Intelligent Machine Learning based Fault Prediction Model for Induction Motor

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Abstract

Industrial sector has taken revolution with the induction motors (INM) playing a crucial role in automating many industrial processes. In this context monitoring, minimization of downtime of induction motors becomes very essential. In this work, all possible faults of induction motors such as bowed-rotor fault, broken-end ring, broken-rotor bar, cage fault, coil- to-coil, eccentricity fault, inner-race fault, misaligned-rotor fault, outer-race fault, phase- unbalancing, phase-to-ground, phase-to-phase, rolling-element fault, single-phasing, turn-to- turn, unbalanced-rotor fault are reported and intelligent machine learning (ML) algorithms are employed to diagnose the faults. A comparative analysis on the performance of the ML models for the fault study is carried out and the ML models executed are Random Forest, Support Vector Machine, Decision Tree, Naïve Bayes, Logistic-Regression and Gradient Boosting. The INM system is analyzed for its healthy case and faulty cases to collect the data which is prepared and then feature engineering is exerted to extract the prominent features using Principal Component Analysis (PCA). The comparative analysis of the performance metrics such as accuracy, precision, recall, and F1-score indicate the efficacious performance of the Random Forest (RF) model in comparison to other ML models.

Keywords: Fault Prediction, Fault Classification, Machine Learning, Induction Motor, Ansys

1 Introduction

Induction motor fault detection has been highly developed through a number of computational methods, each showing unique technical merits. Finite element analysis facilitates accurate broken rotor bar location through calculation of magnetic flux density variation, with the severity of fault being measured by harmonic distortion analysis of the magnetic field [1]. Machine learning methods achieve 92-97% accuracy in fault prediction when working with time-domain stator current features, support vector machines outperforming decision trees on imbalanced data sets [2]. The methods have been optimized for use in electric vehicles, where 3-phase current signatures are handled by convolutional neural networks with 98.4% classification accuracy but computational latency still a problem for real-time execution [3]. Sophisticated diagnosis systems now manage multiple simultaneous faults using hybrid SVM-RF models that combine vibration spectral kurtosis (band 8-12kHz) with existing Park's vector modulus analysis, registering 94.2% F1-score [4]. Power signature analysis techniques identify stator inter-turn faults using negative sequence components greater than 5% of rated power, with fault severity quantified by (P-Q) plane eccentricity ratios [5]. For inverter-driven motors, current analysis in time domain detects IGBT switching frequency sidebands (+/-2sf) with a resolution of 0.5% through windowed RMS computation with 89.3% detection without processing by FFT [6]. Technological advancements in signal processing comprise neuro-wavelet systems utilizing Daubechies-4 wavelets with Elman recurrent networks, decreasing false alarms by 37% versus traditional FFT schemes [7]. Normalized residual harmonic analysis calculates fault indices using spectral deviation metrics (ΔTHD, ΔHR5) with adaptive thresholding with 91% accuracy over 20-100% load range variations [8]. Comparative research indicates deep neural networks (4 hidden layers) perform better than shallow MLP by 12.7% in identifying ≤0.5mm bearing faults when analyzing 200kHz acoustic emission signals [9]. For intricate fault interactions, multi-label random forest classifiers exhibit 86.4% macro-average recall with cost-sensitive learning weighted by fault occurrence frequency [10].

In this work a detailed analysis of an induction motor system and its framework for fault diagnosis with conventional ML techniques is discussed. The lag in the addressal of faults identified and classified through ML approach for all possible fault cases has been overcome through this work. A detailed system description with the structural and operational parameters of the motor along with the relationship between the electrical and mechanical parts of the

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motor being emphasized. All possible faults are categorized into electrical and mechanical faults, and the causes, effects, and significance in motor performance are highlighted. Data collection and preparation, a very basic foundation of the study, involved using simulations in ANSYS. The datasets for both healthy and faulty motor conditions are generated. Dimensionality reduction techniques PCA involves optimizing the data to increase the efficiency of ML models. Various classification algorithms such as are Random Forest (RF), Support Vector Machine (SVM), Decision Tree (DT), Naïve Bayes (NB), Logistic-Regression (LR) and Gradient Boosting are applied in testing faults, and their relative strengths and weaknesses are compared. Model evaluation executed based on performance metrics, and promising results are observed with the most effective algorithms, which can potentially be used to identify and classify faults accurately. The study concludes with the potential of machine learning models in advancing fault diagnosis and predictive maintenance strategies for induction motors.

2 System Description

The induction motor (INM) system represents an electromechanical system that includes an induction motor along with its mechanical load as shown in Fig 1. It encompasses three voltage sources (Va,Vb,Vc) arranged in a star (wye) configuration with a grounded neutral point. Series resistors (RA, RB, RC) and inductors (LA, LB, LC) are in series to frame. The inductive and resistive components (LPhaseA, LPhaseB, LPhaseC) denotes the rotor. The end ring (shorted) part represents the rotor's shorted end rings making it a characteristic of the squirrel-cage induction motor. The mechanical illustration depicts a load operated by a pulley, where the rotor transmits torque to the load via the pulley system emphasizing the relationship between the electrical and mechanical fields, utilized to analyse motor efficiency, fault detection, and load behavior in industrial settings.

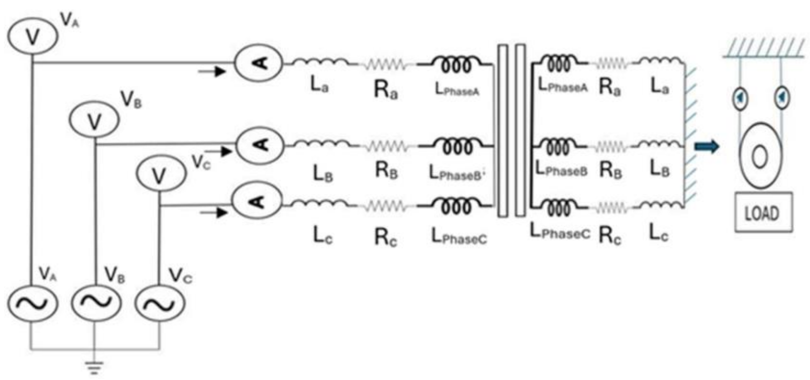

Fig. 1. Schematic of an INM with a load.

The motor is simulated in ANSYS software with the following specifications rated at 30.0 kW with a voltage rating of 400 V in a Y-connection. The motor operates at a frequency of 50 Hz with 6 poles, resulting in a synchronous speed of 1000 rpm and a rated speed of 980 rpm, corresponding to approximately 2% slip. The length of the stator slots is 60 mm, while the rotor slots are 44 mm in size. The motor's winding configuration includes 240 poles per step, distributed as 120 poles per layer across two layers. The core length is 250 mm, and the stator has an outer diameter of 210 mm with an inner diameter of 148 mm, separated by an air gap of 0.35 mm.

3 Faults of an INM system

3.1 Electrical faults

The electrical winding defects are common for both stator and the rotor and are listed below and shown in Fig. 2.

i. Turn-to-turn fault - insulation between adjacent turns of the same coil is short and causes local overheating.

ii. Coil-to-coil fault - insulation between two different coils in the same phase is short, creating uneven magnetic fields, and potential motor breakdowns.

iii. Phase-to-phase fault - insulation between two phases fails, causing a direct short circuit leading to excessive currents, heating, and damage to the winding.

iv. Phase-to-ground fault - insulation between a phase and the ground is short causing electrical leakage, tripping of protection systems, and severe motor damage.

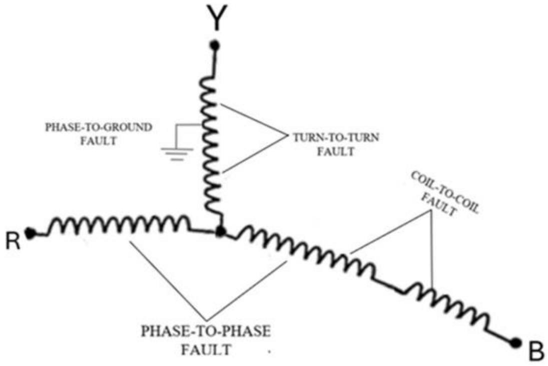

Fig. 2. Winding faults in an INM.

In respect to the structure and supply, the faults are listed below where broken rotor bar and broken end ring is depicted in Fig. 3.

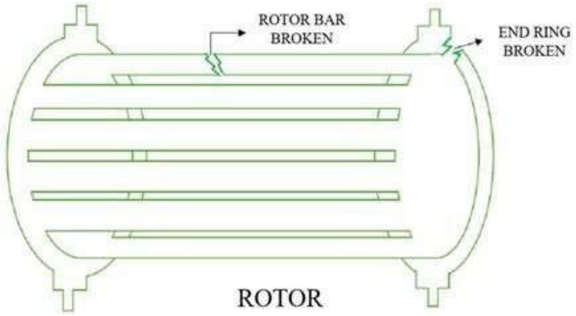

Fig. 3. Rotor part faults in an INM.

i. Broken rotor bar fault is the one where one or more rotor bars crack or break due to mechanical stress or fatigue as shown in Fig 3. This causes uneven torque and reduced motor performance. It can lead to vibrations and noise.
ii. Broken end ring fault occurs when the end ring in a squirrel cage rotor crack or breaks disrupting the current flow in the rotor, leading to uneven rotation and efficiency loss. This fault is typically caused by thermal expansion or mechanical stress.
iii. Phase unbalance fault results from unequal voltage or current levels across phases. It creates uneven torque, overheating, and stress on the motor. Common causes include supply voltage issues or faulty connections.
iv. Single phasing fault happens when anyone phase of a three-phase motor supply is lost and the motor tries to operate on the remaining phases, causing overheating and potential winding damage. It often results from blown fuses or broken connections.

3.2 Mechanical Faults

The various mechanical faults are listed below and shown in Fig 4.

i. Outer race faults are a bearing fault where the outer race surface is damaged due to wear, contamination, or misalignment, causing vibrations, noise, and reduced bearing lifespan.
ii. Inner race fault occurs when the inner race of a bearing is damaged, often due to improper lubrication or excessive load generating vibrations.
iii. Rolling ball fault is a defect in the rolling elements (balls or rollers) of the bearing caused due to fatigue, dirt, or manufacturing defects.
iv. Cage/train fault involves damage to the bearing cage that holds rolling elements in place, leading to uneven movement, increased friction, and eventual bearing failure.
v. Unbalanced rotor fault occurs when the rotor's mass is unevenly distributed, leading to vibrations.
vi. Bowed rotor fault indicates the rotor that is bent or deformed, often due to excessive heat or mechanical stress. It results in uneven air gaps, vibrations, and loss of efficiency.

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vii. Misaligned rotor faults happen when the rotor is not properly aligned with the stator, causing friction, vibrations, and uneven wear on bearings.

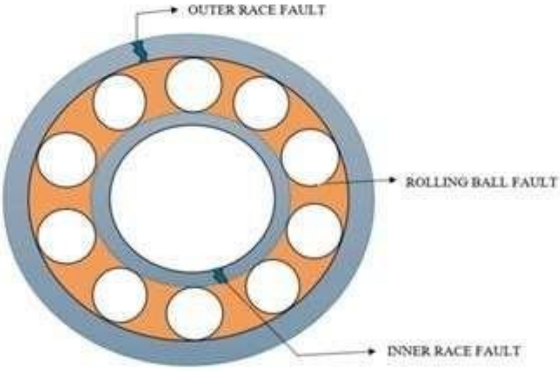

Fig. 4. Few mechanical faults in an INM.

4 Collection and preparation of the data

4.1 Collection of the data

The healthy motor dataset was created using ANSYS simulations as shown in Fig 5 and Fig 6, where the motor was modelled as shown in under optimal operating conditions without any faults.

Key parameters were meticulously monitored and recorded to provide a comprehensive baseline for comparison with faulty scenarios.

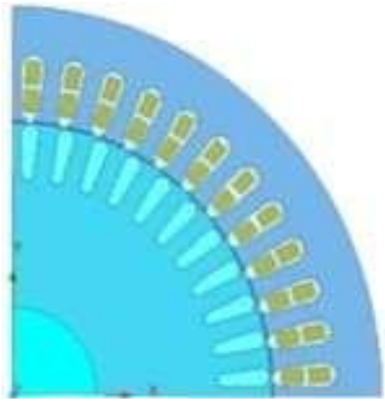

Fig. 5. 2D view of a healthy motor in ANSYS

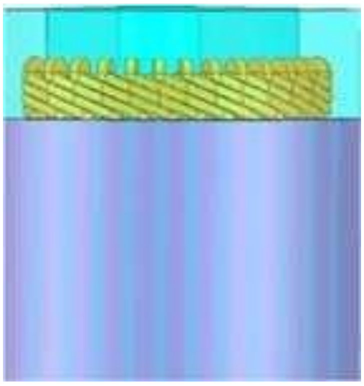

Fig. 6. 3D view of a healthy motor in ANSYS.

The induction motor faults dataset was prepared by ANSYS simulations as shown in Fig 7 and Fig 8. It has simulated a set of the following faults, which are very critical during machine learning training. Bowed rotor fault, Broken end ring, Broken rotor bar, Cage fault, Coil-to-coil fault, Eccentricity, Inner race fault, Misaligned rotor, Outer race fault, Phase unbalancing, Phase-to-ground fault, Phase-to-phase fault, rolling element fault, Single

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phasing, Turn-to-turn short circuit, Unbalanced rotor faults. These faults are modelled to create realistic fault scenarios, allowing for the collection of detailed data across electrical and mechanical parameters.

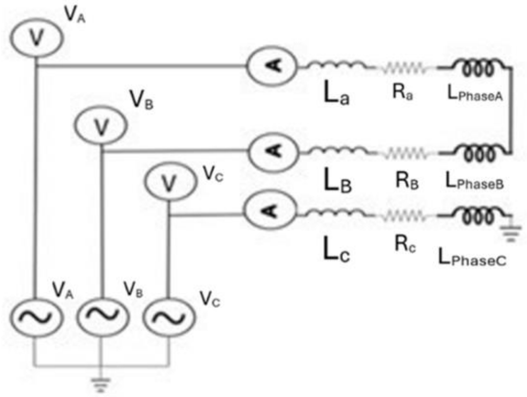

Fig. 7. Electrical fault in an induction motor in ANSYS.

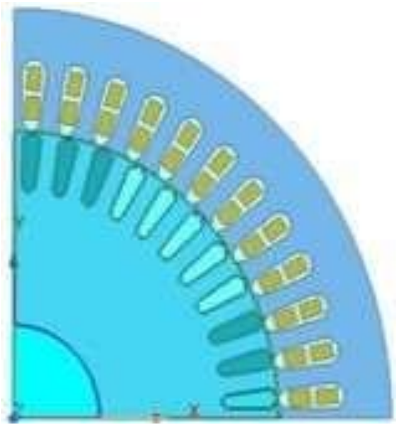

Fig. 8. Mechanical fault in an induction motor in ANSYS.

The electrical parameters collected include phase currents, phase and line voltages, real power, reactive power, apparent power, power factor, supply frequency, motor frequency, energy consumption, and phase imbalance. These parameters are critical to understanding how faults affect the electrical performance of the motor, such as causing imbalances in current or voltage, abnormal power usage, or frequency deviation.

Besides electrical parameters, mechanical parameters like torque of motor, speed of motor, slip speed of motor, temperature of windings, and bearing temperature are also monitored. Such mechanical Indicators such as rotor misalignment or eccentricity faults aid in detecting the consequences of faults that directly change the physical behavior of the motor. For example, bearing defects such as inner and outer race faults may lead to rising bearing temperatures and create abnormal oscillations in torque. Broken rotor bar and bent rotor faults can cause speed instability and slip speed.

4.2 Data Preparation

Fault detection dataset for induction motors covers a wide variety of faults, such as rotor-based faults like bowed rotors, damaged rotor bars, and cage defects, and stator faults like coil-to-coil and turn-to-turn short circuits. It is also supplemented with bearing faults like inner and outer race defects, and electrical faults such as phase unbalancing, phase-to-ground, and phase-to-phase faults. Besides that, mechanical anomalies such as rotor mis- alignment and eccentricity are also noted. Both faulty and healthy datasets comprise 1,000 values, which give strong support for the analysis of faults and their classification.

4.3 Data Visualization

The histogram in Fig 9 is the distribution of motor winding temperature (°C) by class label, illustrating how often different temperature ranges are found under different conditions. It has an overlay of density estimation to bring out trends, which can be seen with peaks at 70°C and 90°C, representing typical operating or faulty temperatures. The

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second histogram in Fig 10 shows the distribution of Phase C current (A) over the same class labels, with a peak of values between 5A and 20A and several peaks indicating differences in motor operation. Both histograms give a comparative picture of how these parameters differ under various conditions, providing information on possible fault patterns or normal operating behavior.

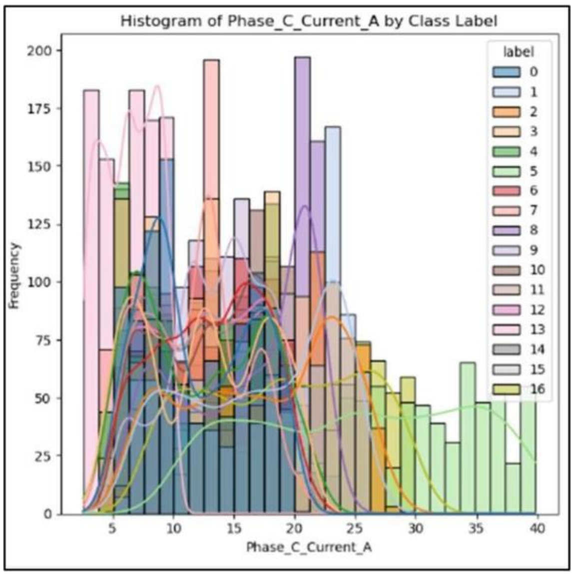

Fig. 9. Histogram of Phase C Current Distribution Across Different Class Labels.

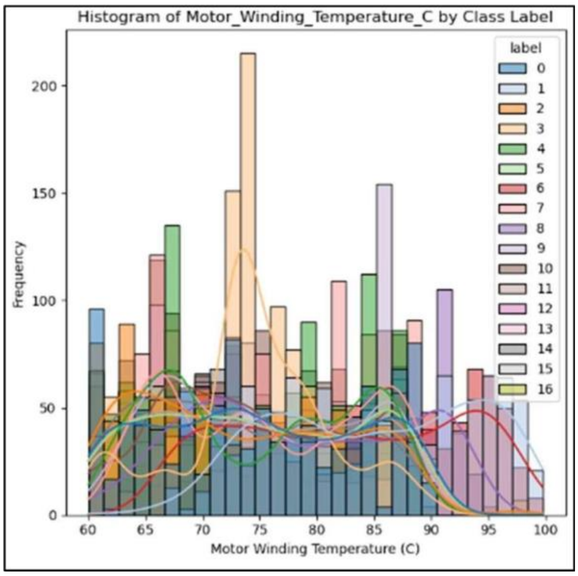

Fig. 10. Histogram of Motor Winding Temperature Distribution Across Different Class Labels.

4.4 Feature Extraction

PCA is an approach that diminishes the data's complexity from high-dimensional sets of the most important information. In motor fault diagnosis, it eases analysis by collecting the strongly correlated features like line-to- line voltages and phase currents into principal components. This reduces redundancy in the dataset without losing critical insights. PCA allows diagnostic models to work efficiently by focusing on a smaller set of representative components while preserving the key patterns necessary for accurate fault detection.

PCA analyses the relationships between features to determine which can be consolidated or retained. Highly correlated features, such as voltage and current measurements, are combined into components that capture their shared variability. Features like motor-winding temperature and efficiency, which are poorly correlated, are retained be- cause these may contribute uniquely for understanding the motor health conditions and performance under faulty conditions. There are moderate correlations, such as temperature with efficiency, so all significant relationships are accounted for. Environmental variables and other weakly correlated features still may be included if they could provide context, which

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may be important for certain faulty conditions. In PCA, the procedure for application includes standardizing data, analyzing correlation, and choosing components that explain more variability in the dataset. Few informative components replace features such as phase currents and motor temperatures, while redundant features-such as closely related voltage measurements-will be removed. This way, there would be a reduced dataset that still retains diagnostic relevance. PCA simplifies the analysis of data but also improves the fault classification models accuracy by focusing on the most meaningful information, making it a important tool in motor fault diagnosis.

5 Fault Prediction and Classification

5.1 Random Forest

Random Forest is an ensemble learning system that makes use of the output of numerous decision trees to increase accuracy and avoid overfitting. While training, every tree is grown on a random subset of the data set, which is known as bootstrapping, and at each split, a random subset of features will be considered. The randomness ensures that the trees are varied. Random Forest aggregates individual tree predictions for classification problems by majority voting and for regression tasks by averaging their outputs. The ability of the model to reduce variance, while maintaining low bias, makes it robust to noisy data and overfitting, but it can also become computationally expensive on large datasets.

5.2 Support Vector Machine (SVM)

Support Vector Machine (SVM) is an algorithm that determines the best hyperplane to classify data points into numerous classes in a higher dimension. It does this by increasing the space between closest data points belonging to different classes, which are referred to as support vectors. For nonlinear instances, SVM maps input data into a higher dimensional space using kernel functions to construct a linear hyperplane. Its optimization problem is that of minimizing the weight vector norm subject to classifying all the data points correctly within the margin. SVM is generally successful in high-dimensional settings and performs well on small samples, though performance suffers with overlapping classes.

5.3 Decision Tree

Decision Tree is an effective model that splits the data into many small sets based on the features and eventually results in a tree-like representation. Each internal node corresponds to a feature-based decision, whereas each leaf node corresponds to a class label or output value. The algorithm selects the characteristics recursively to produce the splits that decrease measurements of impurity, i.e., Gini Index or Entropy. For example, the Gini Index estimates misclassification probability as the sum of the squared probability of each class minus one. Decision Trees can be interpreted and are quick to train but would be overfit as they are built too deep and need techniques like pruning to optimize generalization.

5.4 Naïve Bayes

Naïve Bayes is a probability induced classifier that uses Bayes' Theorem with the premise that all characteristics are independent of the class label. Despite its "naïve" independence assumption, it performs quite well in several circumstances, including text categorization and spam detection. Bayes' Theorem states that the probability of a class given the characteristics is proportional to the product of the class prior and the likelihood of the features given the class. The model calculates posterior probabilities for each class and forecasts the one with the highest likelihood. Its simplicity and efficient way of working make it an excellent choice for big data's.

5.5 Logistic Regression

Logistic Regression is an approach for binary categorization. It uses the logistic function to describe the instances which belong to a certain class, mapping real- valued inputs to a range of 0 to 1. The model calculates a probability using a linear combination of input attributes and weights, followed by the sigmoid function. The model's parameters are trained by maximizing the probability of the observed data or, equivalently, reducing log-loss. While Logistic Regression can be interpretable and rather effective for separable data which are linear, it suffers with nonlinear connections until combined with approaches such as polynomial features.

5.6 Gradient Boosting

The iterative ensemble technique known as gradient boosting develops models one after the other, fixing the mistakes of the models that came before it. To optimize a function of loss, such as loss of log for classification purpose or mean squared error for regression purpose, weak learners—typically decision trees—are added in the direction of the loss function's gradient. Iteratively, the model's predictions are updated by appending a portion of the weak learner's output to the earlier predictions, which are managed by a learning rate.

The algorithms chosen for machine learning are chosen based on their unique strengths, such as simplicity, interpretability, and performance. Random Forest and Gradient Boosting excel in handling complex data, while SVM and Logistic Regression offer optimal decision boundaries and interpretability. Decision Trees and Naïve Bayes are preferred for text classification and probabilistic works.

5.7 Prediction

The 80-20 split in the training phase and testing phase of a ML model ensures a balance between model learning and performance evaluation. During the training process, the model is trained with 80% of the data to understand the intricate patterns and relationships between important features such as phase currents, motor temperatures, voltages, etc. The remaining 20% is then utilized in testing and judging the ability of the model to predict faults on unseen data. This split is important for fault detection because a lower split will give some measure of the reliability of the model in real-world contexts. Table 1. shows various machine learning models, including their hyperparameter setups, validation methods, and feature preparation techniques.

Model	Hyperparameter Configuration	Validation Method	Feature Selection/ Preprocessing
Random Forest	Tuned via GridSearchCV (5-fold CV): 200 trees, unlimited depth, min_samples_split=2, min_samples_leaf=1, max_features=√	5-fold stratified CV for tuning; 20% hold-out test set	All 40 features retained; standardized with StandardScaler
Decision Tree	Default (random_state=42)	20% hold-out test set	All features retained; standardized
Gradient Boosting	Default (random_state=42)	20% hold-out test set	All features retained; standardized
Support Vector Machine	RBF kernel; tuned via GridSearchCV (5-fold CV): C=10, γ="scale	5-fold stratified CV for tuning; 20% hold-out test set	All features retained; standardized
Gaussian Naïve Bayes	Default	20% hold-out test set	All features retained; standardized
Logistic Regression	Default (max_iter=1000, random_state=42)	20% hold-out test set	All features retained; standardized

Table 1. Overview of model validation and features.

The evaluation of the model values, as shown in Fig 11 and analyzed in table 2, reveals that there are strengths and weaknesses in fault classification. The Random Forest model achieves high accuracy on all classes, which indicates that the feature set is indeed capable of discriminating between fault types. The SVM model is performing well on some classes but fails on others; this could be due to a complex decision boundary that requires more kernel tuning or feature refinement. The Decision Tree model has excellent accuracy and good classification performance both for the healthy and faulty states, though prone to overfitting. Gaussian Naive Bayes seems promising for certain classes but suffers from the independence assumption of features that may not be held for the given dataset. Logistic Regression struggles with certain classes and fails to represent non-linear relationships. Overall, the models vary in their ability to identify complex patterns and to correctly classify faults.

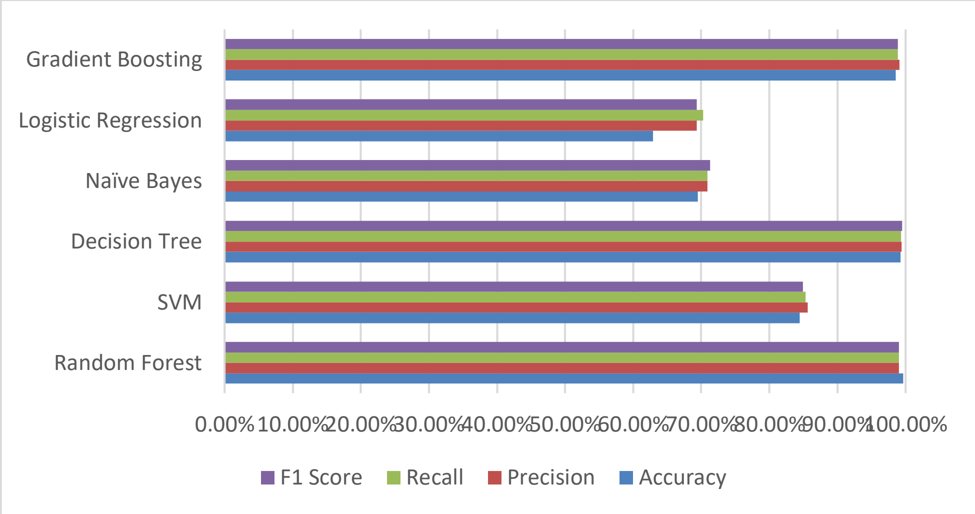

Fig. 11. Performance of various ML classifiers

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Table 2. Quantitative analysis of various ML classifiers

Metric	Random Forest	SVM	Decision Tree	Naïve Bayes	Logistic Regression	Gradient Boosting
Accuracy	99.68%	84.44%	99.26%	69.53%	62.94%	98.59%
Precision	0.99	0.856	0.994	0.709	0.693	0.991
Recall	0.99	0.853	0.993	0.709	0.703	0.989
F1 Score	0.99	0.849	0.995	0.713	0.693	0.989

```
Accuracy: 0.9967647058823529
Classification Report:
              precision    recall  f1-score   support

           0       0.99      0.99      0.99       200
           1       1.00      0.98      0.99       200
           2       0.99      1.00      1.00       200
           3       0.99      1.00      1.00       200
           4       1.00      1.00      1.00       200
           5       1.00      1.00      1.00       200
           6       1.00      1.00      1.00       200
           7       1.00      1.00      1.00       200
           8       0.99      1.00      1.00       200
           9       0.99      0.98      0.99       200
          10       1.00      1.00      1.00       200
          11       1.00      1.00      1.00       200
          12       1.00      1.00      1.00       200
          13       1.00      1.00      1.00       200
          14       1.00      0.98      0.99       200
          15       1.00      1.00      1.00       200
          16       1.00      1.00      1.00       200

    accuracy                           1.00      3400
   macro avg       1.00      1.00      1.00      3400
weighted avg       1.00      1.00      1.00      3400

Confusion Matrix:
 [[199   0   0   0   0   0   0   0   0   0   1   0   0   0   0   0   0]
 [  0 196   2   0   0   0   0   0   2   0   0   0   0   0   0   0   0]
 [  0   0 200   0   0   0   0   0   0   0   0   0   0   0   0   0   0]
 [  0   0   0 200   0   0   0   0   0   0   0   0   0   0   0   0   0]
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 [  0   0   0   0   0 200   0   0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0 200   0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0 200   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0 200   0   0   0   0   0   0   0   0]
 [  3   0   0   0   0   0   0   0   0 197   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0 200   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0 200   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0 200   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0 200   0   0   0]
 [  0   0   0   2   0   0   0   0   0   1   0   0   0   0 197   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0 200   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0 200]]
Error Rate: 0.003235294117647114
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Fig. 12. Detailed performance of RF model.

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The confusion matrix in the RF model shows good classification accuracy regardless of the faults, with negligible misclassifications as shown in Fig 12. Error estimation shows that low error rates exist consistently, so the model does not fail frequently in fault detection.

The type of faults successfully predicted by the Random Forest (RF) classifier is illustrated in Fig 13 showcasing its ability to diagnose faults such as Class 9 (outer race fault) and Class 5 (coil-to-coil fault) based on the given feature values. The numeric values represent system parameters, and the RF classifier's accurate predictions highlight its efficiency in analyzing operational data and diagnosing faults reliably.

Fig. 13. Predicted fault classes with RF model.

6 Conclusion

The work highlights the importance of fault diagnosis in induction motors (INM) to improve reliability and reduce downtime in industrial use. The INM system was simulated in ANSYS, enabling controlled simulation of different faults, such as electrical and mechanical faults. Through systematic data acquisition, healthy and faulty motor conditions were compared, recording important electrical and mechanical parameters critical for fault detection. The gathered dataset was preprocessed, and features were extracted using PCA method for maximizing model performance. Different machine learning models such as Random Forest (RF), Support Vector Machine (SVM), Decision Tree, Naive Bayes, Logistic Regression, and Gradient Boosting were trained and tested on several performance measures. The comparative evaluation proved that Random Forest has performed the best than other models consistently, yielding higher accuracy, precision, recall, and F1-score in all fault classifications.

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