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Original Article

Deep Learning Approaches for Predictive Maintenance and Intelligent Fault Diagnosis

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Abstract *- Deep-learning-based intelligent fault diagnosis methods are the new research hotspots in the fault diagnosis field. Auto detection and correct detection of the emerging micro-fault of rotating machinery, particularly with respect to fault orientation and level of severity, remains a significant issue in the area of intelligent fault diagnosis. To detect an early fault successfully in rotating machinery, this paper presents a Hybrid Recurrent Neural Network and Gated Recurrent Unit (RNN +GRU) that can be used to diagnose intelligent faults on the Case Western Reserve University (CWRU) bearing dataset. The suggested hybrid model covers both the short- and long-term temporal characteristics of bearing vibration signals. Experimental outcomes show high-quality performance with an accuracy of 99.7, a precision of 99.4, a recall of 99 and an F1-score of 99.8, which is considerably better than the traditional machine learning models as well as standalone deep learning models. Such findings confirm how effective and appropriate the proposed solution is in terms of high-precision predictive maintenance and intelligent diagnosis of faults in industries.*

Keywords *- Predictive Maintenance, Intelligent Fault Diagnosis, Deep Learning, Vibration Analysis, Rotating Machinery, Industrial Systems Reliability.*

1. Introduction

The modern manufacturing, energy, and chemical industries depend on these industrial systems that consist of interconnected mechanical, electrical, electronic, and information subsystems [1]. The growing complexity and size of these systems, as well as the growth in performance expectations, have rendered reliability a key component in the quest to have safe and effective operations. Industrial failures may cause substantial losses of money, stagnation of production, equipment destruction, and even safety risks, which is why it is so vital to detect faults in time and implement proactive maintenance plans [2]. Maintenance practices in the past were based on a reactive or time-dependent approach, e.g., scheduled maintenance checks or maintenance after failure [3][4]. With the emergence of artificial intelligence (AI) and data-oriented methods, the practice of maintenance has changed, and predictive maintenance (PdM) methods are now possible, where the maintenance is predicted ahead of time [5][4]. PdM uses the huge amounts of sensor and operational data created by industrial environments and transforms maintenance operation strategies towards proactive rather than reactive maintenance and resource distribution optimization [6][7].

Deep learning (DL) is one of the methods of AI that has been used to become a potent tool, as it can extract features automatically, generalize nonlinear relationships and work with high-dimensional data, as commonly found in industrial settings [8]. Compared to conventional machine learning (ML) algorithms, which frequently involve human intervention and manual feature engineering to correct errors [9]. DL models can learn hierarchical representations directly based on raw sensor signals, and this increases the accuracy and automation of fault diagnosis [10][11]. New developments have examined bringing together DL and digital twin frameworks, enhanced analytics, and sensor unification to improve smart fault diagnostics in rotating machines [12][13]. These methods enable the detection, classification, and prediction of faults with high precision in real-time and thus early interventions, which reduce the operational disruption and minimize maintenance costs. This paper explores the latest advancements in deep learning methods in predictive maintenance and intelligent fault detection with regard to how they can improve the reliability, operational efficiency, and safety of complex industrial systems.

1.1. Motivation and Contribution

Its increasing sophistication of industrial equipment and the high price of unforeseeable failure demand precise and clever predictive maintenance. Conventional maintenance plans and the classical models of machine learning are poor in capturing nonlinear and temporal features of vibration signals. This encourages the adoption of modern deep learning methods, including hybrid RNN+GRU models, to obtain valid fault diagnosis and better maintenance performance. There are some important contributions that are made by this research, which are as follows:

- Proposed a hybrid RNN+GRU deep learning model to be able to both capture both short-term and long-term temporal dependencies on bearing vibration signals.
- Developed a robust preprocessing pipeline encompassing signal down-sampling, noise filtering, entropy-based sampling rate selection, STFT-based

time–frequency transformation, and min–max normalization.
- Validated the model's generalization and robustness through training–testing convergence analysis and confusion matrix evaluation.
- Addressed multiclass fault classification with varying severity levels, highlighting the model's discriminative capability across complex industrial conditions.
- Provided a scalable methodology for industrial predictive maintenance, enabling efficient and precise condition monitoring in rotating machinery.

1.2. Novelty and Justification

This study is novel in that it is able to produce extremely accurate and reliable fault diagnosis in rotating machinery through effective processing of complex vibration signals and multi-type faults. The proposed model has high discriminative ability, unlike the current methods, and this fact makes it strong and practical. It overcomes the shortcomings of the traditional machine learning models, which may not be able to handle temporal relationships and multi-class classification. This research is supportable because it offers a reliable and scalable solution to the industrial predictive maintenance system to guarantee the early identification of faults, minimal downtime, and enhanced operation efficiency in the real-world manufacturing and mechanical systems.

1.3. Organization of the Paper

The rest of the paper is structured as follows: Section II provides a literature review of predictive maintenance and intelligent fault diagnosis. Section III outlines the dataset and data preprocessing methods. In section IV, experimental results and a comparative performance analysis. Lastly, Section V summarizes the paper with the main findings and closes the paper with future research directions.

2. Literature Review

An extensive literature review and critical survey of the recent works on Predictive Maintenance and Intelligent Fault Diagnosis were conducted to inform and support the work creation. Table I synthesizes these studies by providing the proposed models, datasets, main findings and the challenges that have been noted in the current methods.

Zou et al. (2025) mitigate feature degradation in constructing domain-independent features. Additionally, the weighted Lin SoftMax function is introduced as a replacement for the traditional SoftMax, leading to a more stable optimization target and improved model accuracy, with a distance-based penalty weight focusing on significant prediction errors. Experiments on the 2023 PHM Data Challenge dataset demonstrate the effectiveness of the proposed method, achieving a mean absolute error of 0.11, an accuracy of 92.32%, and a fault tolerance accuracy of 98.02% [14].

Zhao et al. (2025) used the random forest (RF) algorithm to build a health state evaluation model, and the BP neural network (BPNN) was used to predict the remaining service life of the system, which provides strong support for the maintenance decision of enterprises. The experimental results show that the fault diagnosis and predictive maintenance methods designed in this study have high accuracy and stability. The classification accuracy of the fault diagnosis model is generally high, reaching an average accuracy of 90%; the predictive maintenance model has high prediction accuracy, and the error is controlled within 5% in predicting the remaining service life [15].

Ma et al. (2024) BLSTM-GRU model is constructed by combining bidirectional long short-term memory network (BLSTM) and gated recurrent unit (GRU) networks, and applied to fault prediction of electricity information collection terminals, as well as issuing warnings based on the prediction results. Based on the selected data samples, experimental analysis is conducted on the proposed method, and the results show that its fault diagnosis accuracy reaches 96.03%, and the fault warning results are reliable [16].

Bai et al. (2023) proposed a method that utilizes Wavelet Packet Decomposition (WPD) to efficiently extract features from the laser gyroscope signal, which are then used as input for our diagnostic model. Furthermore, the KELM model is trained for fault diagnosis. Afterward, they utilize the Improved Dung Beetle Optimizer (IDBO) algorithm to optimize its parameters for improved optimization performance. According to the experimental results, their proposed IDBO-KELM model demonstrates a 3.68% improvement in diagnostic accuracy compared to traditional approaches. Additionally, it offers the advantages of shorter training time and increased precision [17].

Du et al. (2023) proposed a deep learning-based generative adversarial network to integrate with an incremental learning SVM model to diagnose the commonly occurred faults of the data center air conditioning system. The adversarial learning between the generator and the discriminator generates the data of the minority class for training purposes in the HVAC system. The incremental learning strategy is proposed to update the FDD model regularly. The refrigerant leakage faults with intensities of 10%, 20%, 30% and 40% are tested and validated under various operational conditions. The experimental results show that the incremental learning SVM integrated with deep learning GAN reaches acceptable diagnosis accuracies [18].

Soltani et al. (2022) compared Convolutional Neural Networks, Support Vector Machines (SVM), Principal Components Analysis-SVM, Linear Discriminant Analysis-SVM, and Linear Discriminant Analysis classifiers. The results indicate that the fault detection reliability of the algorithms depends heavily on how well the training data covers the operating regime. Furthermore, it is found that a well-trained SVM can simultaneously classify twenty types of fault with 95% accuracy when the verification data is taken from different system configurations [19].

Ghazali et al. (2022) present a fault diagnosis method for twisted pair cable fault detection based on knowledge-based and data-driven machine learning methods. The DSL Access Network is emulated in the laboratory to accommodate VDSL2 Technology with various types of cable faults along the cable distance between 100 m and 1200. The random forest algorithms (RFs), a data-driven method, are adopted to train the fault diagnosis classifier and regression algorithm with the processed fault data. Finally, the proposed fault diagnosis method is used to detect and locate the cable fault in the DSL Access Network System. The results show that the cable fault detection has an accuracy of more than 97%, with a minimum absolute error in cable fault localization of less than 11%. The proposed algorithm may assist the telecommunication service provider in initiating automated cable faults identification and troubleshooting in the DSL Access Network System [20].

Bhatti and Singh (2021) modelled a data-driven and multi-physics robotic linear actuator digital twin and integrated it with a custom-designed fault detection mechanism using a Naïve Bayes classifier. This architecture can autonomously be deployed in tandem with the physical machine to alarm and diagnose electrical faults as soon as they occur in the machine. As compared with conventional diagnostics, this will reduce machine downtime and expedite repairs. The resultant model, built on MATLAB and Simulink, gave an accuracy of 96% and required minimal processing capability to operate [21].

Table 1: Recent Studies on Fault Diagnosis Using Machine Learning Techniques

Author	Approaches	Key Findings	Limitations	Future Work
Zou et al. (2025)	Domain-independent feature construction with Weighted Lin SoftMax loss; evaluated on PHM 2023 dataset	Achieved MAE of 0.11, accuracy of 92.32%, and fault tolerance accuracy of 98.02%; improved optimization stability	Performance validated on a single benchmark dataset; limited real-time deployment analysis	Extend validation to heterogeneous industrial datasets and online PHM systems
Zhao et al. (2025)	Random Forest for health state evaluation and BPNN for remaining useful life prediction	Fault diagnosis accuracy ≈90%; RUL prediction error within 5%, supporting maintenance decisions	Model interpretability and scalability to complex systems are not discussed	Integrate explainable AI and test on large-scale industrial systems
Ma et al. (2024)	Hybrid BLSTM–GRU deep learning model for fault prediction and warning	Fault diagnosis accuracy reached 96.03%; reliable early warning capability	Computational complexity and deployment cost were not analyzed	Optimize model efficiency and evaluate real-time edge implementation
Bai et al. (2023)	WPD-based feature extraction with IDBO-optimized KELM	Diagnostic accuracy improved by 3.68%; reduced training time and higher precision	Handcrafted feature dependence; limited adaptability to new fault types	Combine with adaptive feature learning and online optimization
Du et al. (2023)	GAN-based data augmentation with incremental learning SVM for HVAC fault diagnosis	Improved diagnosis of minority fault classes under varying conditions	Focused on specific HVAC faults; model update frequency not optimized	Extend to multi-fault scenarios and adaptive update scheduling
Soltani et al. (2022)	Comparative analysis of CNN, SVM, PCA-SVM, and LDA-based classifiers	Well-trained SVM achieved 95% accuracy across 20 fault classes	Strong dependence on the training data coverage of operating regimes	Develop domain adaptation techniques for unseen operating conditions
Ghazali et al. (2022)	Knowledge-based feature transformation with RF for cable fault detection and localization	Fault detection accuracy >97%; localization error <11%	Laboratory-based emulation limits real-world generalization	Validate on live telecom networks and diverse cable infrastructures
Bhatti & Singh (2021)	Digital twin of robotic actuator with Naïve Bayes fault detection	Achieved 96% accuracy with low computational overhead	Limited to electrical faults and simple classifiers	Incorporate advanced learning models and multi-fault diagnostics

Research gaps: Although there are immense developments in predictive maintenance and intelligent fault diagnosis, the available literature indicates that there are various gaps that limit practical implementations and generalizations. Most of them, although being highly accurate in laboratory or benchmark data, are sensitive to handcrafted features, single-domain data, or even a type of equipment, limiting their usefulness in a wide range of industrial systems. Moreover, lots of deep learning models, like the BLSTM-GRU or the GAN-based one, are not only costly in calculations but also lack efficient strategies of real-time deployment. There are also some that are highly reliant on full and uniform training data, which constrain their ability to operate in hidden operating conditions or minority fault sets. These shortcomings point to the necessity of predictive maintenance models that are scalable, adaptive, and interpretable and can be extrapolated to different heterogeneous datasets and be used to prescribe fault diagnostics in real time.

3. Research Methodology

The paper presents a predictive maintenance system based on the CWRU bearing system shows in Figure 1, wherein raw vibration data of healthy bearings and faulty bearings undergo pre-processing, including down-sampling, noise removal, time-frequency transformation based on the STFT, and min-max normalization. The obtained processed data are stratified, sampled, and categorized in a hybrid RNN+GRU model that takes into account temporal fault patterns. Accuracy, precision, recall, and F1-score are used to measure the performance of a model. The accuracy, precision, recall, and F1-score variables are measured based on the confusion matrix to assess the effectiveness of the proposed approach.

The next section provides a detailed description of all the stages of the proposed methodology:

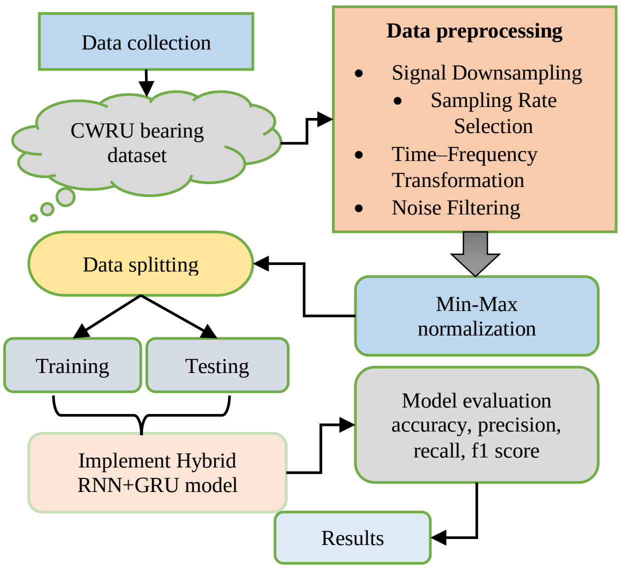

Fig 1: Proposed Flowchart for Predictive Maintenance and Intelligent Fault Diagnosis

3.1. Data Gathering and Analysis

The Case Western Reserve University (CWRU) bearing dataset has become a benchmark resource in the field of machine condition monitoring and predictive maintenance research. Vibration data were typically recorded at high sampling rates of 12 kHz and 48 kHz, allowing for fine-resolution signal analysis suitable for fault detection tasks. This dataset captures various fault conditions at three key locations—Ball, Inner Race, and Outer Race—along with data for a healthy bearing condition ("None"). As shown in Figure 2, there are significant differences in vibration amplitude and waveform between the healthy condition and various fault types in the dataset (e.g., inner race, outer race, and rolling element faults).

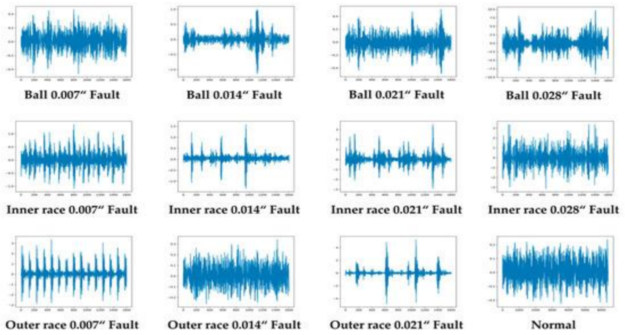

Fig 2: Samples of Raw Vibration Sensor Signals Of All Classes

Fig 2 depicts the complete data of raw vibration sensor signals of twelve bearing conditions in twelve categories according to the type and severity of faults. Ball defects with the largest defects on the top row of 0.007-0.028, with more pronounced irregularities of the waveform. The middle row records the inner race faults, in the same way, increasing in size, and signal distortion. The lower row entails the outer race faults with a different level of severity and ends with the normal bearing condition that has a stable and low-amplitude waveform. These variations of signals underline how fault type and size influence vibration properties, which is essential input in the fault diagnosis and monitoring of conditions in rotating machines.

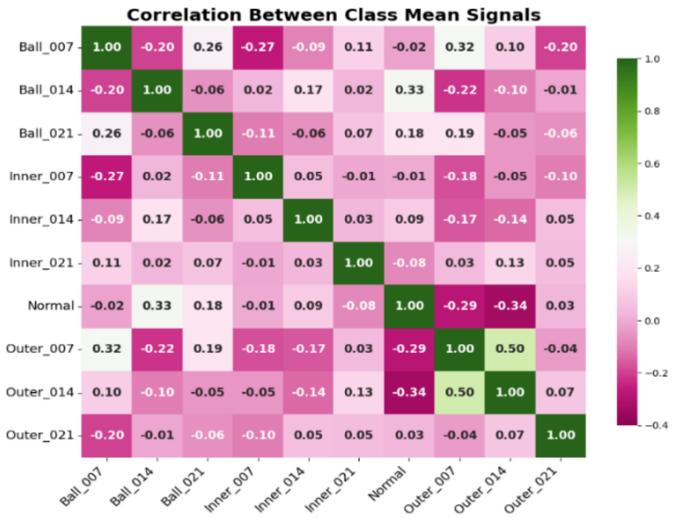

Fig 3: Correlation Heatmap for Mean Signals

Figure 3 shows the relations among the mean signal of various bearing condition classes. The cells are the same as the correlation coefficient between two classes, where warmer colors are used to represent higher positive correlations and cooler colors are used to represent weaker or negative correlations. Diagonal component values are perfectly self-correlated, and the off-diagonal values are used to indicate the extent of similarity between the various fault types and operating conditions. In general, the heatmap shows low to moderate correlations among the majority of class pairs, which shows that there are tangible differences in the signal between ball faults, inner race faults, outer race faults, and normal conditions, which confirms the suitability of the dataset to be trusted in classifying faults.

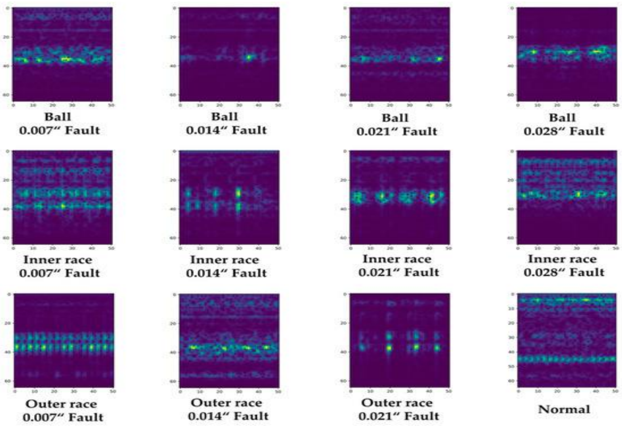

Fig 4: Spectrogram to the Raw Vibration Signal of Each Class

Figure 4 presents spectrograms of raw vibration signals of twelve bearing conditions, each with the time frequency properties of each fault class. The last spectrogram is that of normal bearing. An increase fault severity gives rise to more labor-intensive frequency patterns in the spectrograms, which can be visually differentiated to detect fault types and severity in order to effectively monitor the condition and fault diagnosis.

3.2. Data Pre-processing

The preprocessing phase entailed the treatment of missing data, elimination of outliers, noise filtering, and then a process of data labeling and normalization. The following steps are the main steps of preprocessing:

- Signal Downsampling: The original signals sampled at 12 kHz and 48 kHz were downsampled to reduce data dimensionality and computational complexity while retaining essential fault-related information.
- Sampling Rate Selection: An entropy-based analysis of the generated spectrograms was conducted to identify the most informative sampling frequency, leading to the selection of 6 kHz as the optimal rate.
- Time–Frequency Transformation: Each segmented signal was converted from the time domain to the time–frequency domain using the Short-Time Fourier Transform (STFT) to extract localized spectral characteristics.
- Noise Filtering: A noise filter is an algorithm or system that suppresses or absorbs (or isolates) high/low frequencies or random variations to extract the underlying smoother information of a signal, data, or image, in electronics, audio, video and communications.

3.3. Min-Max Normalization

The normalization of records was carried out using the min–max technique to constrain values within a range between 0 and 1. This was performed to optimize the performance of the classifiers and mitigate the effects of outliers. Normalization was conducted according to the following mathematical formula in Equation (1):

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \qquad (1)$$

Where X represents the original value of the feature, X' is the normalized value, X_{min} is the minimum value of the feature, and X_{max} is the maximum value of the same:

3.4. Data Splitting

The dataset was divided into training and testing subsets in a 70:30 proportion by a stratified sampling approach, where the proportion of classes in both subsets of the partitioned dataset represented the proportion of classes in the original dataset.

3.5. Hybrid Recurrent Neural Network and Gated Recurrent Unit (RNN+GRU) Model

The Hybrid RNN+GRU model integrates the sequential learning strength of the Recurrent Neural Network (RNN) with the efficient memory retention ability of the Gated Recurrent Unit (GRU). The hybrid Recurrent Neural Network and Gated Recurrent Unit (RNN+GRU) model is developed to improve predictive maintenance and intelligent fault diagnosis by effectively modeling temporal dependencies in multivariate time-series sensor data. The architecture combines a traditional RNN layer for initial temporal feature extraction with stacked GRU layers to capture long-term dependencies and nonlinear degradation patterns while alleviating the vanishing gradient problem. This hybrid design enables robust learning of equipment health evolution under varying operating conditions. Hyper parameter training plays a critical role in optimizing model performance. Key hyperparameters include the number of hidden units in RNN and GRU layers, learning rate, batch size, dropout rate, and the number of training epochs, as shown in Table II.

Table 1: Hyperparameters of the Hybrid Rnn+Gru Model

Parameter	Value / Range
RNN Hidden Units	64
GRU Hidden Units	64–128
Number of Layers	2–3
Learning Rate	0.001
Optimizer	Adam
Batch Size	32–64
Dropout Rate	0.2–0.5
Epochs	50
Activation Function	ReLU / Tanh

Overall, the Hybrid RNN+GRU architecture improves convergence speed, mitigates vanishing gradients, and enhances prediction accuracy, making it a powerful framework for modeling dynamic, resource-intensive cloud environments.

3.6. Evaluation Metrics

The proposed design was tested in terms of several performance measures. To thoroughly summarize the results of the classification, a confusion matrix was created that gave the distribution of both correct and incorrect predictions in all the classes. Based on this matrix, some important statistical measures, True Positives (TP), False Positives (FP), True Negatives (TN) and False Negatives (FN) were obtained. The primary performance indicators, i.e., accuracy, precision, recall, and F1-score, were then estimated using these values as mentioned below:

1) Accuracy

The ratio of the number of instances correctly predicted by the trained model to the total number of instances in the dataset (input samples). It is given as Equation (2)-

$$Accuracy = \frac{\mathrm{TP+TN}}{\mathrm{TP+Fp+TN+FN}} \quad (2)$$

2) Precision

Precision is the proportion of positive instances successfully predicted to all positive instances predicted by the model. Precision expressed as Equation (3)-

$$Precision = \frac{\mathrm{TP}}{\mathrm{TP+FP}} \quad (3)$$

3) Recall

This metric is the ratio of events that were accurately predicted as positive to all instances that should have proved positive. In mathematical form, it is given as Equation (4)-

$$Recall = \frac{\mathrm{TP}}{TP+FN} \quad (4)$$

4) F1 score

It is a combination of the harmonic mean of precision and recall, that is, it helps to balance recall and precision. Its range is [0, 1]. Mathematically, it is given as Equation (5)-

$$F1-score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (5)$$

Taken together, these metrics provide a more detailed and reliable evaluation of a classification model's overall performance and its ability to make accurate predictions across different classes.

4. Results and Discussion

This section explains the experimental outline and presents the experimental evaluation and effective processing of the proposed model in both training and testing stages. The experiments were performed on a powerful PC. The proposed model was implemented using TensorFlow 2.3.0 with Python in a Jupyter Notebook environment on a system equipped with an Intel® Core™ i5-8250U processor (1.60–1.80 GHz) and 12.0 GB RAM (11.9 GB usable). Table III indicates that the proposed Hybrid RNN+GRU model has a high prediction accuracy in predictive maintenance and intelligent fault diagnosis based on the CWRU bearing dataset. The model has an excellent accuracy rate of 99.7, and this gives it a high capability of predicting in general. Moreover, the high F1-score (99.8 percent) indicates that there is a good trade-off between precision and recall, or that the model is robust, reliable and effective in terms of precise bearing fault classification in the process of predictive maintenance in the industry.

Table 2: Experiments Results of the Proposed Model for Fault Diagnosis

Performance Matrix	Hybrid RNN+GRU
Accuracy	99.7
Precision	99.4
Recall	99
F1-score	99.8

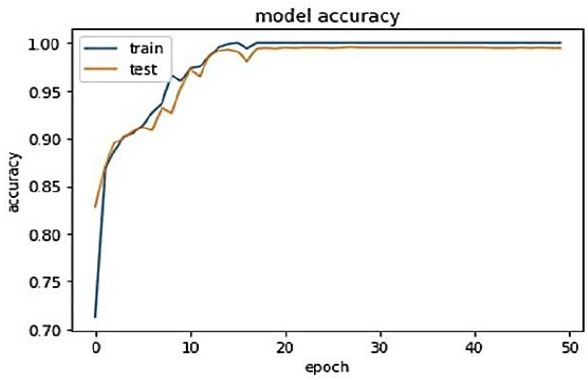

Fig 5: Training and Testing Accuracy for the RNN+GRU Model

Figure 5 shows the curve of accuracy of the RNN+GRU model on 50 training epochs on the training and testing sets. At the beginning, the model quickly becomes more accurate, which means that early epochs are effectively learnt. The accuracy of training and testing occurs in a steady increase as the training continues, as well as the testing, and they closely follow with the values approaching 100% accuracy. This high correlation indicates high generalization and low overfitting. When the number of epochs becomes approximately 15-20, the accuracy curves become flattened, which proves that the model has reached convergence and attained high predictive performance on both seen and unseen data.

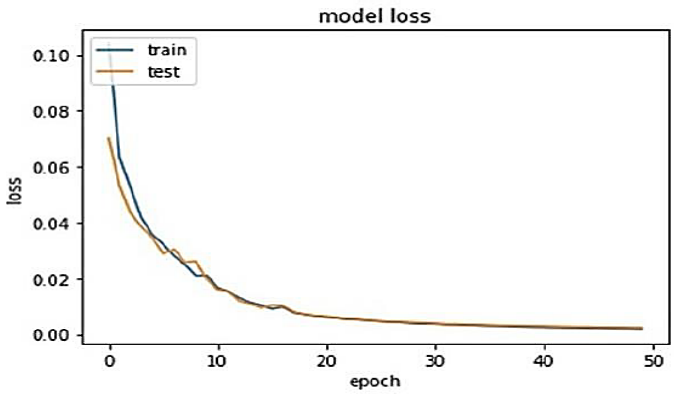

Fig 6: Training and Testing Loss for the RNN+GRU Model

Figure 6 presents the loss curves of the proposed model for both training and testing datasets across 50 epochs. The loss values are high at the beginning of the course of the first stage, but they level off quickly at the early epochs, which suggests good optimization and learning of model parameters. During the continuation of training, training and testing loss counteract in a smooth manner and are highly parallel to each other, which indicates steadiness of learning behavior as well as excellent test generalization ability. Once about 15-20 epochs are finished, the loss curves level off and tend towards near-zero values, signifying the convergence of the model to a minimum overfitting and good performance on unknown data.

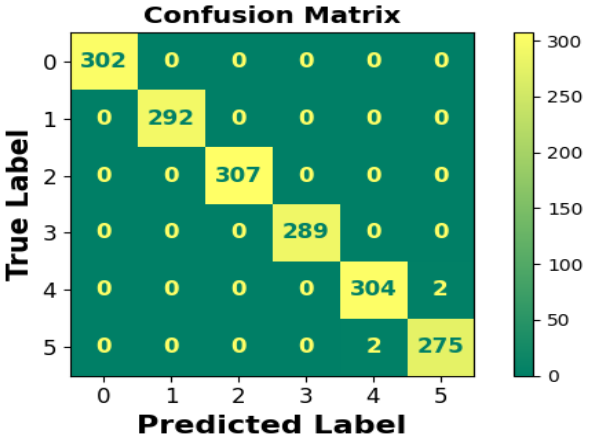

Fig 7: Confusion Matrix for the Propose RNN+GRU Model

Figure 7 shows the confusion of the RNN+GRU model, which has high classification performance with all classes. Most of the samples are properly defined as seen by the high scores in the main diagonal, which implies proper prediction of each of the classes. There are only very few misclassifications that are observed, which mainly occur between classes 4 and 5, which implies that there is a slight overlap between these classes. All in all, the confusion matrix shows that the model was very reliable, had an excellent discriminative ability, and was very robust in its ability to identify various classes with less error.

4.1. Comparative Analysis

Table IV shows that the proposed Hybrid RNN+GRU model has better performance in various assessment metrics and datasets. In the case of the AI4I 2020 Predictive Maintenance Dataset, Logistic Regression (LR) demonstrates that the accuracy is 66.9% with high recall (99.7) and low precision, which means that the number of false positives is large. The performance of Random Forest (RF) and KNN is much better, with an accuracy of 96.2 and 97.3, respectively. Regarding the CWRU bearing dataset, SVM, NB, and ANN models achieve 84.3% 92.4% and 94.3% accuracy, respectively, and the precision, recall and F1-scores depict moderate to good classification. Conversely, the proposed Hybrid RNN+GRU model yields the best results on the CWRU bearing dataset with the accuracy of 99.7, precision of 99.4, recall of 99, and F1-score of 99.8, which clearly shows that the model is efficient, robust and performs better compared to current methods of predictive maintenance and intelligent fault diagnosis.

Table 3: Comparison of Different Ml and Ml Models for Fault Diagnosis Using Different Datasets

Ref	Classifiers	Dataset	Accuracy	Precision	Recall	F1-score
[22]	Logistic Regression	AI4I 2020 Predictive Maintenance Dataset	66.9	46.9	99.7	63.8
[23]	Random Forest		96.2	96.2	96.2	96.5
[24]	K-Nearest Neighbors		97.3	96.2	97.3	96.5
[25]	Support Vector Machine	CWRU bearing dataset	84.3	82.5	80.9	81.7
[26]	Naïve Bayes		92.4	93	92	92
[27]	Artificial Neural Network		94.3	95	95	95
Our	Proposed RNN+GRU Model		99.7	99.4	99	99.8

The proposed Hybrid RNN+GRU model is shown to be very robust in bearing fault diagnosis with very high accuracy, precision, recall and F1-score in the CWRU dataset. It has a good ability to capture time dependencies in vibration data, and it converges quickly without overfitting. The training and testing curve should be close, and this is a confirmation that it has a good ability to generalize. The model also performs better than a number of conventional machine learning and neural network techniques, which makes it robust and reliable when used in predictive maintenance. The model, however, has more complexity in computations because of recurrent layers that make it consume more time in training. It also needs high-quality labeled data that is carefully taken. This can impair its use on low-resource-based or real-time industrial devices.

5. Conclusion and Future Study

Bearing faults are important in the safe, reliable, and efficient operation of rotating machinery because bearings are the carrying structure of rotating shafts with the ability to sustain high loads and stresses. This paper suggested a hybrid RNN+GRU-based predictive maintenance model of intelligent bearing fault diagnosis on the CWRU dataset. The proposed model attained a successful preprocessing and time-frequency analysis with an accuracy of 99.7, precision of 99.4, recall of 99, and an F1-score of 99.8, which implies a high accuracy and stability in fault classification. The training curve and testing curve exhibited rapid convergence in 15-20 epochs with little overfitting, which proved that it had high generalization abilities. Comparison outcomes also revealed that the suggested model is more effective compared to the classical machine learning models, including SVM, NB, and ANN. In general, the findings confirm the usefulness of the hybrid RNN+GRU model in predictive maintenance of industry rotating machines to be accurate and efficient. Further contributions to the model can be made to reduce the computational complexity of the model to allow real-time implementation and enhance scalability to resource-constrained systems. Some of the areas in which research might be pursued include lightweight architectures, optimization of models, and automatic hyperparameter optimization.

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