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Scalable Deep Learning Algorithms with Big Data for Predictive Maintenance in Industrial IoT

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Abstract: Predictive maintenance for industrial machinery makes use of cutting-edge methods and data analysis to predict when machinery may break down. Planning ahead can reduce downtime and maximize operating efficiency via scheduled maintenance. Achieving accurate, consistent, and well-integrated IoT sensor data is difficult, as poor data quality can result in inaccurate predictions and false alerts. In this study, a scalable approach utilizing large data derived from a variety of industrial sensors, a deep learning (DL) framework is suggested for use in predictive maintenance within Industrial IoT settings. Using data gathered from current, non-contact temperature, humidity, and three-axis accelerometers, the method trains a Deep Neural Network (DNN) model. Various fault states, including normal, overcurrent, stop rotation, misalignment, and excessive load, are included in the dataset. These circumstances were recorded in both online and offline settings. Normalization, one-hot encoding, and data division into training and testing sets (70/30) were part of the preparation steps. The DNN model is fine-tuned using graph cut methods to improve performance, leading to a low loss value of 0.0014, a high recall of 99.29%, a precision of 99.07%, and a classification accuracy of 99.45%. The use of fog computing also helps with IIoT system latency and interoperability problems when handling data promptly. Proof that the product works suggested a model for early, non-destructive fault detection, contributing to the goals of smart, efficient, and sustainable industrial operations.

Keywords: Predictive maintenance, industrial IoT, DNN, Sensor data, Fault, Machine learning (ML) and Deep learning (DL).

1. Introduction

In the era of Big Data, vast amounts of information are continuously generated in a variety of formats, including data collected by social media, smart sensors, and other networked devices. This explosion of data has enabled numerous advancements in areas like predictive modeling, behavioral analysis, and emotion detection. The industrial sector, especially has used this data revolution such that automation, operational efficiency, and problem detection may be improved [1]. In this regard, maintenance in IIoT settings has become one of the most explored areas, particularly because companies are determined to cut down on downtime, decrease the repair expenses, and ensure that they remain competitive in a very challenging global economy. It is on this basis that predictive maintenance has emerged as an important solution in IIoT-based smart manufacturing.

Predictive maintenance, opposed to reactive or planned maintenance, employs sensor data to predict equipment failure before it occurs [2]. This will achieve continuous running of the machines, boost productivity and eliminate disastrous breakdowns. Consider a case such as in the industries that include agriculture and power distribution, which work under tight schedules, and unexpected breakdowns may lead to enormous losses. Hence, predictive maintenance integration assists industries in being proactive in responding to possible faults based on the analysis of real-time streamed data. In this regard, predictive analytics, ML and DL transform. ML models can detect latent patterns and outliers in sensor data and give timely alerts about possible faults. Nevertheless, with the rise in data complexity and volume, the traditional ML models might not be sufficient to represent more intrinsic relationships in the data [3][4][5].

Here is where DL has a big jump with the multi-layer neural networks; with DL models, complicated characteristics may be automatically learnt from raw data like vibration signal or thermal image without manually engineering features [6]. Such abilities render DL particularly well adapted to time-series industrial data, which is high-dimensional. Further, scalable DL algorithms placed at the edge, together with fog and edge computing, enable local and low-latency processing. This makes it possible to make real-time decisions close to the data source and reduces reliance on cloud infrastructure, together with improving the responsiveness of the system. In summary, the fusion of Big Data, predictive analytics, and DL provides a powerful and scalable framework for predictive maintenance in IIoT [7][8]. This interconnected approach not only supports real-time fault detection and not only improves operating efficiency, but also helps bring about the larger goal of smart and environmentally friendly manufacturing systems.

1.1. Motivation and Contribution of Study

The rapid evolution of Industry 4.0 technologies has resulted in an unprecedented volume of data generated by smart sensors embedded within industrial machines. These data streams provide valuable insights into machine health but can provide substantial obstacles when considering real-time processing, heterogeneity, and predictive analysis. Traditional time-based or reactive maintenance strategies are increasingly inadequate, particularly in critical sectors such as power distribution and agriculture, where even minor downtime can lead to major operational losses. This study is motivated by the need for intelligent, scalable predictive maintenance solutions that leverage big data analytics, DL, and edge computing to enable proactive, non-destructive fault detection and ensure uninterrupted industrial operations. There are some key contributions are as follows.

- Utilized a real-world sensor dataset composed of time-series data and thermal images collected from electrical power substations and industrial machinery, including parameters such as temperature, vibration, and voltage.
- Applied preprocessing techniques including normalization, outlier removal, and thermal image enhancement to ensure high data quality and relevance for DL models.
- Designed a scalable DNN architecture integrated with thermal image analysis via computer vision techniques, enabling accurate, real-time, non-destructive fault detection in IIoT environments.
- Tested the DNN model on precision, recall, F1-score, and accuracy and demonstrated a high performance on predictive maintenance tasks when compared to the classical ML methods.

1.2. Justification and Novelty of the paper

The novelty and the relevance of the proposed research are justified by the fact that the research aims at providing the opportunity to combine various sensor readings with a sophisticated DL algorithm to ensure fault detection in IIoT real-time and with a high degree of precision. When contrasted with more traditional methods, which are usually realize on limited characteristics or superficial models, this contribution makes use of multi-modal sensor inputs and a DNN to learn intricate patterns linked to equipment faults. The method proposes a versatile and smart system that can adjust to different fault situations and represents a very important improvement compared to the traditional predictive maintenance approaches. What makes it innovative and of practical use in contemporary industrial settings is its capability to generalize its operation across varying operation modes with high-level reliability.

1.3. Organization of the Paper

The following is the structure of the paper: Section II surveys associated research on predictive maintenance and IIoT. Section III explains the suggested DL approach. Section IV provides experimental findings and a performance study. Section V offers experimental results and performance investigation.

2. Literature Review

An appropriate literature study on predictive maintenance and some recommendations for implementing predictive maintenance solutions make up the first part of this section. After that, they zero in on the relevant literature about edge computing gateways that are well-suited for the IOT. Behera et al. (2019) the quantity of data generated by the IIoT has grown at an exponential rate due to the expansion of the industrial sector. The data-driven PDM of cyber-physical systems' industrial equipment is becoming more popular as a result of this. PDM is a well-known method for evaluating the present health condition and the remaining user life (RUL), which may lead to improved CPS dependability and safety and lower maintenance costs. By using ensemble tree learning and enhanced feature engineering, they can gather more insightful data. One well-known health and prognosis management method (PHM) C-MAPSS dataset, is the subject of extensive investigations. Compared to RF, which achieved an accuracy of 91.78%, GBT achieved a much higher performance at 93.91%. But RF was just as quick as GBT in terms of computation time, so it was a close race [9].

Chehri and Jeon (2019) these days, when people talk about the impending fourth industrial revolution, they usually mean the disruption that is rapidly changing around the industrial sector. Words like cyber-physical systems, smart manufacturing, the IoT, and digital transformation often surface in discussions about this. A key component of the smart factory, as outlined in this article, predictive maintenance aims to minimize downtime and maximize the availability of production facilities. To provide a cutting-edge solution for industrial applications, this study aims to develop and examine a solid industrial IoT framework. As part of their efforts to improve process quality, they also do predictive maintenance on production systems, which includes manufacturing machinery [10]. Wang et al. (2019) concentrate on data-based approaches to PdM, provide a thorough survey on its usage, and hit upon giving graduate students, enterprises, and organizations the background knowledge of the current works published in the nearest future. In particular, they shortly present the PdM method, show their PdM program of automatic washing equipment and present challenges that they encounter throughout their PdM investigation. Secondly, they assign six ML and DL algorithms to different types of industrial applications and evaluate them using five different performance indicators.

Furthermore, detailed checks are performed on such PdM applications, which serve as a figure to assess the algorithm's work. It is capable of deducing several valuable findings: 2) academics have shown a growing interest in using DL algorithms to conduct PdM research in the last several years; and 1) The data used in the literature study mostly comes from publicly available sources, including those from intelligent maintenance systems and Case Western Reserve University. In conclusion, they conclude on the shared characteristics concerning the PdM applications that they surveyed and indicate some of the possible avenues [11]. Strauß et al. (2018) incorporate Industry 4.0 because it has the potential to drastically save costs by increasing the efficiency of all equipment and prolonging the life of manufacturing units. The brownfield, which has obsolete machinery without modern sensors or internet access, is where much of the action might take place. Using an Industrial-Internet-of-Things architecture, ML, and inexpensive sensors, this article demonstrates how to adapt manufacturing equipment for predictive maintenance. They will demonstrate an industrial use of an electric monorail system for big lifts at the BMW Group [12].

Paolanti et al. (2018) combined with predictive maintenance enhances the system's dependability and safeguards the industry's electric motors and other equipment from catastrophic economic losses brought on by unexpected motor breakdowns. An paper outlining a Random Forest-based machine learning predictive maintenance architecture. Although working on Data collecting and analysis utilizing the ML technique was part of the system's real-world industrial scenario testing. The results were contrasted with the simulation tool's output. Multiple sensors, machine PLCs, and communication protocols have uploaded data to the Azure cloud. Initially discovered to demonstrate an appropriate manner of the method on forecasting the various machine conditions with great precision [13]. Table I summarizes important studies on industrial IoT predictive maintenance using ML algorithms, summarizes the main contributions of each study, identifies their limitations, and highlights potential directions for future improvements in premium prediction accuracy.

Table 1: Summary of recent studies on machine learning for Predictive Maintenance in Industrial IoT

Author	Data	Techniques	Key Findings	Limitations/Recommendations
Behera et al. (2019)	PHM C-MAPSS dataset (turbofan aircraft engine data)	Data-driven prognostic method, Feature engineering, Ensemble tree learning, Gradient Boosted Trees (GBT), Random Forest (RF)	Although RF had much lower calculation time, it was competitive in terms of accuracy (93.91% vs. 91.78%). The model was successful for RUL estimate across a variety of operational situations.	Need for accurate degradation assessment, Balance between accuracy and compute time, Application to aviation safety and maintenance decision-making
Jeon et al. (2019)	Industrial IoT data from smart factory systems	Industrial IoT framework, Cyber-physical systems, Digital transformation approaches	Predictive maintenance is a crucial part of any smart manufacturing. Producing facilities with a high level of availability Successfully reduced downtime	Focus on industrial applications integration, Need for comprehensive IoT framework, Emphasis on process quality improvement
Wang et al. (2019)	Public datasets (CWRU, IMS), Limited specific application data, Automatic washing equipment case study	Machine Learning algorithms, Deep Learning (DL) methods, Six algorithm classification approach, Five performance metrics comparison	Most research uses public datasets, Increasing focus on DL algorithms for PdM, Limited combination with specific applications like rotating machinery	Need for more real-world application studies, move beyond experimental stage, Integration with specific industrial applications, Address industrial big data challenges
Strauß et al. (2018)	Information about the Electric Monorail System for Heavy Lifts (BMW Group installation)	Low-cost sensor retrofitting, Industrial IoT architecture, Machine Learning, Brownfield equipment enablement	Successful retrofit of old equipment without existing sensors, Cost reduction through improved equipment effectiveness, Extended remaining useful life of production machines	Focus on brownfield applications, Need for low-cost sensor solutions, Industrial implementation challenges, Connectivity requirements for old equipment
Paolanti et al. (2018)	Real industry data from electric motors, Sensor data, machine PLCs, Communication protocols data, Azure Cloud architecture	Random Forest approach, Machine Learning architecture, Data collection and analysis system, Cloud-based data analysis	High accuracy in predicting different machine states, Effective prevention of economic losses from motor failures, Improved system reliability, Successful cloud-based implementation	Preliminary results stage, Need for extensive real-world validation, Comparison with simulation tools required, Integration of various data sources and protocols

3. Methodology

The methodology involves a comprehensive pipeline beginning with gathering information from a variety of sensors, such as those that measure current, humidity, non-contact temperature, and three-axis accelerometers. In addition to normal, overcurrent, halt rotation, misalignment, and high load circumstances, these sensors also record the motor's performance in other problem scenarios, both in online and offline modes. Preprocessing steps include normalization, which scales feature values to ensure uniform influence on the model, label encoding and "one-hot encoding" transforms labels for categories into numerical representations that machines can understand, and dividing datasets so that 70% is utilized for training and 30% is used for testing. The next step is to use a DNN, which is composed of several fully connected layers. The activation function is ReLU, and the loss function is cross-entropy. Key metrics for performance evaluation include precision, which is the percentage of right predictions, recall, which is the retrieval of real positives, and the F1-score, which is a more comprehensive performance indicator that balances precision and recall, all made possible by a confusion matrix. Figure 1 illustrates a flowchart of Predictive Maintenance in Industrial IoT.

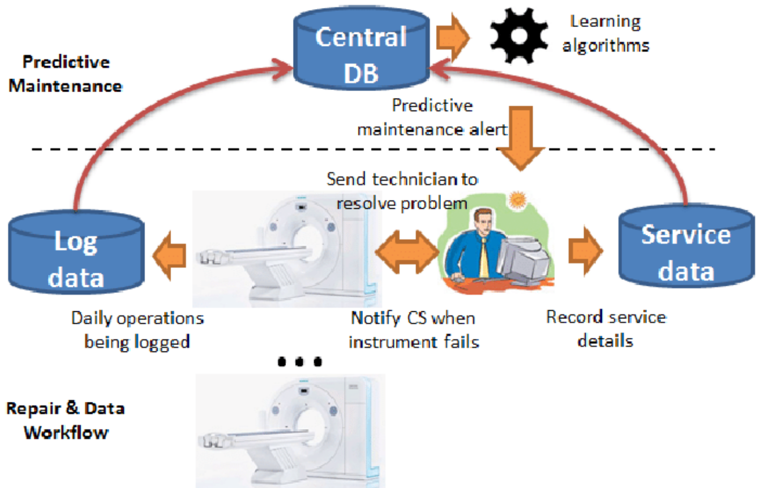

Figure 1: Flowchart of Predictive Maintenance in Industrial IoT

3.1. Dataset Description

Current, non-contact temperature, humidity, and three-axis accelerometer sensors were used to gather sensory data. This is the case when the vibration sensor produces X, Y, and Z data sets. It can see these outcomes in the same column in the dataset, and a fault condition would occur every one second throughout the sampling interval. Both online and offline data collection methods are used by the sensor. Offline data collection yields a rich set of information categorized into normal, overcurrent, halt rotation, misalignment, and high load faults. The necessary dataset was obtained by carefully applying these classes to the motor with the necessary defect.

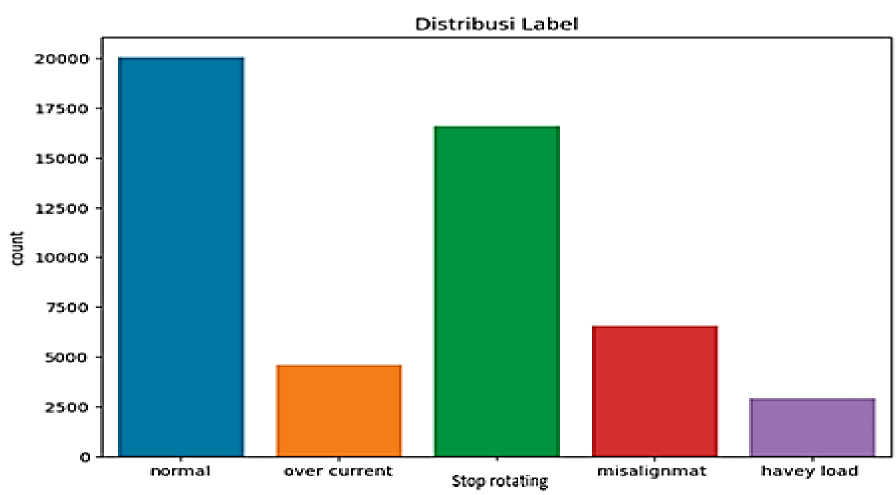

Figure 2: The dataset distribution for five types of classes

Figure 2 presents the distribution of the collected dataset across five fault classes: typical, excessive current, not spinning, not aligned, and high load. The data is imbalanced, with the normal condition having the highest number of samples, exceeding 20,000, followed by stop rotating with a significant count of around 17,000. The misalignment and overcurrent classes have moderate representation, while heavy load has the least number of samples. To avoid the model becoming biased towards majority classes and to guarantee effective defect identification in all scenarios, strong training procedures are crucial, as this imbalance shows.

3.2. Data Preprocessing

The data preprocessing has been condensed into a single comprehensive paragraph that covers all three essential steps: normalization, one-hot encoding, and dataset splitting into training/testing sets with validation considerations.

3.2.1. Data Normalization

ML often begins with the preprocess step of dataset normalization. The feature in the dataset is transferred to common scales, usually between send 1 and send -1. This checks that the learning process of the model is not unduly affected by any one feature. The training process is made faster and the model's performance is enhanced day by day. When features with vast ranges are not allowed to dominate features with smaller ranges, a fair feature contralto is also attained.

$$\text{X scaled} = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{1}$$

Equation (1) represents the min-max normalization technique used in data preprocessing, where each feature value x is scaled to a range between 0 and 1. By doing away with characteristics that have higher numerical ranges, this makes guarantee that all input features have an equal impact during model training. It makes learning more stable and improves model convergence.

3.2.3. One-Hot Encoding

Labels in multiclass tasks are often encoded using one-hot encoding. In one-hot encoding, each class is represented as a vector, where a '1' denotes the correct class and a '0' denotes an empty vector. That way, it can easily compare the likelihood that the model has predicted given the real labels.

3.3. Data Splitting

Dataset partitioning: There is a training set and a testing set inside the dataset. Typically, there is more data in the training set compared to the testing set. With the help of the training set, the model is trained. Testing is used to evaluate the exact performance of both the trained model and the unknown data.

3.4. Proposed Deep Neural Network model

The DL algorithm that is well-known among scholars is the DNN. The simple architecture of DNN is presented in Figure 3. DNN architecture is a network including fully interconnected input, hidden, and output layers. Although all of the neurons in a given layer are directly connected, none of the neurons in higher levels are even remotely related to one another. A network's activation function is applied to its output after each layer to make learning more effective. As such, DNN could also be interpreted as a big perceptron that is made out of several perceptions. Considering the forward propagation calculation of the ith layer, it has the following Equation (2):

$$x_{i+1} = \sigma\left(\sum w_i x_i + b\right) \tag{2}$$

where b is the bias vector, w is the weight coefficient matrix, and x is the input value.

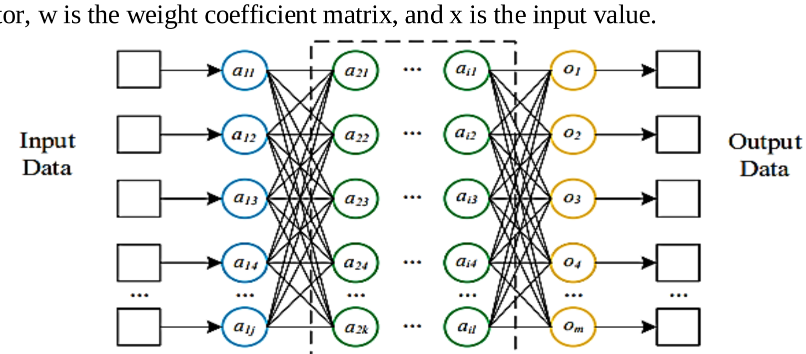

Figure 3: The basic structure of DNN

As an activation function, ReLU is often used in multi-class networks; the following Equation (3) describes it:

$$\sigma(x) = max(0, x) \quad (3)$$

The loss function optimizes the network structure by measuring training sample output loss and computing the back propagation of the network across it. As a loss function, cross-entropy is often used in classification tasks; the following is the Equation (4):

$$c = -\frac{1}{N}\sum_x \sum_{i=1}^{M}(y_i \log p_i) \quad (4)$$

In this context, N is the chance of accurately predicting that category, y_i is the likelihood that classification i is right, and M is the number of categories. This DNN model is built using a lightweight five-layer architecture; the amount of input attributes directly correlates to the input layer's size, and the output layer represents five distinct fault classes. The model is configured with 50 neurons per layer to balance complexity and efficiency.

3.5. Performance Matrix

Tabular summaries of a machine learning classification model's test data performance are known as confusion matrices. For every category, it details the TP, TN, FP, and FN. The class labels in the test set are compared to the model's predicted class labels in order to construct the matrix. Tables showing anticipated and actual class labels are shown in rows and columns, respectively. The findings are either true positives or true negatives when the samples are marked correctly; the opposite is true when the labels are incorrect. To determine additional metrics like as accuracy, precision, and recall, one may look at the confusion matrix, which gives a thorough assessment of the model's performance in all classes.

Accuracy: Accuracy is determined as correct predictions divided by total predictions that the model makes. It can be defined as Equation (5):

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \quad (5)$$

Precision: Precision is a measure that determines the aptitude of the model in the proper diagnosis of positive cases. In order to obtain it, divide the total number of positive predictions by the total amount of real positive forecasts. The outcome is Equation (6).

$$\text{Precision} = \frac{\text{TP+FN}}{\text{TP}} \quad (6)$$

Recall: The ability of the model to detect all positive cases is assessed by the Recall measure. The model finds it as the ratio of positive predictions that come true to those that are really positive, and it may be found using Equation (7):

$$\text{Recall} = \frac{\text{TP+FN}}{\text{TP}} \quad (7)$$

F1_Score: Finally, as seen below, the one measure that strikes a good balance between memory and accuracy is the F1 score Equation (8):

$$F1 = 2 * \frac{(Precision*Recall)}{(Precision+Recall)} \quad (8)$$

4. Result Analysis and Discussion

The experimental conditions and performance matrices of the suggested model will be detailed in this section. The GPU (NVIDIA GeForce GTX 1650) and CPU (Intel(R) Core (TM) i7-9750H CPU @ 2.60 GHz) were used to construct the suggested model architecture. On the CPU, the compressed model was compressed using Tensor Flow Lite. On the TPU, the compressed model was compressed using two quantization algorithms. Table II shows the evaluation measures of the DNN model used in predictive maintenance on Industrial IoT, which shows an excellent performance. The model has attained a high accuracy of 99.45%, which means to the fact that the model can accurately categorize most cases.

The model has a low false positive and false negative rate with a precision of 99.07% and a recall of 99.29 %, which makes it very effective and reliable in real-time fault detection. The F1-score of 99.58 per cent also works to validate the strength of the model in balancing the precision and recall. Also, the loss value of 0.0014 is very low, indicating great convergence on the training, and predicts minimal error.

Table 2: Evaluation Result of the DNN Model on Sensors data in Industrial IoT

Matrix	DNN
Accuracy	99.45
Precision	99.07
Recall	99.29
F1-Score	99.58
Loss	0.0014

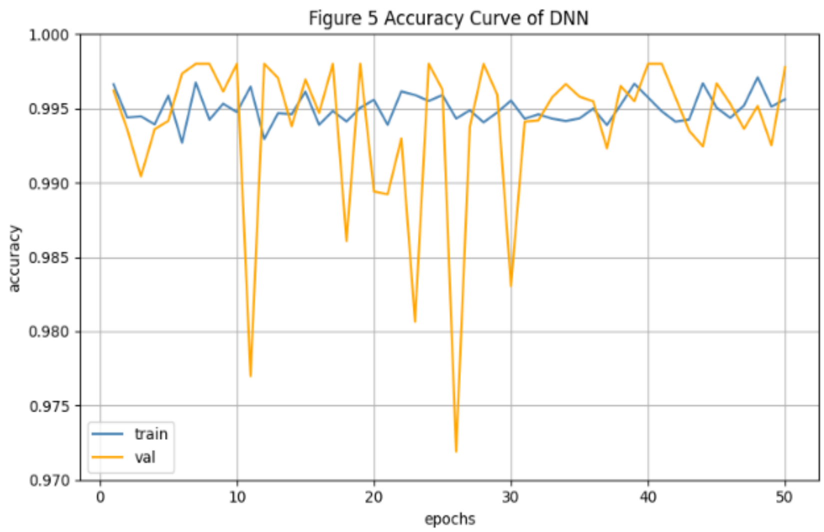

Figure 4: Accuracy curve of DNN

Figure 4 illustrates the accuracy training and validation curves of the DNN during the first 50 epochs. Looking at the graph, it can be seen that both the training and validation accuracies are highly varied, particularly in the validation curve, which has sudden plunges. As the training accuracy tends to stay high, the validation accuracy often tends to decline, which should be taken as an indication of an inconsistent performance and a possible problem with the model generalizing on unseen data. The absence of a strong positive trend or high accuracy of the validation set indicates that DNN may over fit on the training data and needs additional optimization or regularization strategy to increase its stability.

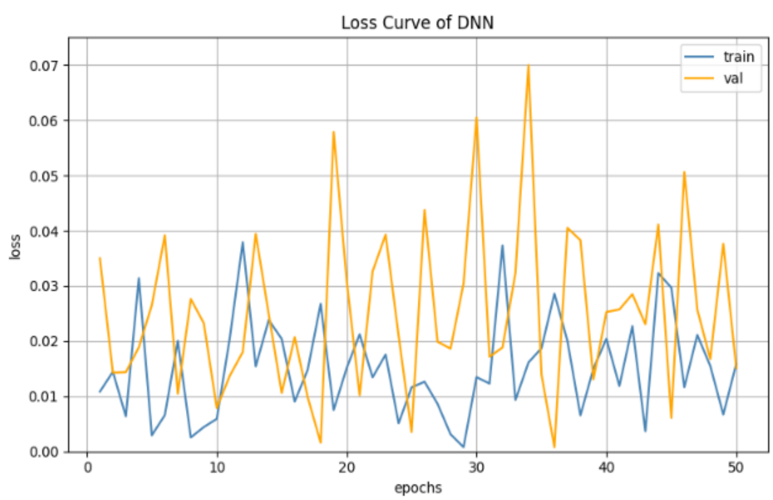

Figure 5: Loss curve of DNN

In Figure 5, the loss curve of DNN is provided during the training process with 50 epochs, monitoring the training loss and validation loss. Training loss is rather low and does not change drastically, mostly staying under 0.02, which means that the model has no issues minimizing training set errors. Nevertheless, the validation loss is showing visible variability, and there are a few sudden increases, especially in the range of epochs 20-33, reaching a maximum of over 0.07. Such fluctuations in validation loss are indicative of a certain degree of overfitting and instability of the generalization error of the model. Although both losses trend downward overall, the inconsistent validation loss highlights the need for tuning strategies such as regularization, learning rate adjustment, or early stopping to enhance the reliability and validity of the model when used with new data.

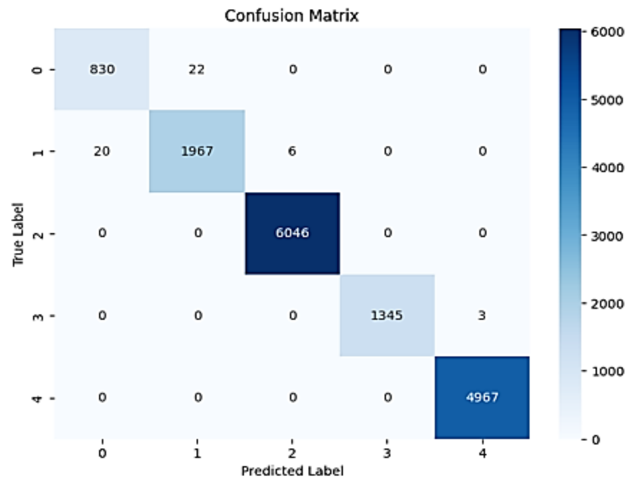

Figure 6: Confusion matrix of DNN

Figure 6 shows the model's confusion matrix, which shows how well the DNN performed across all five classes. High numbers like 830 (class 0) and 1967 (class 1) indicate the diagonal dominance of the matrix, 6046 (class 2), 1345 (class 3), and 4967 (class 4), indicates that the model correctly classifies the majority of samples in each class. Misclassifications are minimal and mostly occur between neighboring classes, such as 22 samples from class 0 misclassified as class 1, and 6 from class 1 as class 2. The near-zero off-diagonal values highlight the model's strong precision and low error rate, reflecting its effectiveness in distinguishing between different classes with high accuracy and reliability when it comes to predictive maintenance duties for industrial settings.

4.1. Comparative Analysis

Table III demonstrates the evaluation in comparison to alternative ML models used as predictive maintenance in an Industrial IoT setting. The analyzed models included DNN, which showed outperforms competitors while maintaining a precision of 99.45%, and is therefore the best model that matches the intricate industry sensor data patterns and dependencies. LR and NB obtained somewhat lower accuracies of 97.95% and 96.61%, respectively, which can be interpreted as their relatively weak capability of operating with high-dimensional non-linear data, as it is common in the IIoT scenarios.

Table 3: Comparative performance of machine learning model for Predictive Maintenance in Industrial IoT

Matrix	Accuracy
DNN	99.45
LR[14]	97.95
Naive Bayes [15]	96.61

The suggested DNN model has demonstrated an impressive accuracy of 99.45 percent in predictive maintenance of Industrial IoT systems, which is substantially higher than the traditional ML models. This level of precision demonstrates the power of the DNN in learning complex, non-linear relationships on large and heterogeneous industrial data easily. The main strength of the DNN is its deep structure that allows extracting features automatically and learning representations hierarchically, being very adaptable to real-time fault identification and maintenance prediction. This ensures ease in making proactive decisions, reducing unplanned equipment failures and it also improves efficiency during operations within industrial settings.

5. Conclusion and Future Scope

The IIoT has reinvented the concept of PdM since it has introduced the potential of real-time monitoring of machinery and equipment. However, the large volumes and complexity of data generated by IIoT sensors pose significant challenges for data processing techniques. The suggested DNN model demonstrated high accuracy (99.45%), with strong precision, recall, and F1-score values, confirming its robustness for non-destructive fault detection in complex industrial environments. The integration of fog computing also addressed challenges like data latency and interoperability. As promising as the results may be, they can be improved in the future by focusing on improving model generalization using advanced regularization techniques and exploring other DL architectures. Moreover, expanding the dataset across diverse industrial domains and incorporating real-time edge deployment will further validate the system's scalability and reliability for large-scale Industry 4.0 applications.

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