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Machine Failure Detection using Deep Learning

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Abstract: This article focuses on the application of deep learning methods for failure prediction. Failure prediction plays a crucial role in various industries to prevent unexpected equipment failures, minimize downtime, and improve maintenance strategies. Deep learning techniques, known for their ability to capture complex patterns and dependencies in data, are explored in this study. The research employs Multi-Layer Perceptron as deep learning architectures. This model is trained on AI4I 2020 Predictive Maintenance data to develop accurate failure prediction models. Data preprocessing involves cleaning, feature engineering, and normalization to ensure the quality and suitability of the data for deep learning models. The dataset is split into training and testing sets for model development and evaluation. Performance evaluation metrics such as accuracy, ROC, and AUC are utilized to assess the models' effectiveness in predicting failures. The experimental results demonstrate the effectiveness of deep learning methods in failure prediction. The models showcase high accuracy and outperform SVM approaches, particularly in capturing intricate patterns and temporal dependencies within the data. The utilization of Multi-Layer Perceptron architecture further enhances the models' ability to capture long-term dependencies. However, challenges such as the availability of diverse and high-quality data, the selection of appropriate architecture and hyperparameters, and the interpretability of deep learning models remain sig-nificant considerations. Interpretability remains a challenge due to the inherent complexity and black-box nature of deep learning models. In conclusion, deep learning method offer significant potential for accurate failure prediction. Their ability to capture complex patterns and temporal dependencies makes them well-suited for analyzing operational and sensor data. Future research should focus on addressing challenges related to data quality, interpretability, and model opti-mization to further enhance the application of deep learning in failure prediction.

Keywords: Failure prediction; Deep learning; Multi-Layer Perceptron

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1. Introduction

In today's industry, efficient and timely maintenance of production equipment is essential to maintain smooth operations and avoid unforeseen breakdowns. Traditionally, maintenance is carried out routinely based on a predetermined schedule or based on visible signs of damage. This approach is often ineffective as overly frequent maintenance can lead to high maintenance costs, while late or improper maintenance can cause severe equipment damage and disrupt production [1].

In the last few decades, technological developments have opened up new opportunities in equipment maintenance through a predictive maintenance approach. Predictive maintenance [2] is an approach that continuously monitors equipment conditions using sensors and related technologies. By analyzing the data generated by the sensor, be it vibration, temperature, pressure, or other parameters, and leveraging machine learning techniques, we can identify the early signs and patterns that lead to equipment failure. This way, we can take the necessary precautions before significant damage occurs.

Research on predictive maintenance using machine learning has become popular in the industry in recent years. Li et al. [3] built failure prediction models to avoid service interruptions and increase rail network velocity. By using SVM to build a predictive model for railway maintenance, the experimental results obtained show that the model built can significantly increase business value. Kanawaday et al. [4] used the AutoRegressive Integrated Moving Average (ARIMA) statistical method to predict the probability of machine failure and production defects resulting from machine slitting, where data is collected through several sensors installed in the engine. The results indicate that the predictive maintenance model can reduce maintenance costs and improve the quality of the manufacturing process.

Amruthnath et al. [5] implemented unsupervised learning to perform early failure detection on submachines. The data used is vibration data originating from an exhaust fan. Of the several methods used, such as Principle Component Analysis (PCA) T2 statistics, Hierarchical clustering, K-Means clustering, C-Means, and Model-based clustering, T2 statistics can outperform other methods in detecting early failures. Gohel et al. [6] proposed using machine learning such as Support Vector Machine (SVM) and Logistic Regression to perform predictive maintenance on nuclear infrastructure.

Sharma et al. [7] conducted a comparative study using machine learning to predict machine failure based on several predictive maintenance datasets. The datasets used include Ai4i2020 Predictive Maintenance Dataset, MZVAV-2-1 Dataset, CWRU - Bearing Modified Dataset and Electrical power transmission fault dataset. The random forest method can outperform other machine learning methods such as SVM, Decision Tree, KNN, and Logistic Regression.

From this literature review, predictive maintenance using machine learning has become a promising research area in increasing the efficiency of equipment maintenance. This approach leverages sensor data and machine learning techniques to identify early signs of failure, so companies can take the necessary countermeasures before significant damage occurs. Previous research has succeeded in developing an accurate damage prediction model using SVM, Arima, Logistic Regression, regression algorithms, and the other machine learning models.

However, despite significant progress in this area, there is still room for further development. In this research, we will take advantage of the experience from previous studies and go a step further by developing a failure prediction model using deep learning techniques based on multi-layer perceptron architecture. Combining sensor data, maintenance logs, and historical breakdown data, we aim to create a more accurate and reliable model for implementing a predictive maintenance approach in the manufacturing industry.

The main objective of this research is to develop a failure prediction model using a multi-layer perceptron technique to implement a predictive maintenance approach. Using data collected in real time, this model will be trained to recognize critical patterns that may indicate equipment damage or failure. Thus, the company can perform maintenance based on the actual condition of the equipment, avoid unnecessary maintenance, and optimize the use of resources.

2. Materials and Experiment Methods

The research methodology consists of ten main steps. First, the problem to be studied in the predictive maintenance domain is identified, focusing on machine failure prediction. The research aims to develop an accurate predictive model to support predictive maintenance. The second step involves collecting dataset. Dataset used in this experiment is AI4I 2020 Predictive Maintenance data [8-10]. After that, third stage, the collected data is processed and cleaned, including missing values, outliers, and noise handling. Explorative data analysis was carried out as the next step, aiming to understand the characteristics, patterns, and relationships between variables.

After that, fourth stage, the prediction model was developed using the Multi-layer Perceptron deep learning method. The model is trained using processed data. The model parameters were adjusted, and cross-validation was performed to improve the performance and generalization of the model.

Finally, model evaluation is performed using appropriate evaluation metrics, such as accuracy, ROC, and area under the ROC curve, to measure model performance. The model is evaluated using the validation data to test the model's predictive ability on data that has never been seen before. If necessary, optimization and tuning of model parameters are performed to improve predictive performance. By following this methodology, it is expected to develop accurate and relevant predictive models to support predictive maintenance efforts in the predictive maintenance domain.

3. Results and Discussion

a. *Machine Failure Dataset*

This study used the AI4I 2020 Predictive Maintenance Dataset [8-10] in an experiment using a Multi-Layer Perceptron (MLP). This dataset has several variables that are used to determine the failure of a machine. These variables include product ID, Ambient Temperature, Process Temperature, Rotation velocity, torque, and wear and tear. This data shows an unequal proportion between failed and normal machine behaviour labels, where the percentages are 4% and 96%, respectively. In the early stages of the experiment, the dataset was undersampled and normalized before entering the modelling stage. In this experiment, the proportion of training and testing data for training was divided into the first three compositions 90%: 10%, the second 80%: 20% and the last 70%: 30%.

b. *Performance evaluation*

In measuring the model's performance, this study uses accuracy metrics, The Receiver operating characteristic (RoC) and Area Under the Curve (AUC). Accuracy is one of the metrics used to evaluate the performance of a classification model. Accuracy [11] measures how precise the model is in making the correct predictions of all the predictions. Accuracy is calculated by comparing the number of accurate predictions with the total number of predictions. The correct prediction is when the model correctly classifies a data sample according to the actual label or class. Accuracy results are expressed in percentage form, where a value of 100% indicates that the model made all predictions correctly. The formula for calculating accuracy [11] is as follows:

$$\text{Accuracy} = (\text{Number of correct predictions} / \text{Total number of predictions}) * 100, \tag{1}$$

Meanwhile, ROC (Receiver Operating Characteristic) [12] is a graph that describes the performance of the classification model at different thresholds. The ROC graph plots the True Positive Rate (TPR) on the Y-axis and the False Positive Rate (FPR) on the X-axis. ROC provides an overview of the model's ability to discriminate between positive and negative classes. The True Positive Rate (TPR), also known as sensitivity or recall, is the percentage of true positives detected from all true positive samples. TPR can be calculated by the formula:

$$TPR = TP / (TP + FN), \tag{2}$$

Where TP (True Positive) is the number of true positive predictions, and FN (False Negative) is the number of false negative predictions. Meanwhile, the 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:

$$FPR = FP / (FP + TN) \tag{3}$$

Where FP (False Positive) is the number of false positive predictions, and TN (True Negative) is the number of true negative predictions.

AUC (Area Under the Curve) [12] is the Area under the ROC curve. AUC is used as a performance evaluation metric for the classification model. AUC is in the range of 0 to 1, where a value of 1 indicates a perfect classification, and a value of 0.5 indicates a random classification. The higher the AUC value, the better the model's performance discriminating between positive and negative classes.

c. Results and Discussion

In this study, the Multi-layer Perceptron (MLP) method is used to predict machine failure in the context of predictive maintenance. AI4I 2020 Predictive Maintenance data are processed and prepared for use in model development. The data is divided into training and testing data with appropriate comparisons in the early stages. Next, the data is normalized or standardized to match the different features.

The MLP model is constructed using the appropriate architecture consisting of input, hidden, and output layers. The number of hidden layers and the number of neurons in each hidden layer are determined based on experiments and the specific requirements of the failure prediction problem. After the model is constructed, training is carried out using the processed training data. The training process involves iteratively adjusting the weights and model parameters using the backpropagation algorithm to optimize model performance. After the model is trained, an evaluation is carried out using confusion matrix. Then Accuracy, ROC and AUC are calculated to measure the model's performance in predicting machine failure.

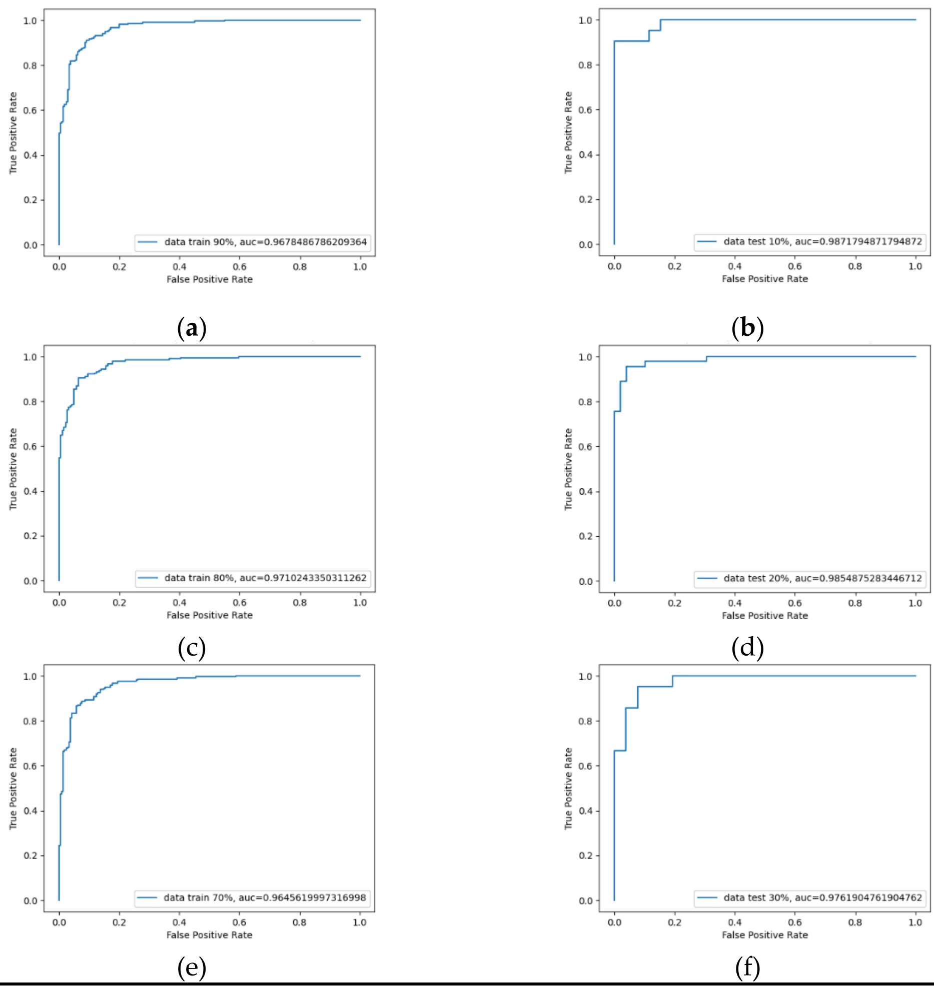
The results of the accuracy of all experiments can be seen in Table 1. It can be seen in Table 1 that the more training data used, the greater the accuracy of the resulting model. The accuracy value of data testing using 90% training data reaches 96%. Meanwhile, the lowest accuracy is obtained when the training data used is only 70%, whereas the accuracy of the data testing results gets 94%.

Furthermore, other metrics, namely RoC and AUC, also show the same thing. The RoC graph of all experiments can be seen in Figure 1. From the ROC graph for all experiments, the AUC value can be derived. The AUC value for all experiments can be seen in Table 2. In line with the high accuracy value, the AUC of data testing from experiments using 90% of the training data is 0.99 or almost perfect, close to 1. These results show that the model built is very precise. Meanwhile, the other AUC results for the proportion of training and testing data 80:20 and 70:30 also offer the same values. The AUC value of data testing for the proportion 80:20 is 0.99, while for the proportion 70:30, the AUC value reaches 0.97.

Compared with the previous research conducted by [idrus], namely on the use of SVM to detect machine failures with data testing accuracy reaching 88%, the MLP here can outperform the research results. It is shown from the three metrics used that the machine failure detection model built using MLP can provide excellent accuracy. This is demonstrated by the accuracy value reaching 96% and the AUC of 0.99. The results of using the MLP method show an accurate and reliable level of prediction in carrying out predictive maintenance. The performance model is evaluated based on the relevant evaluation metrics, and the results show high accuracy and good metric values.

Table 1. Accuracy results of each trial

Experiment	Accuracy of Training	Accuracy of Testing
Train : Test = 90 : 10	91%	96%
Train : Test = 80 : 20	91%	95%



Train : Test = 70 : 30	90%	94%

Figure 1. RoC results from all experiments: (a) RoC Data Training 90%; (b) RoC Data Testing 10%; (c) RoC Data Training 80%; (d) RoC Data Testing 20%; (e) RoC Data Training 70%; (f) RoC Data Testing 30%.

Table 2. AUC results of each trial

Experiment	AUC of Training	AUC of Testing
Train : Test = 90 : 10	0.97	0.99
Train : Test = 80 : 20	0.97	0.99
Train : Test = 70 : 30	0.96	0.97

By using the MLP method, it can be expected that more effective predictive maintenance can be carried out in anticipation of machine failure. This model can extract complex patterns in sensor data and provides reliable predictions about possible failures. However, it should be noted that using an MLP also has some drawbacks. This method requires extensive, high-quality training data and sufficient computational resources to train and implement the model efficiently. In addition, interpreting results from deep learning models can be more complex than straightforward statistical methods.

4. Conclusions

This study uses the deep learning Multi-layer Perceptron (MLP) method to predict machine failure in the context of predictive maintenance. The results of all experiments can be summarized as follows:

1. This method shows a level of prediction that is quite accurate and reliable in identifying machine failures by utilizing operational data and relevant sensors. The accuracy value obtained reaches 96%, and the Area Under Curve value reaches 0.99.
2. Compared with other methods, such as Support Vector Machine (SVM), MLP can extract complex patterns in the data and study non-linear relationships that may exist in the data to provide better performance.

In conclusion, using the MLP method can provide accurate and reliable predictions in carrying out predictive maintenance. However, the drawbacks and complexities of this method must be considered in its application.

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Conflicts of Interest: The authors declare no conflict of interest.

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