the training phase were stored in these kernels. This was done by using a transformation that keeps the output mean output near to 0 and the output standard deviation close to 1.

For feature extraction, these hidden convolutional layers were applied. The model was taught more complicated functions using the Rectified Linear Activation (ReLU), which improved the training process's outcomes. Following the ReLU, a GlobalAveragePooling1D layer keeps a lot of details about the "less important" outputs. To lessen the likelihood of overfitting, dropout layers were implemented. The probability value of the higher dropout layer, at which the layer's outputs are dropped out, was between 0.2 and 0.3. It was discovered that 100 LSTM cells were the ideal quantity. The GlorotUniform or Xavier Uniform was the standard weight initializer for both versions. In order to facilitate the algorithm's learning process, an attention mechanism was employed. The Adam Optimization Algorithm has been applied to both models, with a constant learning rate of 0.03. After the dropout layers, there was a concatenation layer, which arranged all of the previous outputs along a given dimension into a single vector-valued column from many columns.

The recently produced outputs were fed into the machine learning method (AdaBoost in our instance), which employs a Randomized Search CV to let the models choose the combinations at random (changing the parameters to boost the model generalizability). Our suggested ALSTM-FCN with AdaBoost is illustrated in Fig. 7. The third DHL model, CNN with XGBoost, has a similar design to the first two, but it lacks the ALSTM process and features dense (completely linked) neuron layers instead.

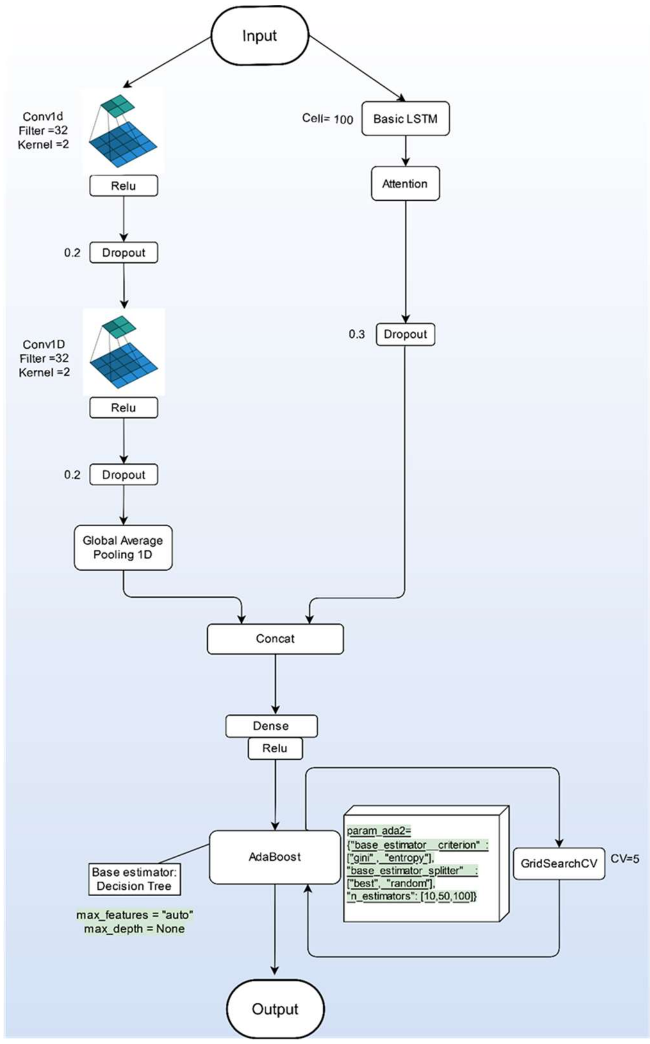

Fig. 7. ALSTM-FCN with AdaBoost model.

3. Results and Discussion

We obtained a confusion matrix for each DL and ML model. However, just one of them is used as an example in this article. The confusion matrix for the LightGBM model is shown in Fig. 8. Accuracy, precision, recall, and F1 score are performance measurement variables that are obtained utilizing confusion matrix. It is worth noting that particularly in a mass production setting, the misclassification cost of a false negative is substantially larger than the cost of a false positive. An overview of the ML and DL models' performance metrics is shown in Table 3.

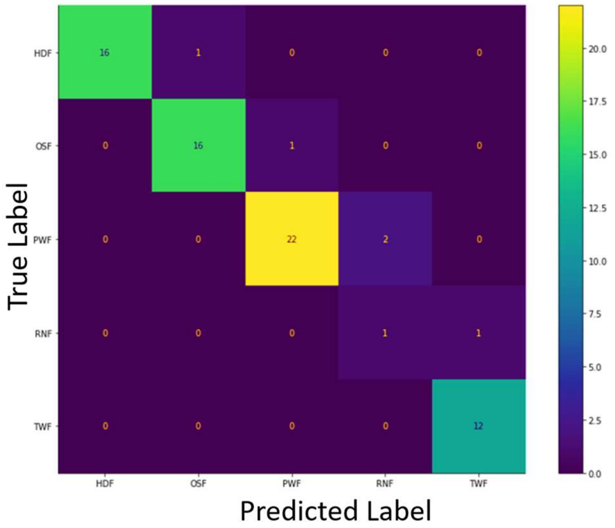

Fig. 8. Confusion matrix for the LightGBM model.

Table 3. Summary of performance measurements for ML and DL models.

Models	Accuracy	Precision	Recall	F1 score
LightGBM	0.93	0.94	0.93	0.93
DT	0.82	0.82	0.82	0.82
MLP	0.61	0.73	0.61	0.60
CNN	0.68	0.66	0.68	0.64

According to the results listed in Table 3, it can be concluded that LightGBM has the best performance (about 93% accuracy and recall). Moreover, Table 3 shows that DL models have performed worse than ML models, and this might be due to the DL learning algorithm's requirement to fine-tune a significant number of parameters [35]. As a result, as compared to ML models, DL models are at a disadvantage when it comes to failure detection. Performance measurement values for each of the suggested DL models ranged between 60% and 73%.

An overview of the DHL models' performance metrics can be seen in Table 4. The performance metric results revealed that DHL models perform between ML and DL models. Performance measurement values for each of the proposed DHL models were between 75% and 83%.

Table 4. Summary of performance measurements for DHL models.

DHL Model	Accuracy	Precision	Recall	F1 score
ALSTM-FCN with AdaBoost	0.75	0.76	0.75	0.76
CNN with XGBoost	0.78	0.80	0.78	0.78

4. Conclusion

To perform an early failure detection job on a synthetic predictive maintenance dataset, this research examined the reliability and effectiveness of several ML, DL, and DHL models. All models have demonstrated inherent advantages and disadvantages in terms of detecting faults. For instance, some models had extremely high failure detection accuracies (of up to 93%), whilst others displayed severely poor performance (about 60%). However, using synthetic datasets limits the ability to understand the underlying patterns and relationships in the data, which can impact the interpretability of ML/DL models trained on this data. Through a design of experiments method, future work may be done to confirm the dependability of such a predictive maintenance strategy. Future study might also concentrate on confirming the effectiveness of the same models by using them on various datasets.

Acknowledgements

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