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HYBRID FRAMEWORK FOR PREDICTIVE MAINTENANCE IN SMART MANUFACTURING SYSTEMS

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Abstract: Predictive maintenance (PdM) is one of the key components of smart manufacturing systems. It employs data-driven solutions to reduce maintenance expenses, minimize downtime, and optimize system efficiency. The most widely used machine learning techniques for PdM come with many challenges, especially on the transparency and explainability front. In this research, a new smart predictive maintenance system using deep learning (DL) and the CWRU bearing data set is presented for defect classification of industrial equipment. The cleaned, normalized, labeled, and standardized data are then split into a training set and a test set to assess the model. Various models have been developed and tested, including RF, MLP, KNN and the proposed GRU+BiLSTM model. Among the models tested, the proposed hybrid model achieved the best results with a 99.8% F1 score (F1), 99.1% recall (REC), 99.5% precision (PRE) and 99.8% accuracy (ACC). The results indicate that the temporal relationships of vibration signals can be effectively captured by using the combination of GRU and BiLSTM, which can achieve more accurate and reliable defect identification. This proposed approach can be used to provide smart maintenance capabilities with a predictive approach in the context of Smart Manufacturing Systems.

Keywords: Predictive Maintenance, Machine Learning, Smart Manufacturing, Industrial IoT.

1 INTRODUCTION

Predictive Maintenance, or PdM for short, is a cutting-edge maintenance technology that leverages data-driven methods, sensor monitoring, and smart data analysis to enable businesses to predict equipment failures. In contrast to more conventional approaches, predictive maintenance involves constant monitoring of critical machine characteristics like vibration, temperature, pressure, and acoustic signals in order to detect machine deterioration early on [1]. The typical benefits of maintenance practices like reactive maintenance (repair-on-failure) and scheduled maintenance are downtime, cost of maintenance and loss of resources. PdM can help to increase productivity, reduce downtime and improve reliability by offering maintenance activities when necessary based on equipment condition.

In the era of rapid development of Industrial 4.0 and smart manufacturing, the application of automation, Industrial IIoT & cyber-physical systems, is increasingly on the rise in modern industrial systems that are becoming increasingly smarter and more intelligent. Operational data from industrial equipment such as machine health parameters and process conditions is constantly generated by embedded IoT sensors, and is a huge amount of data [2][3]. These systems depend on data, and advanced analytics can turn data from the sensors into meaningful insights. Predictive maintenance is therefore becoming an essential element in smart manufacturing, which helps to prolong the lifespan of equipment, optimize maintenance schedules, lower operation expenses and boost production efficiency in industrial applications [4][5]. The implementation of AI and ML has revolutionized the concept of Predictive Maintenance by giving a smart interpretation of industrial data from the historical and current status. In high ACC, advanced analytical algorithms can identify hidden patterns, classify fault conditions and predict potential failures. In the case of multiple sensor data, a smart system can be useful for data-driven decision-making in order to optimize maintenance tasks [6]. Overall, AI-driven predictive maintenance systems can contribute to minimizing unscheduled downtime, improving equipment reliability, and promoting sustainable manufacturing practices in industrial environments with complex operations.

Smart manufacturing's predictive maintenance solutions have gotten even better with the advent of deep learning and hybrid AI. Intelligent architectures have recently emerged as a means to automatically extract complicated features from high-dimensional sensor and time-series data. These features can subsequently be employed for precise fault diagnosis and equipment health prediction [7][8]. Hybrid frameworks that combine AI, DA, the IoT, and real-time monitoring systems provide industries with predictive maintenance solutions that are more robust, adaptable, and scalable [9]. Given the above, the goal of the AI-Driven Hybrid Framework for Predictive Maintenance in Smart Manufacturing Systems is to improve equipment reliability, optimize resource use, and pave the way for the development of autonomous and smart manufacturing systems by combining intelligent analytics with real-time industrial monitoring.

1.1 Motivation and Contribution

The goal of this research is to increase industrial equipment's dependability and efficiency by using intelligent predictive maintenance approaches to identify problems early. With more downtime and maintenance costs, more accurate data-driven solutions are needed. The challenge with traditional methods is dealing with complex vibration patterns and real-time data on sensors. Therefore, this paper aims to develop a more accurate and reliable technique for fault diagnosis of smart manufacturing systems. This study has significant contributions to the field as follows:

- Using the CWRU bearing dataset for defect classification, suggests a DL-based approach for smart predictive maintenance.
- Creates and evaluates a number of ML models, such as ML Perceptron, KMeans, RF, and a GRU+BiLSTM hybrid.
- Proposes a hybrid GRU+BiLSTM network to model both short-term and long-term temporal contexts in vibration signals.
- The suggested model does better than the usual ones in terms of ACC, PRE, REC, and F1, with a high PRE.
- Offers a dependable and effective method for smart manufacturing system problem detection and predictive maintenance.
- Solve problems related to predictive maintenance in smart manufacturing with data-driven methods.

1.2 Justification and Novelty

The growing need for effective and dependable predictive maintenance solutions within the framework of smart manufacturing systems is driving this research. The ability to identify problems quickly is essential to minimizing maintenance expenses and downtime in these systems. Poor performance in the actual industrial setting is a direct result of existing ML models' incapacity to grasp the intricate temporal connection in vibration sensor data. The novelty is the usage of a hybrid GRU+BiLSTM deep learning model that can learn short and long-term patterns in the vibration signals of the bearings for better performance in the fault classification task. Compared with the traditional model approach, which is suitable for intelligent prediction maintenance in Smart Manufacturing Systems, this approach is more important and effective.

1.3 Organization of the Paper

The paper is organized is as follows: An outline of recent developments in SMSS predictive maintenance is provided in Section II. Included in Section III are the specifics of the study's intended approach. The experimental results and an in-depth explanation are presented in Section IV. The study is concluded and recommendations for further research are provided in Section V.

2 LITERATURE REVIEW

The suggested work is based on an exhaustive literature evaluation that critically analyzes the most recent research on Smart Predictive Maintenance. This literature review is presented in tabular form, as shown in Table 1.

M. Ibtihazzaman et al. (2025) provides a ML based solution that utilizes the AI4I 2020dataset for predictive maintenance to predict equipment conditions and failures. Two models, XGBoost and RF, were created and evaluated following FeatureExtraction and preprocessing. Both the RF model and XGBoost achieved competitive results, with the former scoring 98.23% ACC and the latter an AUC of 0.97 [10].

L. N, R. Jayashri, and R. M (2025) utilize the Adaptive Neuro-Fuzzy Inference Systems (ANFIS) model to obtain the nonlinear dynamics and uncertainty in machine behaviour using fuzzy logic and LSTM to predict fault probability in a real-time series manner. The predictions are analyzed and learned by the SAC (Soft Actor and Critic) agent, which makes the action based on the maintenance scheduling. The proposed work achieved 93.8% ACC with a 0.92 F1, demonstrating 3.5% higher ACC than the conventional model when tested on the smart manufacturing processing dataset from Kaggle [11].

J. Y. Jo et al. (2025) present a framework leveraging RTDB sensor data from a papermaking process to predict binary alarm events before they occur. Using RF models trained with lead-time shifted labels, achieve reliable performance with an ROC AUC of 0.78 and an F1 of 0.62 at a 5 -step horizon. The proposed approach demonstrates both academic contributions to explainable predictive maintenance and industrial relevance for smart manufacturing in papermaking [12].

L. N and R. Maranan (2025) propose a cross-attention model for the fusion of heterogeneous sensor data from different sectors of a manufacturing unit, with transfer performed using a Federated learning-based MA approach that operates on gradients rather than raw data. The proposed work was evaluated using numerical and signal-based sensor information from the Smart Manufacturing process dataset and the Gearbox Spectrogram dataset from Kaggle, achieving 89.9% global ACC 5% higher than the conventional method and demonstrating good performance in the latency vs ACC trade-off [13].

A. Lazzaro et al. (2024) focus on the application of PdM technique in order to predict the type of chips produced by a lathe through a machine learning algorithm. Moreover, being application a delay-sensitive one, to drastically decrease the time delay in prediction, solution proposes the combination of PdM with the Edge Computing paradigm. To simulate this paradigm, the chosen machine learning models were deployed on STM microcontrollers obtaining both high ACC (98%) and an inference time in the order of milliseconds [14].

G. A. Sampedro et al. (2023) A residual connection enhances the multi-learning flow process of Multi-Flow BiLSTM, allowing for a more thorough comprehension of patterns in historical data. The results show that the suggested Multi-FlowBiLSTM outperforms the alternatives with a MAE of 2.95 and a R 2value of 0.9121, which is rather good. The suggested predictive maintenance method can guarantee the 3D printers' effective and uninterrupted operation, which in turn increases the manufacturing plant's overall productivity [15].

Y. K. Teoh et al. (2023) use real-time data sets to construct a Predictive Maintenance model using two-class LR. The proposed approach outperformed Minmi, Maximin, FCFS, and Round Robin with respect to Execution Time, cost, and Energy Consumption. Execution Time is 0.48% quicker, cost is 5.43% cheaper, and energy consumption is 28.10% lower compared to the second-best results. On both the training and test sets, the prediction model attains an ACC of 95.1% [16].

TABLE. 1. RECENT STUDIES ON SMART PREDICTIVE MAINTENANCE USING MACHINE LEARNING TECHNIQUES

Author	Methods	Dataset	Results	Limitations & Future Work
M. Ibtihazzaman et al. (2025)	Random Forest and XGBoost with feature extraction and preprocessing for predictive maintenance and failure prognosis	AI4I 2020 Predictive Maintenance Dataset	Random Forest achieved 98.23% accuracy with AUC 0.97, while XGBoost achieved 97.30% accuracy with AUC 0.97	Limited to a single benchmark dataset and offline analysis. Future work can focus on real-time deployment and multi-sensor industrial environments.
L. N, R. Jayashri, and R. M (2025)	ANFIS-LSTM integrated with SAC reinforcement learning for maintenance scheduling	Smart Manufacturing Processing Dataset (Kaggle)	Achieved 93.8% accuracy and 0.92 F1-score, improving performance by 3.5% over conventional methods	High computational complexity and training cost. Future work may include lightweight architectures and adaptive real-time systems.
J. Y. Jo et al. (2025)	Random Forest with explainable AI for predictive alarm generation using RTDB sensor data	RTDB Sensor Data from Papermaking Process	Achieved ROC-AUC of 0.78 and F1-score of 0.62 at a 5-step prediction horizon	Prediction performance decreases for long-term forecasting. Future work can explore hybrid deep learning temporal models.
L. N and R. Maranan (2025)	Federated learning-based cross-attention framework for heterogeneous sensor fusion	Smart Manufacturing Process Dataset and Gearbox Spectrogram Dataset	Achieved 89.9% global accuracy, improving performance by 5% compared to conventional approaches	Communication overhead and latency issues remain. Future work may improve scalability and edge-device optimization.
A. Lazzaro et al. (2024)	Edge computing-based predictive maintenance using machine learning deployed on STM microcontrollers	Industrial Lathe Manufacturing Dataset	Achieved 98% accuracy with inference time in milliseconds	Limited hardware resources and small-scale deployment. Future work can focus on large-scale industrial implementation.
G. A. Sampedro et al. (2023)	Multi-Flow BiLSTM with residual connections for predictive maintenance in additive manufacturing	Additive Manufacturing and FDM 3D Printer Sensor Data	Achieved MAE of 2.95 and R^2 value of 0.9121	Model complexity and computational overhead are high. Future work may improve energy efficiency and real-time deployment.
Y. K. Teoh et al. (2023)	Logistic Regression integrated with GA-based resource management for predictive maintenance in fog computing	Real-Time Industrial Datasets	Achieved 95.1% training accuracy and 94.5% testing accuracy with reduced execution time, cost, and energy usage	Scalability and network dependency issues exist in fog environments. Future work can explore cloud-edge collaborative systems.

Research gaps: A number of knowledge gaps persist in smart manufacturing systems, even if predictive maintenance has made great strides with the help of DL and ML. Current research has been mostly limited to offline analysis, and is not deployable on the industrial level. Moreover, most classical models have limited capability to model the short-term and long-term temporal dependencies found in vibration sensor data. High computational complexity, limited scalability, and insufficient integration of hybrid deep learning frameworks further reduce practical applicability in industrial environments. Therefore, there is a need for an efficient, accurate, and real-time capable hybrid predictive maintenance framework for intelligent fault detection in smart manufacturing systems.

3 RESEARCH METHODOLOGY

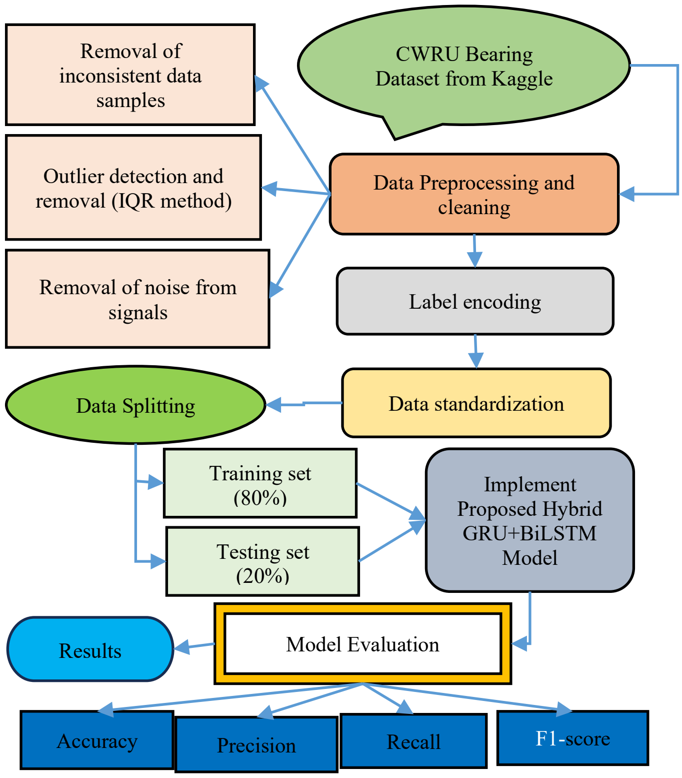

Figure: 1 Proposed flowchart for Smart Predictive Maintenance using machine learning

The proposed methodology uses the CWRU bearing dataset for predictive maintenance and fault classification. Data is cleaned, normalized, labeled, and standardized as part of the pre-processing steps before being split into training and testing sets. The next step is to use a hybrid GRU+BiLSTM DL model to classify the bearing defect. The ACC, PRE, REC, and F1 metrics are used to assess the performance of the DL model. The proposed Smart Predictive Maintenance flowchart is shown in Fig. 1. The whole framework is designed to achieve the efficient learning of features and enhance the ACC of fault prediction in industrial applications.

The suggested framework's individual steps are described in depth in the section that follows:

1.4 Data Gathering and Analysis

The CWRU bearing dataset collected from Kaggle was used for data collection and analysis in this study. Class distribution, feature relationships, and correlation patterns were investigated using data visualization tools such as bar plots and heatmaps, as demonstrated below:.

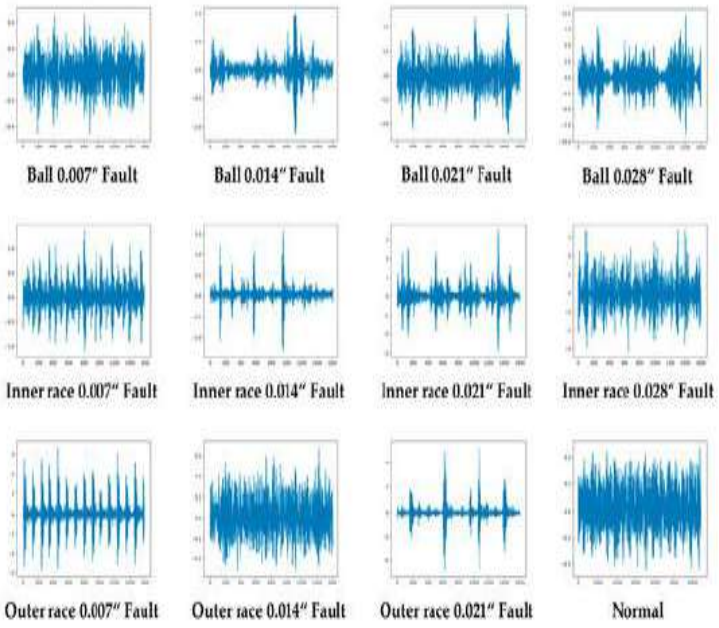
Ball 0.007" Fault
Ball 0.014" Fault
Ball 0.021" Fault
Ball 0.028" Fault
Inner race 0.007" Fault
Inner race 0.014" Fault
Inner race 0.021" Fault
Inner race 0.028" Fault
Outer race 0.007" Fault
Outer race 0.014" Fault
Outer race 0.021" Fault
Normal

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

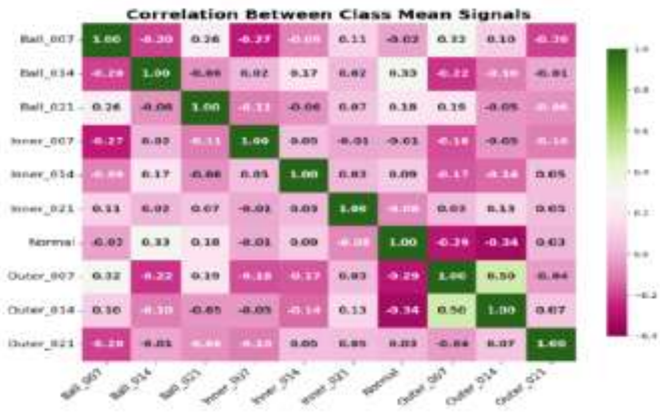

Figure: 3 Correlation Heatmap for Mean Signals

Fig 2 shows vibration sensor data from several bearing problem scenarios, including normal operation, outer race fault, inner race fault, and ball defect. The waveforms generated by the different fault types are very different in behaviour and severity. Fig 3 presents the correlation heatmap illustrates the relationships between different bearing fault conditions and the normal operating state in the dataset. The results for most classes are weak to moderate correlations, which means that each type of fault has a unique pattern of vibrations in the signal, and there are some stronger correlations between certain outer race fault types because they have similar vibration characteristics in the signal.

1.5 Data Pre-processing and Cleaning

Data concatenation, cleaning, labeling, and normalizing are some of the pre-processing steps used to improve the dataset's quality and performance. In order to smooth out the sensor signals, use noise filtering techniques like the MovingAverageFilter and the SavitzkyGolayFilter. Then use the IQR method to find and ignore any outliers. Interpolation, averaging and normalization techniques are used in order to obtain reliable input data for predictive maintenance models for missing and inconsistent values.

1.6 Label Encoding

The Label Encoder function transforms the category class labels into integers. The four possible states of bearing failure are normal operation, inner race fault, outer race fault, and ball fault. These states were formally defined by assigning.

1.7 Data standardization

Data normalization, often called data scaling, is a crucial pre-processing technique utilized in numerous data analysis and DL endeavors. The goal of data standardization in the suggested study is to increase the model's ACC by converting the properties of a dataset into a common scale (between 0 and 1). Equation (1) provides the relationship that is utilized to achieve standardization:

$$z = \frac{x-\mu}{\sigma} \tag{1}$$

where z represents the altered feature value, x stands for the initial feature value for every descriptor, μ is the feature's mean, and σ denotes its Standard Deviation within the dataset.

1.8 Data Splitting

Data splitting is a common technique for model validation; it involves separating a dataset into a training set and a testing set. The dataset is split into sections for testing (20%) and training 80%.

1.9 Proposed Hybrid GRU + BiLSTM Model

This work introduces a DL-based model for optimizing investment portfolios using a GRU and a BiLSTM hybrid. Merging the strengths of GRU and BiLSTM networks, the proposed hybrid model efficiently captures both short-term and long-term relationships in sequential data. The BiLSTM improves context knowledge and prediction ACC through forward and backward processing of the sequence, while GRUs are efficient in computation and ease the vanishing gradient problem. This hybrid method is well-suited if time series patterns are essential, such as time-series forecasting or sequence modeling. Here are the GRU updates: (2-5):

$$z_t = \sigma(W_z x_t + U_z h_{t-1} + b_z) \tag{2}$$

$$r_t = \sigma(W_r x_t + U_r h_{t-1} + b_r) \tag{3}$$

$$\bar{h}_t = tanh(W_h x_t + U_h (r_t \odot h_{t-1}) + b_h) \tag{4}$$

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \bar{h}_t \tag{5}$$

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The hybrid GRU+BiLSTM model performs well in terms of both computational efficiency and predictive power. For this reason it is a good choice for handling sequential data. The GRU component facilitates learning without destroying critical memories, which enhances prediction ACC, and the BiLSTM component keeps the bidirectional dependency. Experimental results show that this architecture is more effective at reducing errors and converging faster than individual GRU or LSTM models.

1.10 Evaluation Metrics

The proposed model has been evaluated using different standard measures derived from the confusion matrix. Each confusion matrix contains the following information: TP, FP, TN and FN classifications. These values are used to calculate key evaluation measures like ACC, PRE, REC and F1 to test the effectiveness of the model:

Accuracy: A measure of how many out of every given number of instances in the dataset (input samples) the trained model correctly forecasted. The formula is as follows: Equation (6)-

$$Accuracy = \frac{\mathrm{TP+TN}}{\mathrm{TP+Fp+TN+FN}} \tag{6}$$

Precision: The PRE measures how many of the model's predictions were correct relative to the total number of forecasts. PRE indicates. The amount of good performance of the classifier in predicting class positive is represented by Equation (7)-

$$Precision = \frac{\mathrm{TP}}{\mathrm{TP+FP}} \tag{7}$$

Recall: the proportion of positive occurrences accurately anticipated relative to the total number of positive occurrences. In mathematical form it is given as Equation (8)-

$$Recall = \frac{\mathrm{TP}}{TP+FN} \tag{8}$$

F1 score: It is a combination of the harmonic mean of PRE and REC, that is, it helps to balance PRE and REC. Its range is [0, 1]. Mathematically, it is given as Equation (9)-

$$F1 - score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{9}$$

A summary of these metrics provides a complete and accurate measure of classification models and therefore demonstrates their performance in predicting various classes.

4 RESULTS AND DISCUSSION

The experimental setup should include information about how the hardware was set up, including the parameters used for training and testing the DL models.

1.11 Experimental Setup

The trials are executed on an HPC system with CPU: Intel Xeon Gold 6148, GPU: NVIDIA Tesla V100, RAM: 256 GB, operating system: Ubuntu 18.04. The proposed DL models are implemented in Python programming language with the help of TensorFlow (TF) 2.4 framework, and accelerated by CUDA 11.0 and cuDNN 8.0. This configuration guarantees effective training of the model and high computational performance.

1.12 Model Evaluation Results

The CWRU bearing dataset was employed to test and train the proposed Hybrid GRU+BiLSTM model. The evaluation results of ACC, PRE, rec and F1 are shown in Table 3. The model has high ACC (99.8%) and high PRE, REC and F1 (99.5%, 99.1%, 99.8%) in fault classification and predictive maintenance, which shows the excellent performance of the model. The outcome shows the effectiveness, reliability and robustness of the proposed model for smart manufacturing applications.

TABLE. 2. EXPERIMENTS RESULTS OF THE PROPOSED MODEL FOR SMART PREDICTIVE MAINTENANCE

Matrix	GRU+BiLSTM Model
Accuracy	99.8
Precision	99.5
Recall	99.1
F1-score	99.8

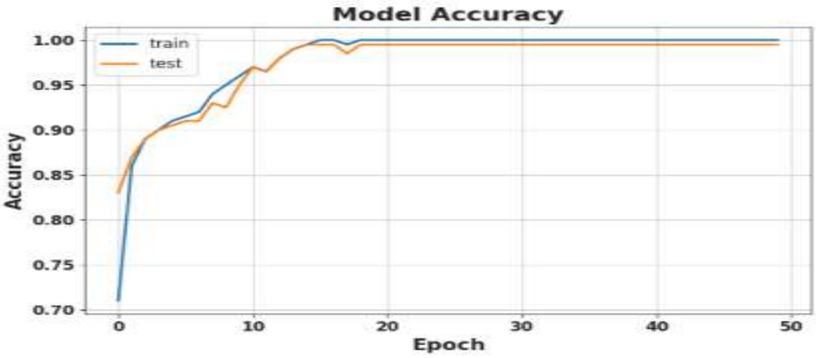

Figure: 4 Training and Testing Accuracy for the Hybrid GRU+BiLSTM Model

Fig. 4 presents the training and testing ACC curves of the proposed Hybrid GRU+BiLSTM model over multiple epochs. The ACC of both training and testing gradually increases and approaches nearly 100%, which means there is a good learning and prediction capacity. The curves are very similar, indicating that the model is not overfitting and has stable performance.

The proposed Hybrid GRU+BiLSTM model's training and testing loss curves spanning multiple epochs are illustrated in Fig. 5. The curves show that learning is stable and the model is optimized effectively, as both curves level off to a minimum loss value. The close proximity between training and testing loss indicates good generalization capability and less overfitting.

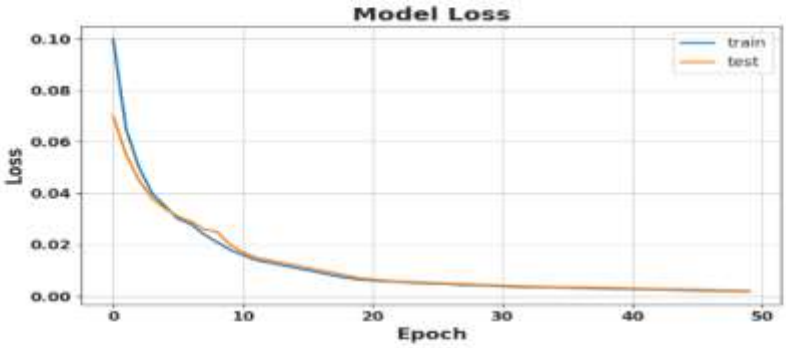

Figure: 5 Training and Testing Loss for the Hybrid GRU+BiLSTM Model

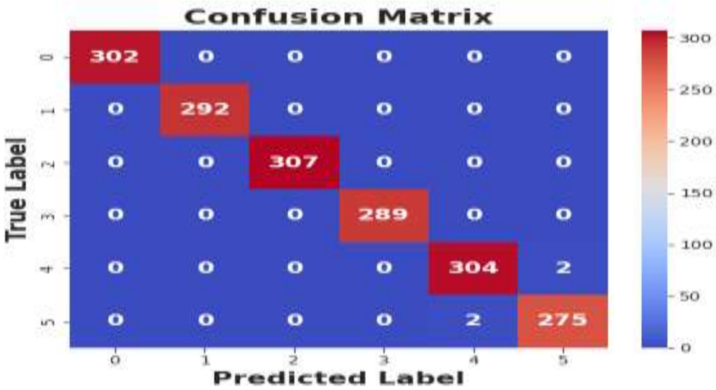

Figure: 6 Confusion Matrix for the Propose Hybrid GRU+BiLSTM Model

Fig. 6 displayed the confusion matrix of the proposed Hybrid GRU+BiLSTM model for Smart Manufacturing. As seen in the matrix, most of the samples are classified correctly with high values on the diagonal elements. The proposed model has shown its robustness and effectiveness in predictive maintenance applications, with only a few samples being misclassified. The results reveal that the Hybrid GRU+BiLSTM model is effective and provides high classification ACC and reliable performance for fault detection.

1.13 Comparative Analysis

For the purpose of examining the effectiveness of the proposed model, a comparative ACC evaluation with other models is provided in Table III. The comparison is made with classifiers like DT, SVM, MLP, KNN and Random Forest, with the dataset of AI4I 2020 of predictive maintenance and the CWRU bearing data set. The highest ACC was obtained for SVM, which was 96.5% for the AI4I 2020 dataset, and RF, which was 98.17% for the CWRU bearing dataset among the dataset models. The proposed Hybrid GRU+BiLSTM model achieved the highest ACC of 99.8%, PRE of 99.5%, REC of 99.1% and F1 of 99.8% when compared to all the existing methods. The results suggest that the CWRU bearing dataset performs better than the AI4I 2020 dataset when predicting bearing failure, and that the proposed hybrid model is highly suitable for smart predictive maintenance applications

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