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Research Paper Open Access

Machine Intelligence Based Health Condition Prediction for Industrial Machinery in Multilevel Fault Environments

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Abstract

Industrial Machinery (IM) has a crucial contribution in current manufacturing processes and industrial production. Continuous condition monitoring is necessary for providing reliability during operations. In addition, it is very important for avoiding sudden malfunctions of machines and reducing maintenance expenses. Despite the fact that predicting the health of machines under different defect conditions is very complicated because of the variability of the defects. Therefore, this paper proposes a machine intelligence (MI)-based system for estimating the health of two specific industrial machines. These machines include the water pump (WP) and milling machines (MM). The proposed framework employs a hybrid MI model by integrating CatBoost (CTB), Decision Tree (DCT), and Naïve Bayes (NIB) to enhance classification performance. The effectiveness of the proposed framework is evaluated against several well-established MI models, including CTB, AdaBoost (ADB), XGBoost (XGB), DCT, Neural Network (NNW), Stochastic Gradient Descent (SGD), Random Forest (RNF), NIB, K-Nearest Neighbour (KNN), and Support Vector Machine (SVM). Experimental evaluation is conducted using both 5-fold cross-validation and 80%:20% training:testing strategies on WP and MM datasets. The performance is assessed using classification accuracy (CAC), F1-score (F1), precision (PRS), and recall (RL). For the MM dataset, the proposed framework achieved CAC, F1, PRS, and RL values of 93.8%, 93.7%, 93.8%, and 93.7%, respectively, using 5-fold cross-validation, which further improved to 95.9%, 95.8%, 95.9%, and 95.9%, respectively, under the 80%:20% training:testing strategy. Similarly, for the WP dataset, the proposed framework obtained CAC, F1, PRS, and RL values of 95.4%, 95.2%, 95.3%, and 95.4%, respectively, using 5-fold cross-validation, and 97.2%, 97.2%, 97.1%, and 97.1%, respectively, under the 80%:20% training:testing strategy. One-way ANOVA further demonstrated statistically significant differences among the competing models for both datasets under the two evaluation protocols (F = 28235.80, 23522.51, 24171.49, and 23199.06, $p < 0.001$), confirming the statistical significance of the proposed framework. Descriptive statistical analysis indicated stable classification performance with low standard deviation across all experimental settings, while the percentage improvement analysis showed that the proposed framework outperformed the second-best model (CTB) by 1.80%–2.29%. Overall, the proposed framework consistently outperformed the competing MI models across all evaluation metrics, demonstrating its effectiveness and reliability for accurate multi-level fault classification, intelligent health condition prediction, and predictive maintenance of industrial machinery. All simulations and experimental analyses are implemented using Python in Jupyter Notebook 7.

Keyword: Industrial Machinery, Machine Intelligence, Predictive Maintenance, Multi-level Fault Diagnosis, Water Pump, Milling Machine, Classification Accuracy, F1-Score, Precision, Recall.

Introduction

Industries have been increasingly using Industrial machines in various processes related to the overall manufacturing process, production and transportation of the goods, and automation of processes [1–25]. The usage of advanced machines has led to improvements with regard to productivity, efficiency of operations, quality of products produced, and precision of manufacturing while decreasing the manual labor and time of production. The list of Industrial machines includes milling machines, lathes, CNC machines, drilling machines, grinding machines, conveyors, hydraulic presses, and irrigation pumps. These machines are widely used in agriculture, automobile production, iron and steel production, construction, heavy machinery production, metallurgy, oil and gas production, chemical industry, aircraft production, paper mills, and others. Agriculture is one of the main application branches of Industrial machines. Tractors, combine harvesters, seeders, sprayers, balers and irrigation pumps are employed in modern agriculture for productivity improvement and decrease of human efforts.

Automation technologies such as robotic harvesting systems, driverless tractors, and drones are being used more and more frequently for precision agriculture, monitoring of crops, and for supervision of the fields [26-35].

Numerous mechanical and electromechanical components are part of industrial manufacturing systems, such as servo motors, servo drives, controllers, piston pumps, proportional valves, hydraulic systems, manifold assemblies, and electrohydrostatic units. Heavy equipment used in the construction sector includes excavators, bulldozers, cranes, loaders, graders, pavers, trenchers, and tunnel boring machines. The above machines usually operate under severe working conditions and can undergo wear and tear as well as suffer from unexpected breakdowns. The same goes for the foundry industry which uses different equipment for molding, casting, melting, pouring, finishing, and handling processes with the need to ensure the feasibility of their operations at all times.

The oil and gas industry is the next one to use industrial manufacturing systems with various equipment operating continuously even under severe working conditions such as drilling machines, compressors, boilers, heat exchangers, pipes, transformers, generators, switchgears, cranes, and transportation vehicles. Besides, chemical industries use technologies such as heat exchangers, centrifugal separators, hot air generators, mixers, reactors, and processing units. The aircraft manufacturing industry is also highly reliant on industrial manufacturing systems as it utilizes computer-managed machining systems to produce components like landing gears, actuators, turbines, structural components, motion control assemblies, and many others [36-40].

The proper functioning of IM is largely dependent on constant testing of a large number of operating parameters collected from various instruments. The instruments are responsible for recording the temperature, pressure, vibrations, torque, acceleration, humidity, rotational speed, displacement, and numerous other physical values. The temperature measuring instruments constantly take temperature readings from the various machine components, while the pressure measuring ones are used in hydraulic and pneumatic systems. Micromechanical sensors take readings of acceleration, vibrations, inclination, and movements, while the torque measuring ones measure the force being created during the operation of the machine [41-45].

In contemporary industrial maintenance practices, continuous monitoring of health conditions has become a key factor. The readings from the sensor devices during the machine operations can help detect all abnormal operating situations before the damages can take place. The received information can be sent via different industrial networks or wireless sensor networks to the systems responsible for processing the information. After the analysis of the received data, the intelligent predicting systems come into play. These systems help in the estimation of machine health and detection of faulty situations based on the analysis of the sensor data received. These predictive forms of maintenance are very useful in reducing unexpected unavailability periods of machines, costs connected with maintenance, along with losses in productivity of manufacturing, while at the same time ensuring the proper functioning of the equipment.

Despite the existence of a number of MI-based approaches for the health monitoring, it is rather difficult to predict the health condition of the different IMs in a multi-fault environment because of the problems posed by the nonlinear behavior of the sensors used in industrial practices, the changing conditions of operation, the class imbalance, as well as the various types of faults.

The main contributions of this work are summarized as follows.

- A MI-based approach is proposed to predict the health condition of IM such as WP and MM under a multi-level fault environment.
- The proposed framework integrates CTB, DCT, and NIB to develop a hybrid prediction model for health condition prediction.
- The proposed model is compared with CTB, ADB, XGB, DCT, NNW, SGD, RNF, NIB, KNN, and SVM.
- Experimental results demonstrate that the proposed method achieves superior performance in terms of CAC, F1, PRS, and RL for both WP and MM datasets.
- Both 80%:20% training:testing and 5-fold cross-validation strategies are employed to validate the robustness of the proposed approach.
- The proposed framework is implemented and evaluated using Python-based Jupyter Notebook 7.

Section 2 to 8 describes related works, IM basic concepts, problem statement, methodology, results and discussion, statistical analysis and conclusion respectively.

2. Related Works

Numerous authors have studied about health condition prediction of IM [1-45]. Arena et al. [1] have discussed about a framework to aid in the selection of the ML algorithm to be used for different predictive maintenance use cases. They have considered supervised as well unsupervised ML algorithms. They have compared various ML algorithms based on their type, advantages, limitations and application/equipment/system applicable to. Then based on the dataset and learning objectives, several decision variables are considered. They have applied their conceptual framework to two use cases and demonstrated the advantages. Arafat et al. [2] have studied about the use of predictive maintenance techniques for improving the accuracy of failure prediction of microgrids. Nowadays, microgrids are being increasingly connected to the overall power system network. Microgrids often utilize renewable energy sources such as solar power and wind power. This makes our electricity generation more sustainable. ML techniques can be used to reduce downtimes and improve safety and overall efficiency of the microgrid. Sherin Elkateb et al. [3] have proposed ML combined with IoT technique to predict the occurrence of failure in a circular knitting machine used in textile industry. Their system comprises of a customized Printed circuit board with a micro-controller with several sensors. They use machine speed sensor and yarn feed sensor. There are also several machine stop detection sensors which sense the way in which the machine stops. The data collected during runtime is stored in a database and analyzed using ADB. Alshboul et al. [4] have proposed a ML technique to proactively identify maintenance needs and reduce downtime of machines used in concrete production. The authors used a dataset of more than 10,000 entries for 66 machines. The dataset contained sensor readings like vibration, heat, ultrasonic and thermal. Thereafter seven ML algorithms are used to analyze the data which are Logistic regression, DCT, artificial NNW, LightGBM, XGB, CTB and RNF.

Xu et al. [5] have proposed a novel health indicator model based on unsupervised learning. They have used NNW to predict remaining useful life of the roller bearing in rotating machinery. They have measured similarity using the Wasserstein distance method. Their proposed model is able to give better prediction results and avoids false alarms compared to similar models proposed in this field. Qin et al. [6] have proposed a supervised auto-encoder for predicting the degradation state of rotating machinery. Vibration sensors are used to capture the vibration signals in the rotating machinery. Experiments are conducted on a wind turbine gearbox bearing dataset and an aero propulsion simulation dataset. The proposed method is found to be superior to existing state of the art models. Lin et al. [7] have studied about the prediction of remaining useful life of rotating machinery. They have considered a CNN model that is pre-trained to recognize the various faults. After that, CNN and GRU are used to build the target network. A specific loss function is also used to transfer the features from source network to target network. An et al. [8] have discussed about the application of ML in healthcare industry. Data collected from the body area network is transferred to the cloud via internet. Thereafter ML algorithms like data mining, classification, prediction, deep learning, NNW are used to remotely monitor the patient's health.

Moshawrab et al. [9] have discussed about the use of federated learning in ML. Organizations do not want to share their data due to data privacy issues. Hence a way to circumvent this problem is to use federated learning. This technique allows the organization to share parameters rather than share their data to train a model. This allows the organizations to maintain data privacy as well contribute to the development of robust ML models. Feng et al. [10] have proposed a GA based system for predicting the health of surface wear of gear of a manufacturing system. The proposed scheme can predict the remaining useful life of the gearbox system. A GRU network is used for predicting the remaining useful life. The developed system is compared with other ML systems like CNN, LSTM and Deep belief networks. It is found that the developed system is superior to other systems. Yan et al. [11] have studied about the health state and remaining useful life of a machine. They have proposed a deep learning model consisting of four modules. A shared module consists of a bidirectional LSTM layer, an encoding layer and sampling layer. MMOE layer, HS layer and RUL layer are the other layers. The MMOE layer is built to identify different information, the HS layer is used to evaluate health state of the machine and RUL layer the remaining useful life of the machine. Soori et al. [12] have studied about the application of ML to predict the tool wear in CNC machines. Deep learning techniques are used to obtain tool wear data. The cutting forces in milling operation are analyzed using ML. Further the cutting power used in CNC machining operations is estimated using ML techniques.

3. Basic Concepts on IM

That is why industrial machines (IM) become an important part of modern manufacturing and industrial systems. Using those types of machines allows the companies to execute complicated, repetitive, and high-load work with better precision, efficiency and reliability when compared to the use of human labor. Consequently, the implementation of industrial machines enables increasing production capacity, decreasing labor costs, improving quality of products and decreasing times of manufacturing.

The use of industrial machines is particularly common in industrial sectors connected with material handling, machining, assembly, transport and automation of processes. Such industrial machines as cranes and forklifts are used for loading and transporting various materials, while machine tools such as milling machines, lathes, drilling machines, grinding machines and CNC machines are responsible for production of accurate units. These machines help to produce complex mechanical parts with the required dimensional accuracy allowing the enterprises to operate in various industries, especially in such sectors where there are strict requirements for quality of processes and products.

There is a reliance on heavy industries on equipment to ensure mass production which comprises iron and steel production, among other processes. Automobile companies' technologies rely on automated assembly lines that apply robotic devices for handling operations such as welding and inspection tasks. The mining sector utilizes various technologies that include excavators and dump trucks to achieve the required efficiency even in harsh climatic conditions. The logistics sector utilizes some technologies in the transportation of raw materials and products.

Most equipment in the manufacturing sector operates constantly under fluctuating loads and environmental conditions. This is the factor that leads to a gradual malfunction of equipment and any unwanted failures. Failure of important parts of the equipment may lead to stopping the production process, increasing the maintenance costs, and putting employees at risk. Therefore, there is a need for constant health monitoring of manufacturing equipment.

4. Problem Statement

Industrial equipment functions in different working environments and experiences numerous fault levels due to its constant working cycle, wear of its components, and changes in load conditions. Accurate prediction of machinery status is important to avoid unexpected faults and high maintenance costs. However, it is difficult to create a good machine health prediction model because real industrial datasets are usually unbalanced and some health conditions are more represented than others, which makes most of the machine learning models biased towards the majority classes. To address this challenge, this work proposes a novel MI-based hybrid framework for predicting the health condition of industrial machinery operating in a multi-level fault environment. The proposed approach is designed to effectively learn from imbalanced datasets and accurately classify different machine health conditions. By improving the discrimination capability among majority and minority classes, the proposed method enhances the prediction performance in terms of CAC, F1, PRS, and RL, thereby providing a reliable solution for industrial health condition monitoring and predictive maintenance.

5. Proposed Methodology

In this section, initially the system model is discussed. The system model provides the abstraction of the system with three important components such as a hypothetical machine, ML-integrated computer system, and output of the prediction. Secondly, the dataset preparation step is presented. After that, the balanced splitting is explained. Then, the proposed fault classifier is explained. At last, the evaluation metrics are discussed.

5.1 Proposed System Model

In this model, a hypothetical machine is considered that is continuously monitored by *n* different sensors (S_1, S_2, ….., S_n) deployed at different components of the machine. These sensors record the component readings in an assigned time intervals. The sensors' readings are supplied to a ML-integrated computer system that continuously gathers the data, and predicts the fault-level of the machine in real-time using a pertained ML model. The sketch of the proposed system model is presented in Fig.

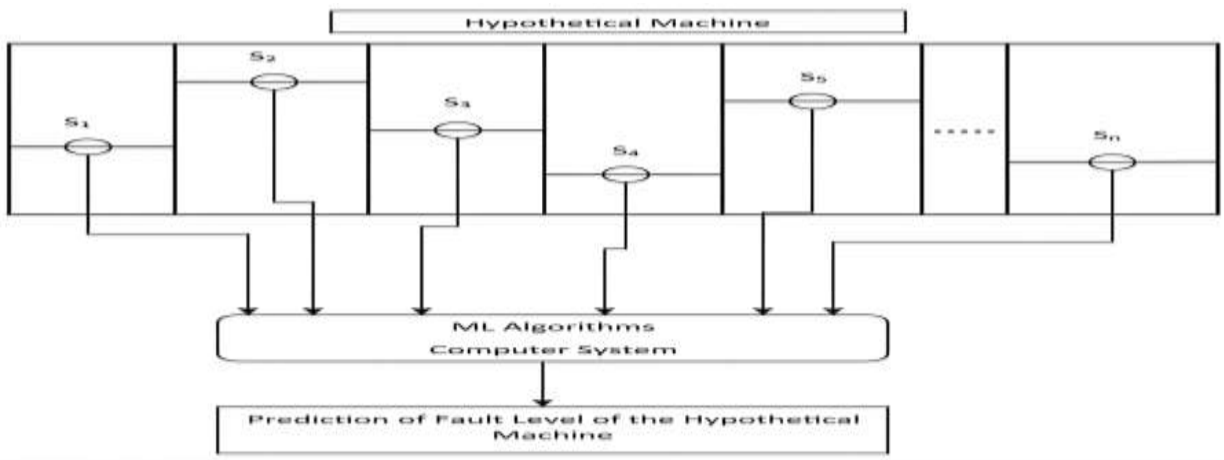

Fig. 1: Proposed System Model

5.2 Dataset Preparation

5.2.1 Dataset acquisition and balancing

Algorithm 1 describes the acquisition of dataset. It explains how the sensor readings can be accumulated to form a dataset. Here, data is collected from n sensors in regular time interval. The dataset is prepared with n attributes (columns) and m readings (rows) using Algorithm 1. D_t is the data point accumulated in time t having all j^{th} attributes i.e., D_{tj} is the reading at time t by j^{th} sensor. The last attribute $D_{t(n+1)}$ is the fault-level assigned to the data point or row D_t.

Algorithm 1: Dataset Acquisition (S, n, F_L)

Input: $S \leftarrow \{\ \}$ //Initially no data present
    n ← Number of sensors
    F_L ← $\{f_1, f_2, ..., f_k\}$ Set of faults
Output: Dataset D

1. $D \leftarrow \{\ \}$
2. for $t \leftarrow 1$ to m (//time)
3. $D_t \leftarrow \{\ \}$
4.   for $j \leftarrow 1$ to n + 1 (//Sensor + Label)
5.   if (j < = n)
6. $D_{tj} \leftarrow D_{tj} \mid S_{tj}$
7.   if (j = = n + 1)
8. $D_{tj} \leftarrow D_{tj} \mid F\_L_t$
9. return D

Step 2 for-loop is meant for time and Step 4 for-loop is the data accumulated in time t by n sensors with classification label information (fault-level) in (n+1) location. The operation '|' is used in Steps 6 and 7 for concatenation of readings to make a row. Step 9 returns the dataset D.

The dataset generated by Algorithm 1 is passed through the Algorithm 2. If the dataset is imbalanced one then it is balanced by Algorithm 2 otherwise the same dataset is retuned by Algorithm 2.

Algorithm 2: Imbalance Data Treatment (D)

Input: D
Output: Balanced Dataset D

1. if D is imbalanced
2.   Apply upsampling to minority class and downsampling to majority class
3. return D

Algorithm 2 describes the process to convert the imbalanced dataset to balanced dataset. If the dataset is imbalanced, resampling method is adopted to make it a balanced one. The resampling method includes both upsampling and downsampling to achieve the same (Step 2).

5.2.2Preparation of train and test sets

We employ two methods: balanced hold out, and balanced k-fold cross validation for preparation of train and test sets.

Balanced hold out

- Decide a ratio of split (x:y) where x% of samples are considered for training and rest y% is used for testing.
- Both the training and testing set contain balanced samples that means must cover all the classes with same number of samples.
- Suppose the balanced dataset D contains t classes and m records then each class will contain m/t records.
- So, x% × |D| /t of each class is given to train set and y% × |D| /t is given to test set.

Balanced k-fold cross validation

- In balanced k-fold method, each fold contains |D| /k samples and each fold has |D| /k ×m number of samples from each class where m is the number of classes.

5.3 Proposed fault classifier

The proposed framework adopts a stacking-based ensemble strategy by combining CTB, DCT, and NIB as the primary learning models, while RNF serves as the meta-classifier for the final prediction of the health status of MM and WP. The overall architecture of the proposed framework is illustrated in Fig. 2. Initially, the input dataset is independently processed by the three base learners (CTB, DCT, and NIB), each of which generates its own prediction based on the learned data patterns. The outputs obtained from these base models are subsequently combined and supplied as input to the RNF meta-classifier. The meta-classifier integrates the complementary strengths of the base learners and produces the final prediction of the IM health condition. The selection of CTB, DCT, and NIB as the base models, together with RNF as the meta-classifier, is intended to improve the overall classification capability by reducing individual model limitations and enhancing predictive robustness. As a result, the proposed stacking framework achieves more accurate and reliable health condition prediction than the individual MI models considered in this study.

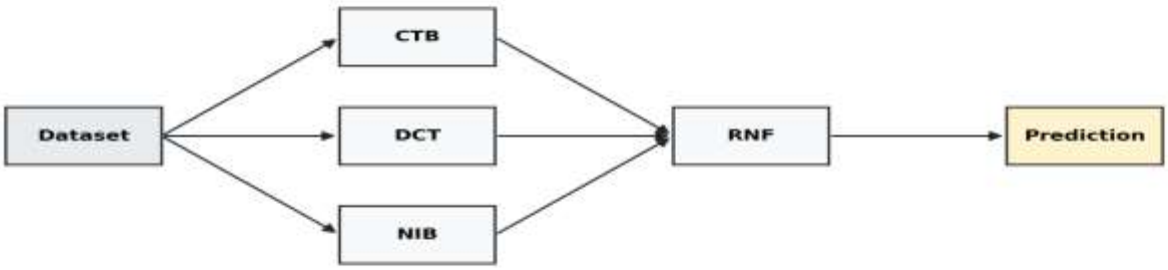

Fig. 2 Proposed Stacking

During the training phase, the dataset is partitioned into k equal folds for cross-validation. For each iteration, the CTB model is trained using k−1 folds, while the remaining fold is used for validation and prediction. This procedure is repeated until every fold has served once as the validation set. After completing the cross-validation process, the CTB model is retrained using the entire training dataset to generate predictions for the test dataset. The same procedure is independently performed for the DCT and NIB models. The prediction outputs obtained from these three base models on the training data are then combined to form a new feature set, which serves as the input to the RNF meta-classifier. Finally, the RNF integrates the information learned from the base models to generate the final prediction of the IM health condition on the test dataset, thereby improving the overall classification performance of the proposed stacking framework.

The proposed stacking method works as follows.

- **Train Base Models**

Suppose there are n different base models such as $MD_1, MD_2, \ldots, MD_n$. Each model is trained on the training dataset DT.

For each base model MD_n, MD_n can be trained using the train data to get the model parameter P_n. For a new input i, the the prediction from MD_n can be $MD_n(i, P_n)$.

- **Generate Predictions for Meta-Model Training**

Cross-validation method can be used to generate predictions from the base models. For each data point i_d, the predictions from the base models can be obtained as $MD_n(i_d, P_n)$. These predictions can be collected into a new dataset D′.

- **Train Meta-Model**

The meta-model MM can be trained on the dataset D′. This model learns to combine the base models' predictions to make the final prediction.

- **Generate Final Predictions**

For a new data point i_{dnew}, the predictions from all base models can be collected. These predictions can be combined using the meta-model to get the final prediction.

5.4 Evaluation Metrics

We use four evaluation metrics to measure the performance of classification models. A comparison among the classification models is presented based on these four metrics: classification accuracy (CAC), F1 score (F1), precision (PRS) and recall (RL).

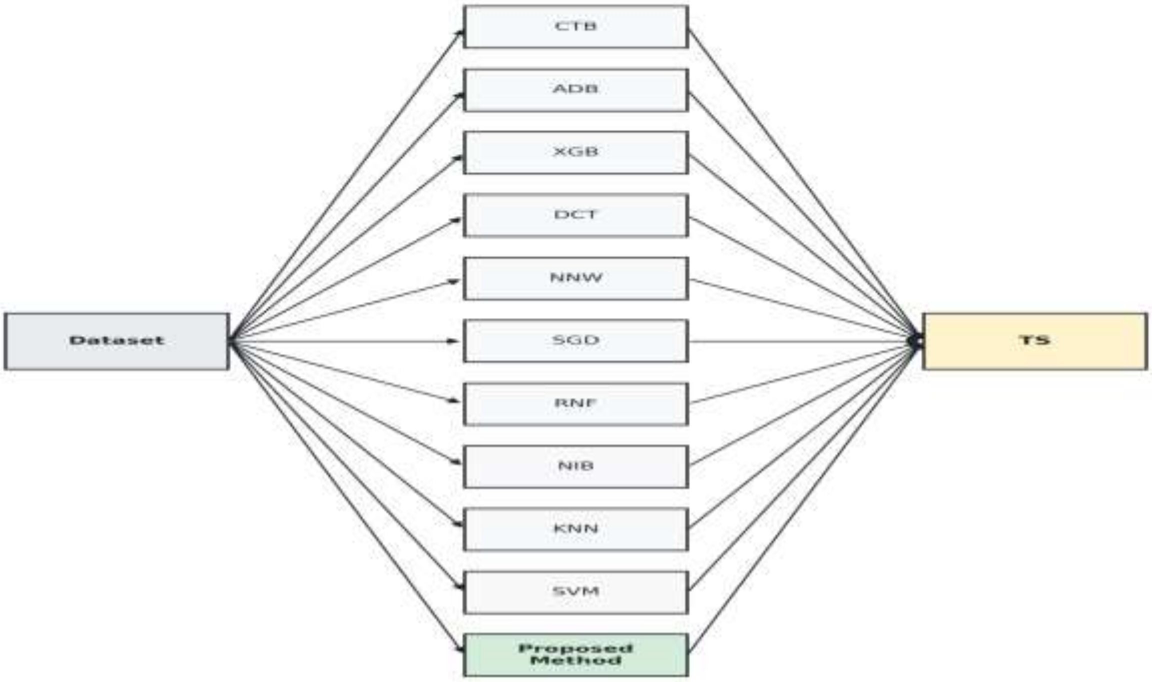

Fig. 3:Methodology

Fig. 3 describes the methodology. Here, the WP and MM dataset are processed using the MI based methods such as CTB, ADB, XGB, DCT, NNW, SGD, RNF, NIB, KNN and SVM and the proposed method which is the hybridization/staking of CTB, DCT and NIB to track the health status of IM using test and score (TS) mechanism. Here, RNF is considered as metal model for final health status prediction of IM. The proposed approach and other methods are compared in terms of CAC, F1, PRS and RL to predict the health codition of IM such as WP and MM.

6. Results and Discussion

The simulation of this work is carried out using Python based Jupyter Notebook 7. This work is focused on the MM and WP datasets taken from the source [46, 47] and [48] respectively. The MM dataset consists of 10000 data points and the WP dataset consists of 10445 WP sensor data with 7, 10000 and 438 numbers of broken, normal, and recovering cases respectively with 52 sensors units. The results of several methods using k-fold cross validation (5-fold cross validation) for MM and WP datasets are mentioned in Table 1 and Table 2 respectively. The results of several methods using 80%:20% training: testing mechanism for MM and WP datasets are mentioned in Table 3 and Table 4 respectively.

Table 1: Results of several methods using k-fold cross validation for MM dataset

Model	Performance Metrics (in %)			
	CAC	F1	PRS	RL
Proposed Method	93.8	93.7	93.8	93.7
CTB	91.7	91.7	91.6	91.6
ADB	88.7	88.6	88.6	88.7
XGB	87.2	87.1	87.1	87.1
DCT	85.3	85.2	85.3	85.2
NNW	83.9	83.8	83.8	83.9
SGD	81.7	81.5	81.5	81.6

RNF	81.2	81.1	81.1	81.1
NIB	80.4	80.4	80.3	80.3
KNN	79.5	79.4	79.4	79.5
SVM	78.4	78.3	78.4	78.3

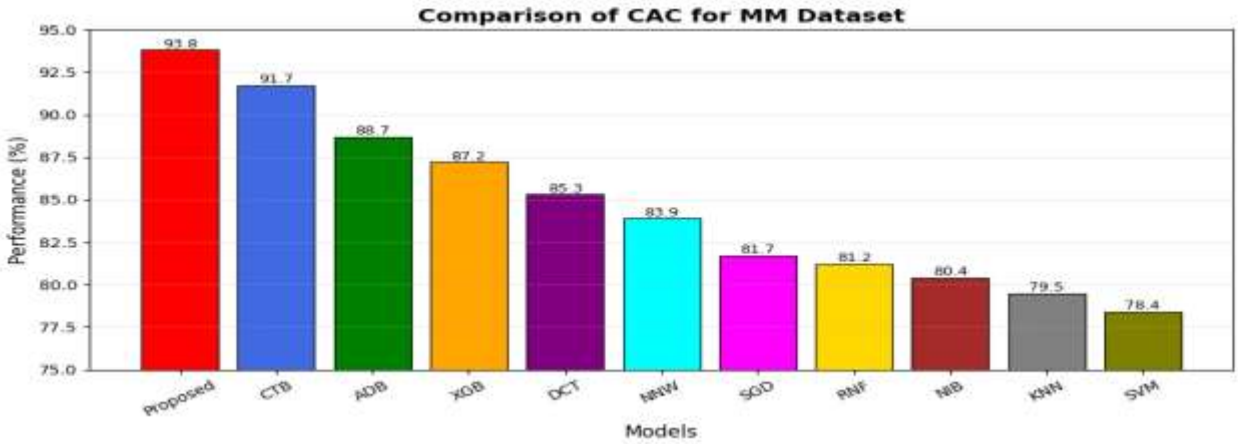

Fig. 4 Results representation in terms of CAC for MM Dataset using k-fold cross validation

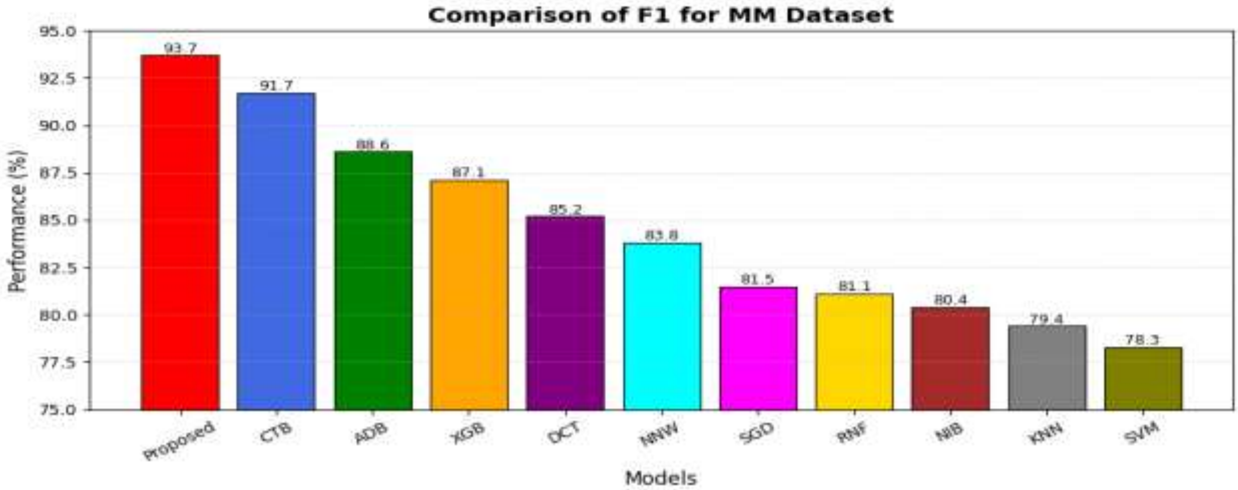

Fig. 5 Results representation in terms of F1 for MM Dataset using k-fold cross validation

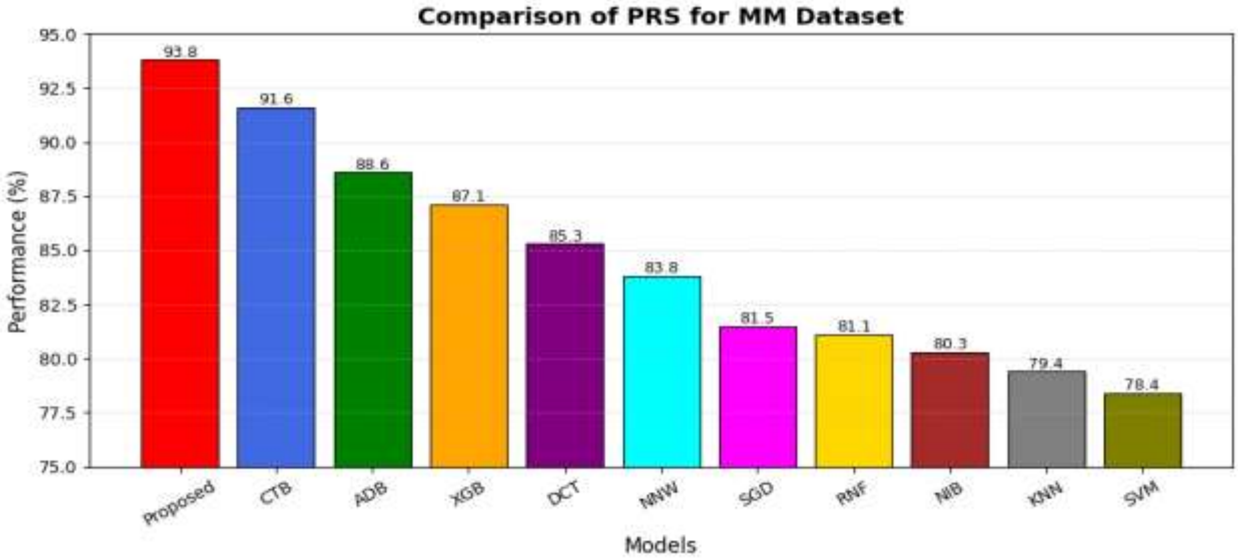

Fig. 6 Results representation in terms of PRS for MM Dataset using k-fold cross validation

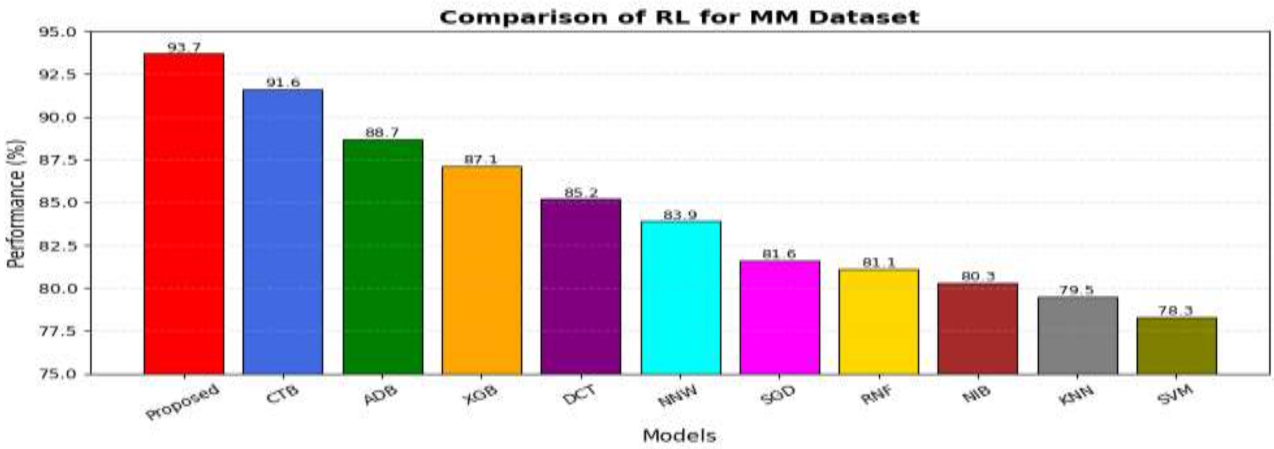

Fig. 7 Results representation in terms of RL for MM Dataset using k-fold cross validation

Table 2: Results of several methods using k-fold cross validation for WP dataset

Model	Performance Metrics (in %)			
	CAC	F1	PRS	RL
Proposed Method	95.4	95.2	95.3	95.4
CTB	93.6	93.6	93.6	93.6
ADB	89.8	89.7	89.7	89.8
XGB	88.4	88.3	88.3	88.2
DCT	86.7	86.6	86.6	86.6
NNW	84.9	84.8	84.8	84.9
SGD	82.6	82.5	82.5	82.6
RNF	82.4	82.3	82.3	82.4
NIB	81.5	81.4	81.3	81.3
KNN	80.6	80.5	80.5	80.5
SVM	79.6	79.4	79.4	79.4

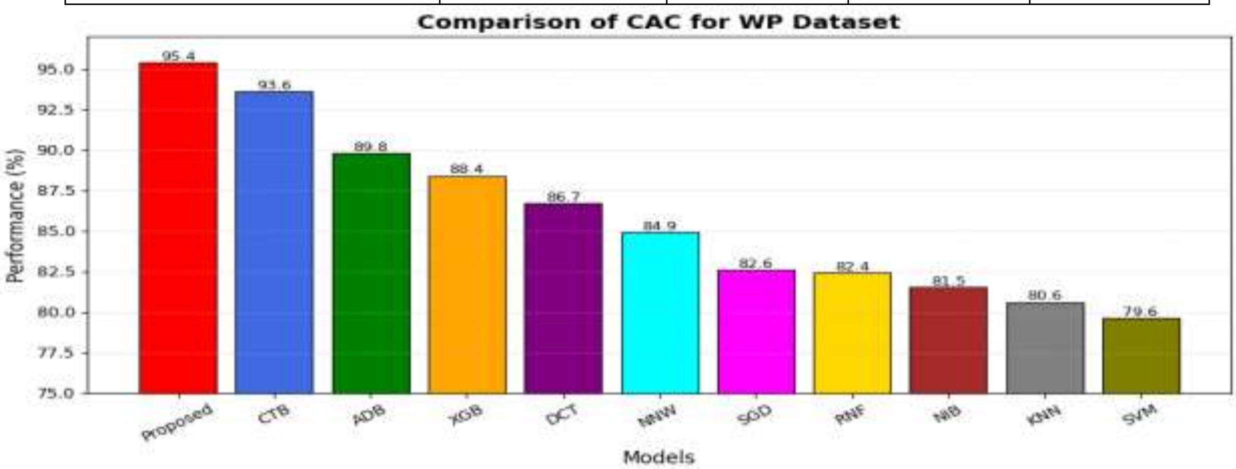

Fig. 8 Results representation in terms of CAC for WP Dataset using k-fold cross validation

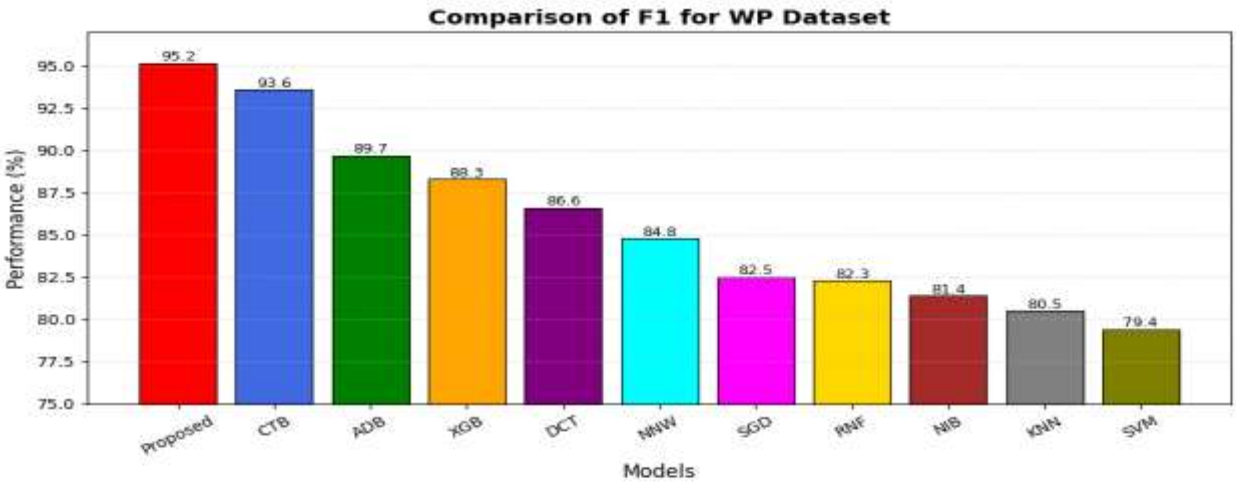

Fig. 9 Results representation in terms of F1 for WP Dataset using k-fold cross validation

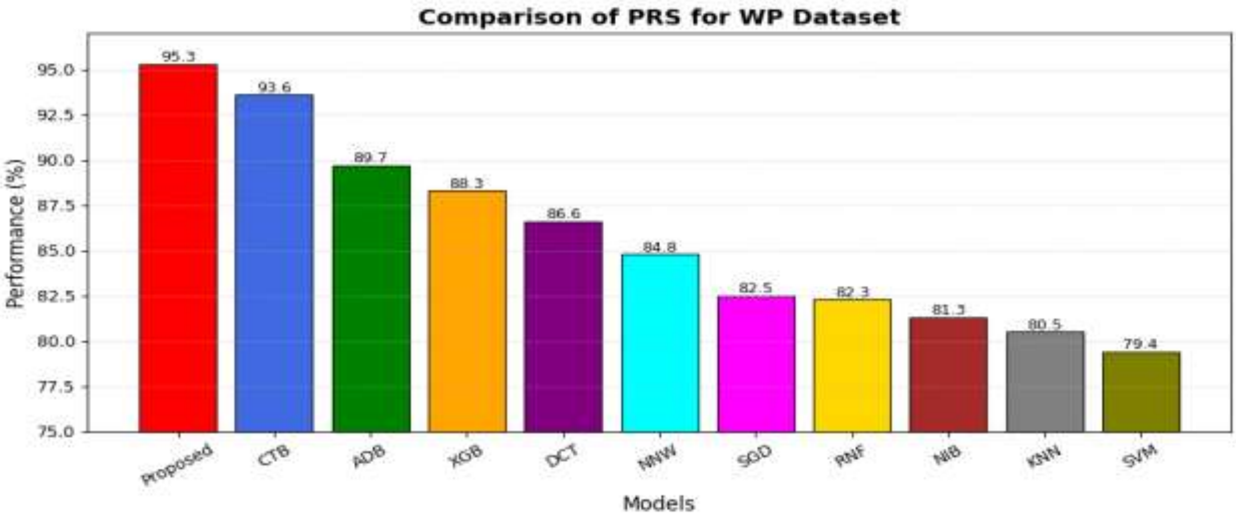

Fig. 10 Results representation in terms of PRS for WP Dataset using k-fold cross validation

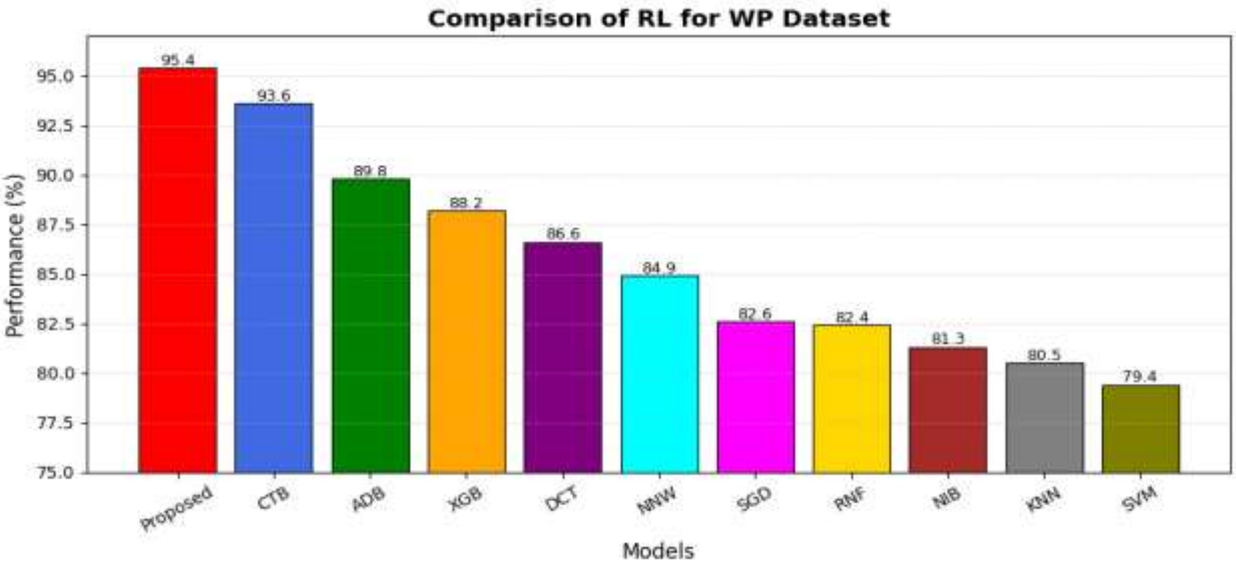

Fig. 11 Results representation in terms of RL for WP Dataset using k-fold cross validation

Table 3: Results of several methods using 80% : 20% Training:Testing for MM dataset

Model	Performance Metrics (in %)			
	CAC	F1	PRS	RL
Proposed Method	95.9	95.8	95.9	95.9
CTB	94.2	94.2	94.1	94.2
ADB	91.2	91.1	91.1	91.1
XGB	90.8	90.8	90.7	90.8
DCT	88.7	88.7	88.6	88.6
NNW	87.9	87.8	87.8	87.9
SGD	85.6	85.6	85.6	85.6
RNF	84.3	84.3	84.2	84.3
NIB	83.7	83.6	83.6	83.5
KNN	82.6	82.5	82.6	82.4
SVM	81.6	81.5	81.4	81.5

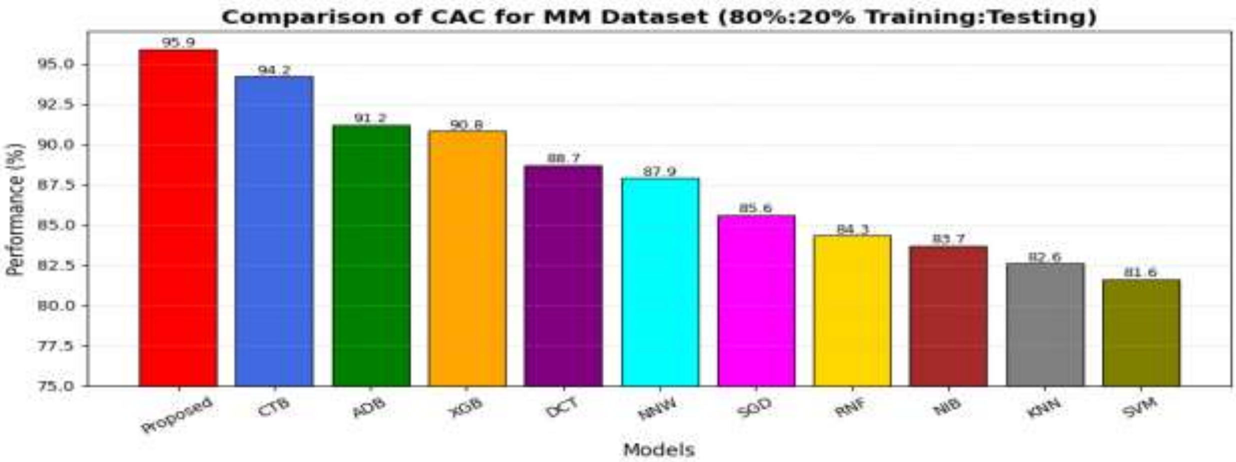

Fig. 12 Results representation in terms of CAC for MM Dataset using 80%:20% training:testing

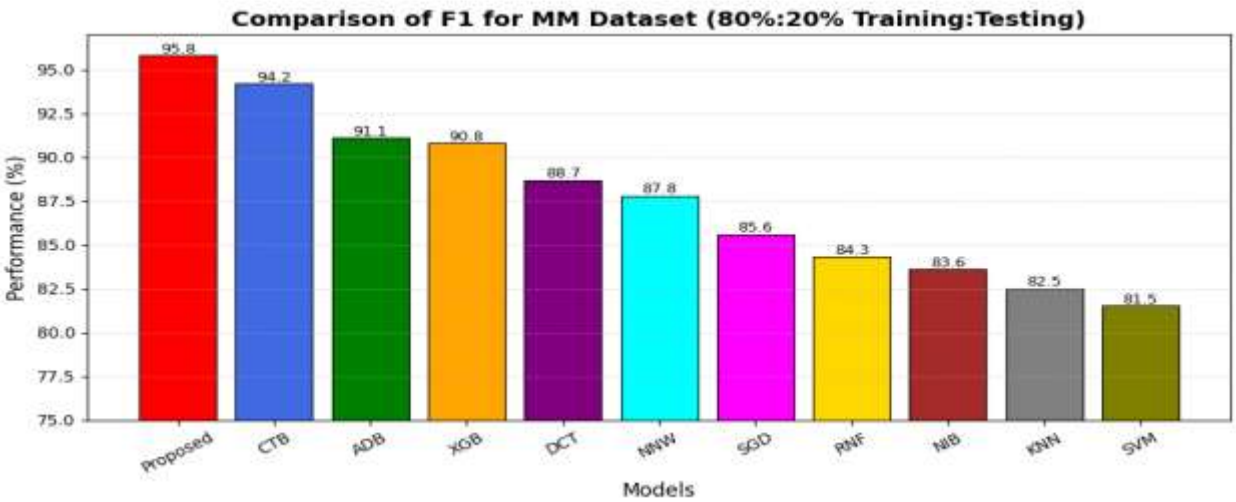

Fig. 13 Results representation in terms of F1 for MM Dataset using 80%:20% training:testing

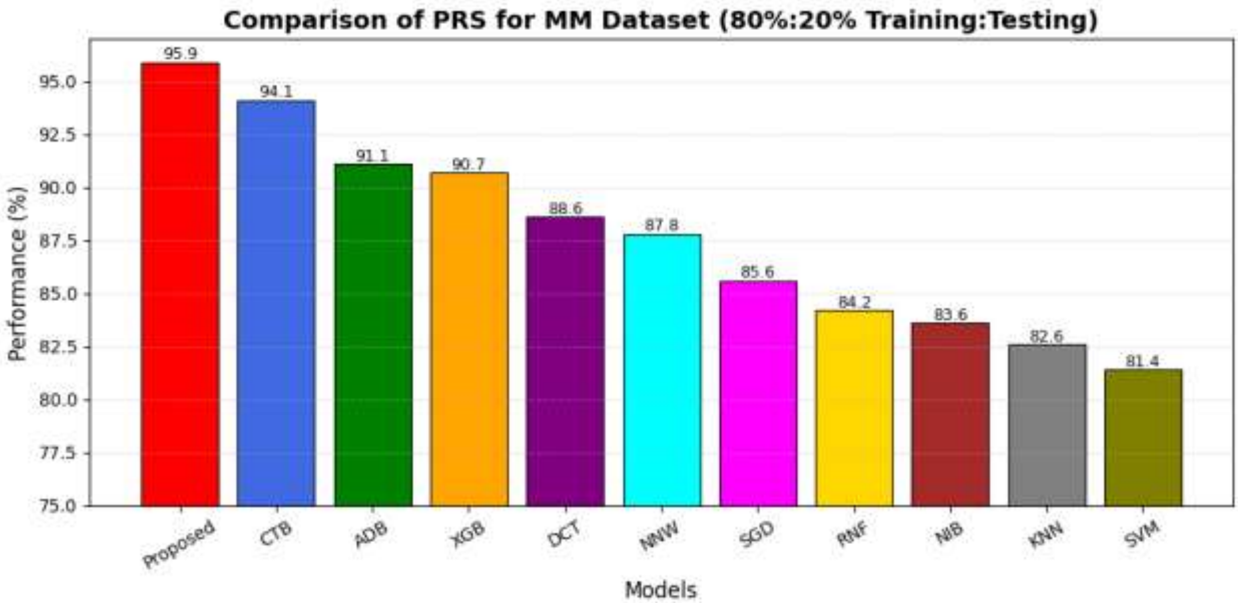

Fig. 14 Results representation in terms of PRS for MM Dataset using 80%:20% training:testing

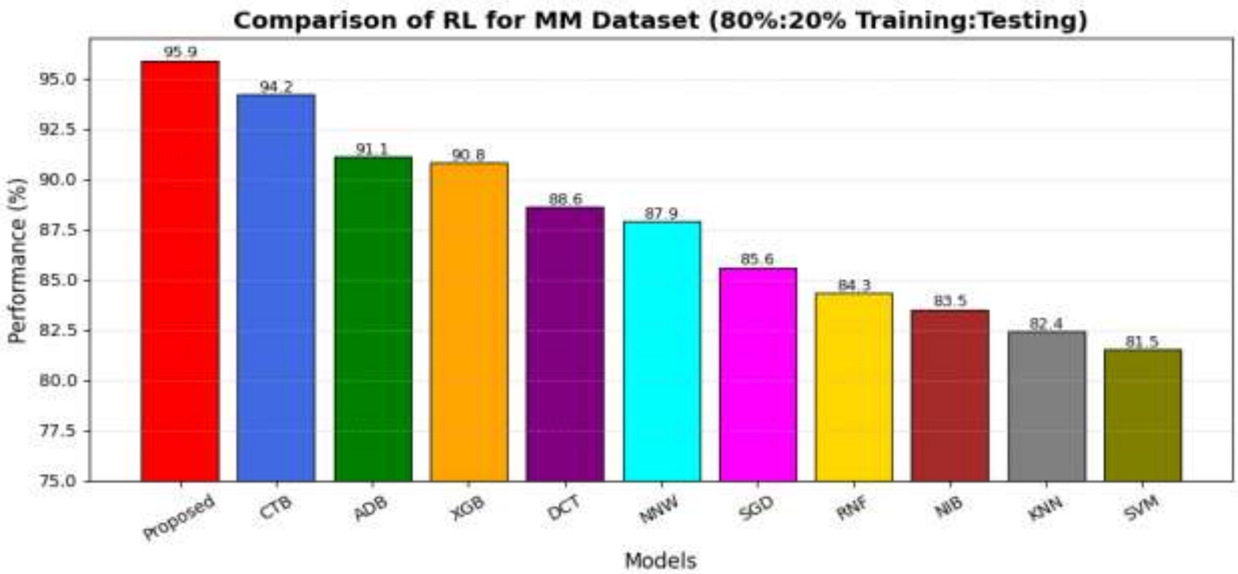

Fig. 15 Results representation in terms of RL for MM Dataset using 80%:20% training:testing

Table 4: Results of several methods using 80% : 20% Training:Testing for WP dataset

Model	Performance Metrics (in %)			
	CAC	F1	PRS	RL
Proposed Method	97.2	97.2	97.1	97.1
CTB	95.3	95.2	95.2	95.3
ADB	92.4	92.4	92.3	92.4
XGB	91.6	91.6	91.6	91.6
DCT	90.7	90.6	90.6	90.6

NNW	89.9	89.8	89.8	89.9
SGD	88.6	88.5	88.5	88.6
RNF	87.3	87.3	87.2	87.3
NIB	86.7	86.6	86.6	86.5
KNN	85.6	85.5	85.5	85.5
SVM	83.5	83.4	83.4	83.4

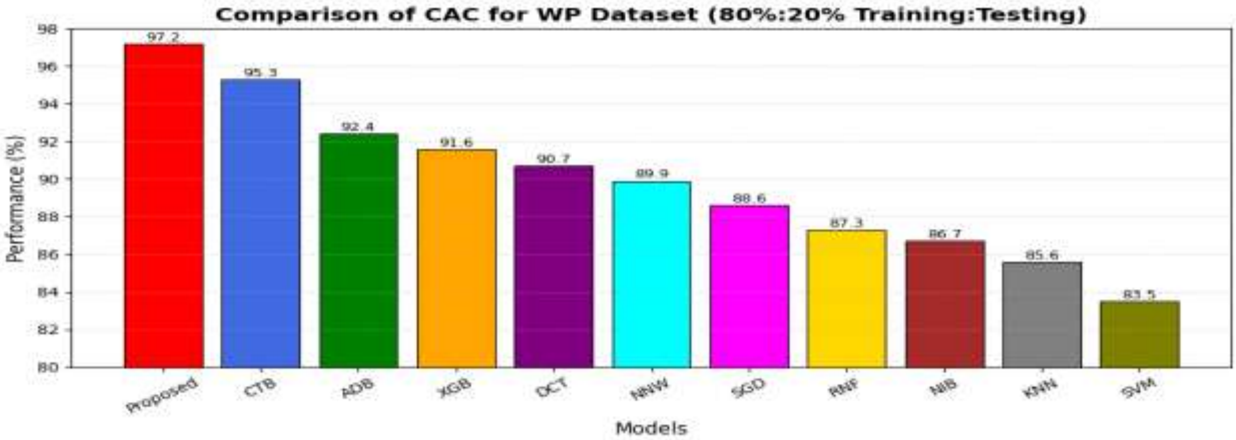

Fig. 16 Results representation in terms of CAC for WP Dataset using 80%:20% training:testing

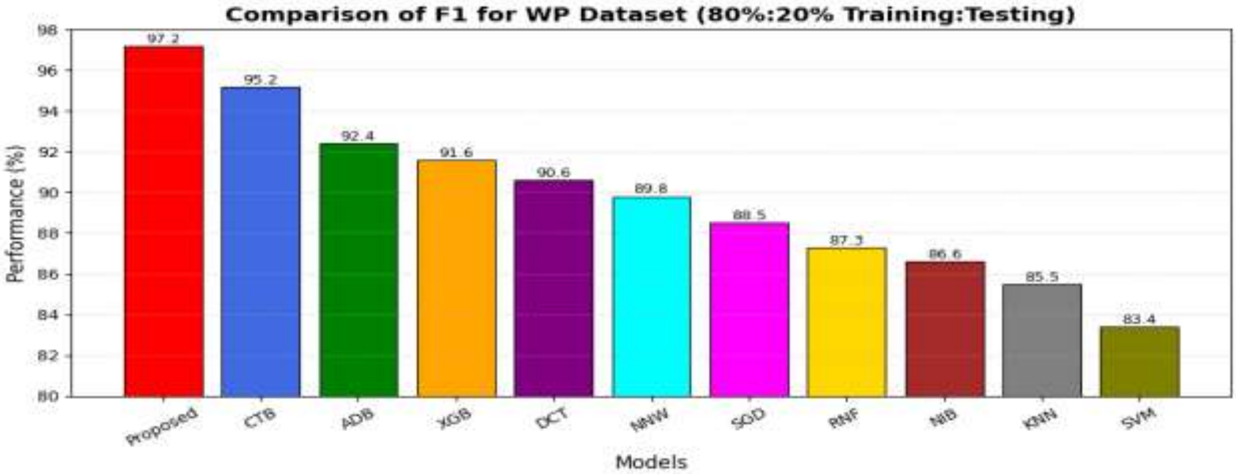

Fig. 17 Results representation in terms of F1 for WP Dataset using 80%:20% training:testing

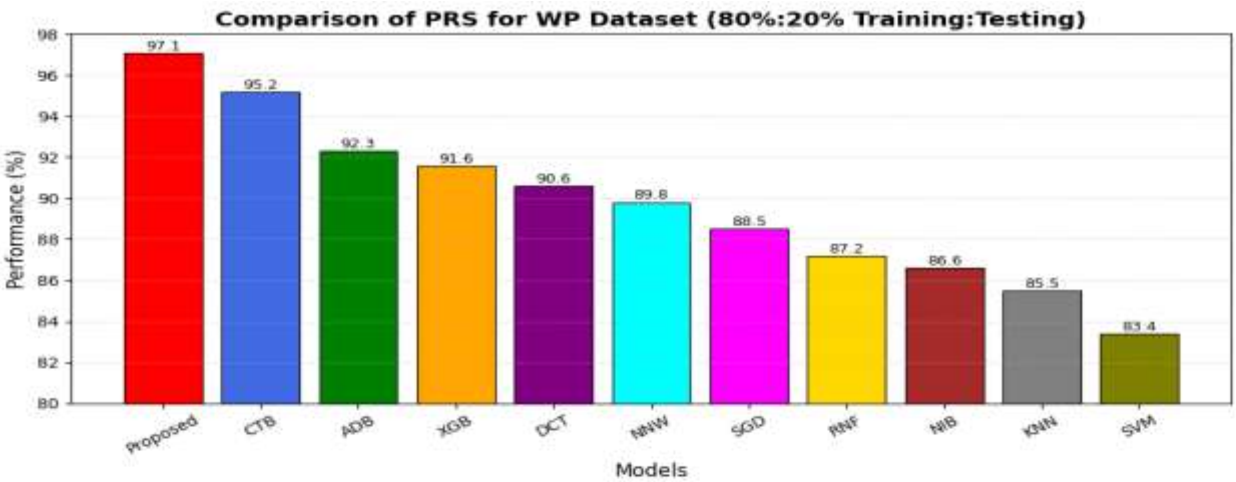

Fig. 18 Results representation in terms of PRS for WP Dataset using 80%:20% training:testing

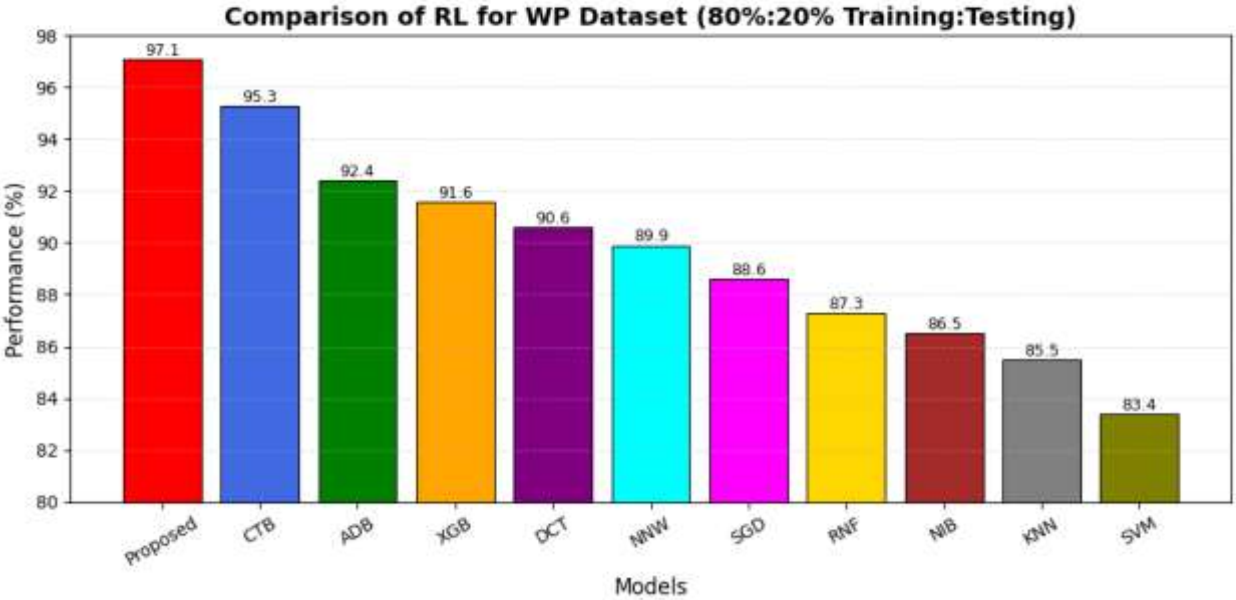

Fig. 19 Results representation in terms of RL for WP Dataset using 80%:20% training:testing

From Tables 1–4 and Fig. 4 - Fig. 19, it is observed that the proposed method consistently outperforms CTB, ADB, XGB, DCT, NNW, SGD, RNF, NIB, KNN, and SVM for the health condition prediction of both MM and WP under different evaluation strategies. The exceptional performance of the method reveals its ability to accurately classify various health conditions while ensuring consistency in prediction results across various validation techniques. In terms of MM data, the proposed method utilizes both the 5-fold cross-validation and 80%:20% training:testing strategies to successfully predict the machine health statuses like HDF, OF, PF, RF, TWF, and NF. The method provides the CAC, F1, PRS, and RL values of 93.8%, 93.7%, 93.8%, and 93.7%, respectively, in the case of the 5-fold cross-validation strategy, while the corresponding performance values obtained through the 80%:20% training:testing strategy amount to 95.9%, 95.8%, 95.9%, and 95.9%, respectively. The findings demonstrate that the technique provides better prediction results as compared to the other models used for comparison, according to all evaluation parameters.

Likewise, applying the proposed method to the WP dataset leads to the prediction of machine health conditions as broken, recovering, and normal. When tested using the 5-fold cross-validation method, the method attained CAC, F1, PRS, and RL scores of 95.4%, 95.2%, 95.3%, and 95.4%, respectively. Testing the method under the 80:20 training:testing method resulted in scores of CAC, F1, PRS, and RL, which are 97.2%, 97.2%, 97.1% and 97.1%. The experimental results showed that the proposed method outperforms CTB, ADB, XGB, DCT, NNW, SGD, RNF, NIB, KNN, and SVM regarding classification.
A comparison between the two evaluation methods shows that the 80:20 method has better results than the 5-fold cross-validation method for both datasets. However, the proposed method still has high CAC, F1, PRS, and RL ratings in both evaluation methods, which proves its sustainability and capability for health condition assessment in multi-fault conditions.

7. Statistical Analysis

7.1 One-Way ANOVA Analysis

Table 5. One-Way ANOVA for MM Dataset (k-fold Cross Validation)

Source	F-value	p-value	Significance
Between Models	28235.80	<0.001	Significant

The one-way Analysis of Variance (ANOVA) has been applied to the results of prediction models that are developed for the MM dataset based on the data gotten from k-fold cross validation, and its results can be found in Table 5. The test results show F-value of 28235.80 which has p < 0.001 that means the differences in performance of the examined models are statistically significant. Therefore, the null hypothesis which states that the performance of the examined models is equal has been denied. The proposed method has consistently attained the highest performance metrics for CAC, F1, Precision, and Recall. Thus, it can be concluded that the superiority of the suggested method is statistically grounded and cannot be attributed to random variation.

Table 6. One-Way ANOVA for WP Dataset (k-fold Cross Validation)

Source	F-value	p-value	Significance
Between Models	23522.51	<0.001	Significant

For the WP dataset, the ANOVA also demonstrates a statistically significant difference among all evaluated models (F = 23522.51, p < 0.001) as mentioned in Table 6. The proposed method significantly outperforms CTB, ADB, XGB, DCT, NNW, SGD, RNF, NIB, KNN, and SVM. Hence, the proposed approach exhibits superior predictive capability under k-fold cross validation.

Table 7. One-Way ANOVA for 80:20 Train-Test Evaluation

Dataset	F-value	p-value	Significance
MM Dataset	24171.49	<0.001	Significant
WP Dataset	23199.06	<0.001	Significant

The ANOVA results for the 80:20 train-test experiments further validate the effectiveness of the proposed method. Both datasets exhibit extremely high F-values with p < 0.001 as mentioned in Table 7, indicating statistically significant performance differences among the compared models. These findings confirm that the proposed method maintains its superiority irrespective of the evaluation protocol.

7.2. Descriptive Statistics

Table 8. Descriptive Statistics of Average Performance (%)

Dataset	Mean	Standard Deviation	Maximum	Minimum
MM (k-fold)	85.26	5.16	93.75	78.35
WP (k-fold)	87.10	5.33	95.33	79.45
MM (80:20)	88.10	4.80	95.88	81.50
WP (80:20)	89.91	4.39	97.15	83.43

Table 8 demonstrates the statistical measures reveal that prediction performance improves consistently from MM dataset to the WP dataset and from k-fold validation to 80:20 train-test evaluations. The suggested approach performs well with consistent average performance throughout the experimentation, while the low standard deviation of the proposed technique shows that the classification performance is consistent and reliable.

7.3. Percentage Improvement Analysis

Table 9. Improvement of Proposed Method over the Second-Best Model (CTB)

Dataset	Proposed (%)	CTB (%)	Improvement (%)
MM (k-fold)	93.75	91.65	2.29

WP (k-fold)	95.33	93.60	1.85
MM (80:20)	95.88	94.18	1.80
WP (80:20)	97.15	95.25	1.99

This technique is better than CTB by constant margin in all evaluation scenarios which is shown in Table 9. The improvement in the proposed approach is between 1.80% and 2.29%, which indicates that the framework performs better in terms of prediction accuracy while still improving its F1 score, precision, and recall. This shows that the approach is getting more and more reliable and generalizable in different datasets and validation techniques.

8. Conclusion

This work presented a MI-based approach for predicting the health condition of IM, including WP and MM, in a multi-level fault environment. The proposed method is based on the hybridization of CTB, DCT, and NIB, and its performance is evaluated against CTB, ADB, XGB, DCT, NNW, SGD, RNF, NIB, KNN, and SVM using both 5-fold cross validation and 80%:20% training:testing mechanisms. For the MM dataset, the proposed method achieved CAC, F1, PRS, and RL values of 93.8%, 93.7%, 93.8%, and 93.7%, respectively, using 5-fold cross validation, which further improved to 95.9%, 95.8%, 95.9%, and 95.9%, respectively, using the 80%:20% training:testing mechanism. Similarly, for the WP dataset, the proposed method achieved CAC, F1, PRS, and RL values of 95.4%, 95.2%, 95.3%, and 95.4%, respectively, using 5-fold cross validation, while the corresponding values increased to 97.2%, 97.2%, 97.1%, and 97.1%, respectively, using the 80%:20% training:testing mechanism. These results demonstrate the consistent superiority of the proposed method over all benchmark models across both datasets and evaluation strategies. The statistical analyses further validated the effectiveness and robustness of the proposed method. The one-way ANOVA results revealed statistically significant differences among the competing models for both MM and WP datasets under 5-fold cross validation ($F = 28235.80$ and 23522.51, respectively; $p < 0.001$) as well as under the 80%:20% training:testing mechanism ($F = 24171.49$ and 23199.06, respectively; $p < 0.001$), confirming that the observed performance improvements are statistically significant rather than due to random variation. Furthermore, the descriptive statistical analysis showed stable classification performance with mean values of 85.26%, 87.10%, 88.10%, and 89.91% for the MM (k-fold), WP (k-fold), MM (80:20), and WP (80:20) datasets, respectively, together with SD values ranging from 4.39 to 5.33, indicating reliable and consistent model performance. The percentage improvement analysis further demonstrated that the proposed method outperformed the second-best model (CTB) by 2.29%, 1.85%, 1.80%, and 1.99% for the MM (k-fold), WP (k-fold), MM (80:20), and WP (80:20) datasets, respectively, highlighting its superior predictive capability and generalization performance. In conclusion, the MI-based framework that has been suggested is an efficient, accurate, and highly reliable solution for the multi-level fault prediction and smart health condition monitoring of induction motors. Future research will be aimed at improving and extending the framework that has been put forward through the introduction of more advanced ensemble and deep learning algorithms, larger and more varied datasets, and real-time IIoT-enabled predictive maintenance systems.

References

1. Arena, S., Florian, E., Sgarbossa, F., Sølvsberg, E., & Zennaro, I. (2024). A conceptual framework for machine learning algorithm selection for predictive maintenance. Engineering Applications of Artificial Intelligence, 133, 108340.
2. Arafat, M. Y., Hossain, M. J., & Alam, M. M. (2024). Machine learning scopes on microgrid predictive maintenance: Potential frameworks, challenges, and prospects. Renewable and Sustainable Energy Reviews, 190, 114088.
3. Elkateb, S., Métwalli, A., Shendy, A., & Abu-Elanien, A. E. (2024). Machine learning and IoT–Based predictive maintenance approach for industrial applications. Alexandria Engineering Journal, 88, 298-309.
4. Alshboul, O., Al Mamlook, R. E., Shehadeh, A., & Munir, T. (2024). Empirical exploration of predictive maintenance in concrete manufacturing: Harnessing machine learning for enhanced equipment reliability in construction project management. Computers & Industrial Engineering, 190, 110046.
5. Xu, Z., Bashir, M., Liu, Q., Miao, Z., Wang, X., Wang, J., & Ekere, N. (2023). A novel health indicator for intelligent prediction of rolling bearing remaining useful life based on unsupervised learning model. Computers & Industrial Engineering, 176, 108999.
6. Qin, Y., Yang, J., Zhou, J., Pu, H., & Mao, Y. (2023). A new supervised multi-head self-attention autoencoder for health indicator construction and similarity-based machinery RUL prediction. Advanced engineering informatics, 56, 101973.
7. Lin, T., Wang, H., Guo, X., Wang, P., & Song, L. (2023). A novel prediction network for remaining useful life of rotating machinery. The International Journal of Advanced Manufacturing Technology, 124(11), 4009-4018.

8. An, Q., Rahman, S., Zhou, J., & Kang, J. J. (2023). A comprehensive review on machine learning in healthcare industry: classification, restrictions, opportunities and challenges. Sensors, 23(9), 4178.
9. Moshawrab, M., Adda, M., Bouzouane, A., Ibrahim, H., & Raad, A. (2023). Reviewing federated machine learning and its use in diseases prediction. Sensors, 23(4), 2112.
10. Feng, K., Ji, J. C., Ni, Q., Li, Y., Mao, W., & Liu, L. (2023). A novel vibration-based prognostic scheme for gear health management in surface wear progression of the intelligent manufacturing system. Wear, 522, 204697.
11. Yan, J., He, Z., & He, S. (2023). Multitask learning of health state assessment and remaining useful life prediction for sensor-equipped machines. Reliability Engineering & System Safety, 234, 109141.
12. Soori, M., Arezoo, B., & Dastres, R. (2023). Machine learning and artificial intelligence in CNC machine tools, a review. Sustainable Manufacturing and Service Economics, 2, 100009.
13. Bajaj, N. S., Patange, A. D., Jegadeeshwaran, R., Pardeshi, S. S., Kulkarni, K. A., & Ghatpande, R. S. (2023). Application of metaheuristic optimization based support vector machine for milling cutter health monitoring. Intelligent Systems with Applications, 18, 200196.
14. Ejlali, M., Arian, E., Taghiyeh, S., Chambers, K., Sadeghi, A. H., Taghiye, E., ... & Handfield, R. B. (2024). Developing hybrid machine learning models to assign health score to railcar fleets for optimal decision making. Expert Systems with Applications, 250, 123931.
15. Zheng, Z., Wang, F., Gong, G., Yang, H., & Han, D. (2023). Intelligent technologies for construction machinery using data-driven methods. Automation in Construction, 147, 104711.
16. Ruiz-Sarmiento, J. R., Monroy, J., Moreno, F. A., Galindo, C., Bonelo, J. M., & Gonzalez-Jimenez, J. (2020). A predictive model for the maintenance of industrial machinery in the context of industry 4.0. Engineering Applications of Artificial Intelligence, 87, 103289.
17. Rosati, R., Romeo, L., Cecchini, G., Tonetto, F., Viti, P., Mancini, A., & Frontoni, E. (2023). From knowledge-based to big data analytic model: a novel IoT and machine learning based decision support system for predictive maintenance in Industry 4.0. Journal of intelligent manufacturing, 34(1), 107-121.
18. Zhang, W., Li, X., Ma, H., Luo, Z., & Li, X. (2021). Federated learning for machinery fault diagnosis with dynamic validation and self-supervision. Knowledge-Based Systems, 213, 106679.
19. Huang, J., Zhan, J., Wang, Q., Jia, J., & Zhang, B. (2026, March). Stable fault diagnosis under data imbalance via self-supervised learning in industrial IoT. In 2026 5th International Conference on Electronics Technology and Artificial Intelligence (ETAI) (pp. 424-429). IEEE.
20. Achouch, M., Dimitrova, M., Dhouib, R., Ibrahim, H., Adda, M., Sattarpanah Karganroudi, S., ... & Aminzadeh, A. (2023). Predictive maintenance and fault monitoring enabled by machine learning: experimental analysis of a TA-48 multistage centrifugal plant compressor. Applied Sciences, 13(3), 1790.
21. Azari, M. S., Flammini, F., Santini, S., & Caporuscio, M. (2023). A systematic literature review on transfer learning for predictive maintenance in industry 4.0. IEEE access, 11, 12887-12910.
22. Ghasemkhani, B., Aktas, O., & Birant, D. (2023). Balanced k-star: An explainable machine learning method for internet-of-things-enabled predictive maintenance in manufacturing. Machines, 11(3), 322.
23. Le-Nguyen, M. H., Turgis, F., Fayemi, P. E., & Bifet, A. (2023). Exploring the potentials of online machine learning for predictive maintenance: a case study in the railway industry: M.-H. Le-Nguyen et al. Applied Intelligence, 53(24), 29758-29780.
24. Winkel, F., Deuse-Kleinsteuber, J., & Böcker, J. (2023). Run-to-failure relay dataset for predictive maintenance research with machine learning. IEEE Transactions on Reliability, 73(1), 101-114.
25. Mohammed, N. A., Abdulateef, O. F., & Hamad, A. H. (2023). An IoT and machine learning-based predictive maintenance system for electrical motors. Journal Européen des Systèmes Automatisés, 56(4), 651.
26. Xu, Y., He, D., Jin, Z., Sun, H., Zhang, X., Zhang, S., & Fu, Y. (2026). A fault diagnosis method for ship motors based on a multi-source data three-level fusion strategy. Ocean Engineering, 358, 125758.
27. Chang, Y., Chen, J., Lv, H., & Liu, S. (2022). Heterogeneous bi-directional recurrent neural network combining fusion health indicator for predictive analytics of rotating machinery. ISA transactions, 122, 409-423.
28. Xie, Y., Mei, S., Wang, F., & Zhang, C. (2026). A multi-level multi-source digital twin model for performance enhancement and optimization decision-making in precision milling machines. Journal of Industrial Information Integration, 101080.
29. Geng, Z., Zhou, S., Ren, Z., Yu, T., Dong, F., & Wang, X. (2026). A novel information fusion fault diagnosis framework for rotating machinery based on pixelated sdp and multi-level fusion network. Journal of Vibration Engineering & Technologies, 14(1), 43.
30. Zabin, M., Choi, H. J., & Uddin, J. (2023). Hybrid deep transfer learning architecture for industrial fault diagnosis using Hilbert transform and DCNN–LSTM: M. Zabin et al. The Journal of supercomputing, 79(5), 5181-5200.
31. Lv, J. Q., Xu, J. M., He, W. K., Wang, H. C., Liang, C. G., Cheng, Z. R., ... & Cheng, H. Y. (2026). Machine learning-driven prediction and control system for practical application of sulfur-based autotrophic denitrification biofilters. Water Research, 126302.

32. Jia, Y., Yao, D., Yang, J., Jia, L., Zhou, T., & Long, Q. (2026). A multi-scale wavelet and spectral kurtosis-guided framework for noise-resistant rolling bearing fault diagnosis. Mechanical Systems and Signal Processing, 242, 113662.
33. Zhong, D., Xia, Z., Zhu, Y., & Duan, J. (2023). Overview of predictive maintenance based on digital twin technology. Heliyon, 9(4).
34. Liao, R., He, Y., Feng, T., Yang, X., Dai, W., & Zhang, W. (2023). Mission reliability-driven risk-based predictive maintenance approach of multistate manufacturing system. Reliability Engineering & System Safety, 236, 109273.
35. Han, P., Liu, Z., He, X., Ding, S. X., & Zhou, D. (2025). Multi-condition fault diagnosis of dynamic systems: A survey, insights, and prospects. IEEE Transactions on Automation Science and Engineering, 22, 15728-15744.
36. Chakroun, A., Hani, Y., Elmhamedi, A., & Masmoudi, F. (2024). A predictive maintenance model for health assessment of an assembly robot based on machine learning in the context of smart plant. Journal of Intelligent Manufacturing, 35(8), 3995-4013.
37. Sharma, S., Ivy, B. P. U., Uppal, M., Mapari, S., & Gupta, D. (2026, January). Enhancing Fault Detection in Wireless Sensor Networks using Digital Twin and Predictive Maintenance. In 2026 International Conference on AI-Driven Smart Systems and Ubiquitous Computing (ICAUC) (pp. 581-585). IEEE.
38. Pei, X., Gao, Y., Li, X., Gao, L., & Zhao, X. (2025). Multilevel feature alignment method for advancing remaining useful life prediction of rolling bearing. IEEE Internet of Things Journal, 12(12), 22023-22035.
39. Sobhi, S., Reshadi, M., Zarft, N., Terheide, A., & Dick, S. (2023). Condition monitoring and fault detection in small induction motors using machine learning algorithms. Information, 14(6), 329.
40. Khaleel, M., ŞİMŞİR, M., Yusupov, Z., Yasser, N., Elkhozondar, H., & Ahmed, A. A. (2023). The role of fault detection and diagnosis in induction motors. Int. J. Electr. Eng. Sustain., 1(1), 31-40.
41. Borré, A., Seman, L. O., Camponogara, E., Stefenon, S. F., Mariani, V. C., & Coelho, L. D. S. (2023). Machine fault detection using a hybrid CNN-LSTM attention-based model. Sensors, 23(9), 4512.
42. Abdallah, M., Joung, B. G., Lee, W. J., Mousoulis, C., Raghunathan, N., Shakouri, A., ... & Bagchi, S. (2023). Anomaly detection and inter-sensor transfer learning on smart manufacturing datasets. Sensors, 23(1), 486.
43. Lin, Q., Zhou, X., Hong, W., & Wang, K. (2025). A comprehensive survey of multi-view intelligent fault diagnosis tailored to the sensor, machinery equipment, and industrial system faults. Journal of Vibration Engineering & Technologies, 13(5), 335.
44. Van Oudenhoven, B., Van de Calseyde, P., Basten, R., & Demerouti, E. (2023). Predictive maintenance for industry 5.0: behavioural inquiries from a work system perspective. International Journal of Production Research, 61(22), 7846-7865.
45. Pimenov, D. Y., Bustillo, A., Wojciechowski, S., Sharma, V. S., Gupta, M. K., & Kuntoğlu, M. (2023). Artificial intelligence systems for tool condition monitoring in machining: analysis and critical review. Journal of Intelligent Manufacturing, 34(5), 2079-2121.
46. https://www.kaggle.com/datasets/shivamb/machine-predictive-maintenance-classification
47. https://archive.ics.uci.edu/ml/datasets/AI4I+2020+Predictive+Maintenance+Dataset
48. https://www.kaggle.com/datasets/nphantawee/pump-sensor-data