2025 26th International Middle East Power System Conference (MEPCON)

Open-Circuit and Voltage Unbalance Faults Diagnosis for Induction Motors Using Artificial Intelligence Algorithms

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***Abstract*— The dependability of three-phase induction motors is vital in industrial applications, requiring accurate and robust fault detection strategies. This paper introduces an automated diagnostic framework for two critical electrical faults: Open Circuit and Unbalanced Voltage faults. Three machine learning classifiers: Artificial Neural Networks, Support Vector Machines, and K-Nearest Neighbours were employed to develop and evaluate the models. A comprehensive dataset of approximately 100,000 samples was collected under different load scenarios (Full, Half, and No load), incorporating important features such as stator currents, rotor speed, and electromagnetic torque. Hyperparameter tuning was performed using Grid Search to enhance model generalization and optimize performance. Standard evaluation metrics, including the confusion matrix, ROC curve, F1-score, precision, and recall, confirmed highly reliable results. All models achieved 100% classification accuracy on both training and unseen test datasets across all load conditions. These outcomes demonstrate the effectiveness of machine learning in building load-independent fault diagnosis systems, offering significant potential for predictive maintenance in industrial environments.**

Keywords—Induction Motor, Machine learning Algorithms, Artificial Intelligence techniques, fault diagnosis.

I. INTRODUCTION

The induction motor (IM) is regarded as one of the most important types of electrical machines due to its direct influence on overall efficiency and performance in a wide range of industrial applications. Its primary benefits include ease of control, low maintenance requirements, great power density, and a very basic design. IMs are widely recognized for their longevity, cost-effectiveness, dependable operation, and excellent speed control capabilities, making them a popular choice in a variety of industrial and engineering applications[1].

In spite of its many benefits, IMs are nevertheless quite prone to a number of issues in industrial environments. Among other problems, electrical, mechanical, and mostly bearing issues have the greatest impact on IMs. According to IEEE standard 3004.8, IM faults are classified as shaft or coupling faults, rotor bar faults (7%), stator winding faults (21%), and bearing failures (69%). Electrical and mechanical defects are the two primary categories of faults. There are bearing and broken rotor bars under mechanical fault eccentricity, stator and rotor faults under electrical fault [2].

In this study, the focus will be on two common electrical faults that may occur in IMs, namely the Unbalanced Supply Voltage (UNBV) Fault and the Open Circuit (OC) Fault, due to their significant impact on the motor's efficiency and operational stability. Three-phase IM output is negatively impacted by voltage unbalance. While a balanced system maintains consistent voltage magnitude and angles in three phases, achieving a fully balanced condition is challenging. In contrast, three-phase source voltage can become unbalanced in a different ways. A motor may be realistically impacted by imbalanced instances, which might vary in several ranges. An UNBV in a three-phase IM can have a number of negative effects. These outcomes include higher losses, which in turn lead to a temperature drop in the motor's torque, efficiency, and insulating lifespan [3]. OC fault might be taken into consideration in severe cases of uneven running. However, in the event of a failure, it should be taken into account if one phase of a three-phase source fails. A three-phase motor may attempt to produce the most horsepower required to satisfy the demand when operating in this mode. Until it is damaged or the protective components move the motor out of the line, the motor will keep attempting to run the load. Phase currents are increased by single phasing OC fault, which leads to overheating and motor destruction [4].

979-8-3315-7716-2/25/$31.00

In order to minimize downtime and ensure optimal productivity, early detection of defects in IMs is crucial. Since traditional fault detection techniques mostly rely on current and vibration signals, as well as basic approaches like overcurrent, overvoltage, and earth-fault monitoring, researchers have been studying motor maintenance and failure analysis for years. As technology has advanced, fault detection strategies have become more effective by combining conventional and new methodologies. Such fault diagnosis is especially important for industrial applications since motor problems can have a direct effect on total system reliability, safety, and efficiency [5].

In recent years, advanced diagnostic techniques based on machine learning (ML) and artificial intelligence (AI) have become effective techniques for identifying electrical machinery faults. Compared to traditional techniques, these methods are more accurate and sensitive in detecting minor anomalies that are indications of issues because they use ML algorithms to evaluate complex patterns in motor data. Large motor data databases are especially well-suited for AI-based fault detection approaches, which enable them to continually monitor machine health and identify patterns that could indicate future issues [6]. The most popular supervised learning methods for pattern recognition are Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Artificial Neural Networks (ANN). SVM is very accurate and appropriate for high-dimensional issues because it uses kernels like the Radial Basis Function to handle both linear and nonlinear data efficiently while maximizing the margin between classes. In contrast, KNN is a straightforward instance-based approach that uses the majority vote of its nearest neighbors to classify a sample. It is simple to use, doesn't require model training, and is resilient to noisy data, but it becomes computationally costly when dealing with huge datasets. An ANN classifier can be thought of as a parallel computing system made up of a very large number of interconnected basic processors. A multilayered feed-forward perceptron, which is made up of multiple layers of neurons connected to one another, is one popular kind of ANN. The multilayered perceptron, which typically consists of three or more types of layers, can separate nonlinear data [7].

Numerous research gaps and limitations have been found after a thorough examination and analysis of several previous studies. First, rather than investigating hybrid or comparative approaches, the majority of research relied on a single ML or AI technique for fault detection [8]-[12]. Second, most research concentrated on identifying a single fault type, not expanding the models to detect numerous faults at once, which is essential for proving robustness and efficacy [13]-[16]. Third, many studies feature extraction procedures only included a few signals, like temperature, vibration, or current, rather than combining several characteristics, such torque, speed, and current, to provide a more thorough study [17]-[22]. Lastly, the majority of previous study has failed to achieve high efficiency under various loading conditions [23]-[30].

This research introduces several significant advancements to the field of AI-based IM fault diagnostics, distinguishing itself from current literature through the following contributions:

- *Multi-Fault Diagnostic Capability:* Unlike common research that focuses on single-fault detection, this study successfully developed and validated models capable of accurately diagnosing and distinguishing between two critical electrical faults: OC and UNBV conditions, in addition to the healthy state.
- *Demonstration of Load-Independent Diagnosis:* The models were extensively tested and proven to maintain their diagnostic integrity across widely varying operational states (Full Load, Half Load, and No Load). This achievement ensures the reliability and practical applicability of the system in dynamic industrial environments.
- *Achievement of Absolute Diagnostic Certainty:* All three implemented AI models (ANN, SVM, and KNN), following rigorous optimization, achieved a perfect 100% classification and detection accuracy across all training, testing, and variable loading conditions. This establishes a new benchmark for diagnostic precision in the sector.
- *Rigorous Hyperparameter Optimization:* The performance success is directly attributable to the systematic application of the Grid Search technique for hyperparameter optimization, ensuring the selection of mathematically optimal parameters for each specific ML model.
- *Utilization of a Comprehensive and Robust Dataset:* A large-scale, high-resolution dataset, comprising approximately 100,000 samples per loading condition, was leveraged. This dataset is enriched by using a multi-feature analysis approach, incorporating stator currents, motor speed, and electromagnetic torque, rather than relying on a single feature, thereby capturing more complex fault signatures.
- *Validation Through Algorithm Diversity:* The performance and robustness of three fundamentally different AI methodologies (ANN, SVM, and KNN) were simultaneously evaluated and confirmed, providing strong comparative evidence and validating the effectiveness of the optimized features and data processing pipeline.

There are various sections to this research. The introduction and main contribution of the study are outlined in the first part. The methodology is the subject of the second section, which provides a detailed explanation of the procedures and strategies used in this work. Presenting the results, talking about the findings, and evaluating their importance take up the third section. The references section, which details all of the sources and papers that were used in this research, comes at the end of the paper.

As illustrated in Fig. 1, the many stages at which this study was carried out. First, a motor simulation was run in both good and faulty conditions based on MATLAB/Simulink during various loading conditions. The data was then gathered, saved, and analyzed in order to extract features and assess their effect on the effectiveness of defect detection and classification. The retrieved features were then used to create and train ML and deep learning models. Ultimately, the models performance was evaluated, proving their efficacy and capacity to reliably, accurately, and quickly identify these issues.

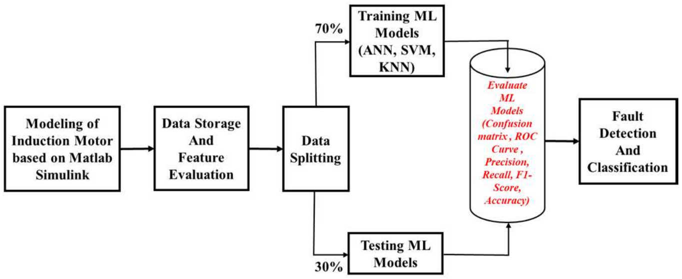

Fig. 1 Structure of research work.

II. MODELING OF INDUCTION MOTOR

Modeling of IM with parameters as illustrated in APPENDIX A under various faults and loading conditions is the first step in our work. In this phase we are using MATLAB simulation for modeling IM during both healthy and faulty conditions (UNBV, and OC faults) under different loading conditions by using the Asynchronous Machine block in MATLAB/Simulink [31].

A. *Modeling of unbalanced supply voltage fault.*

The method used to simulate UNBV fault involved altering the three phases' voltages in terms of both their magnitudes and phase shift angles as depicted in Fig. 2. In particular, the phase angles between the three phases were also changed to precisely represent the fault situations and reflect the behavior of the motor under UNBV scenarios, and the voltage levels were changed to simulate under-voltage and over-voltage faults.

To simulate this fault, the voltage of phase A was modified only in terms of its phase angle, while its magnitude was kept constant. For phase B, both the voltage magnitude and phase angle were altered, with the magnitude increased to 1.25 of the rated motor voltage. Similarly, for phase C, the applied voltage was adjusted to 0.75 of the rated voltage, along with no change in its phase angle as depicted in TABLE I. The simulation was carried out for a total duration of one second, where the motor operated under healthy conditions until 0.5 seconds, after which the fault was introduced and sustained until the end of the simulation period.

TABLE I. Supply voltages in case healthy and UNBV fault

3-Phase Supply Voltage	Healthy Condition	UNBV Fault Condition
V_{sa}	$230\angle 0^{\circ}$ V	$230\angle -30^{\circ}$ V
V_{sb}	$230\angle -120^{\circ}$ V	$287.5\angle -90^{\circ}$ V
V_{sc}	$230\angle 120^{\circ}$ V	$172.5\angle 120^{\circ}$ V

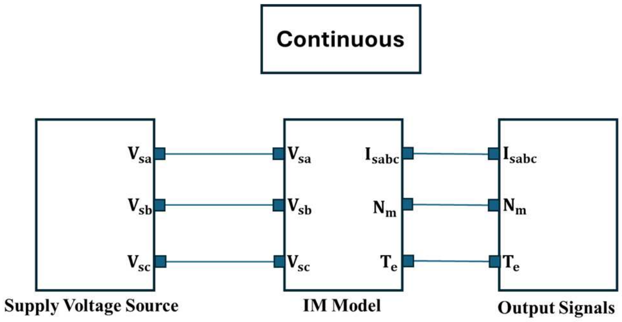

Fig. 2 Modeling of IM during UNBV fault condition.

B. *Modeling of Open Circuit fault*

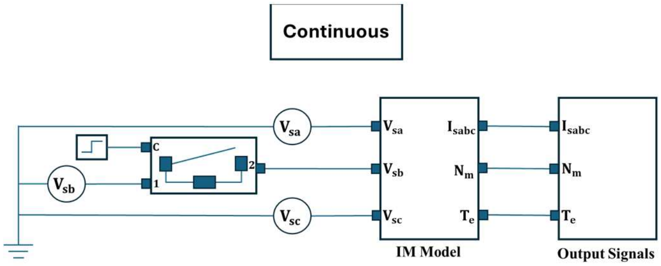

Fig. 3 Modeling of IM during OC fault condition.

TABLE II. Supply voltages in case healthy and OC fault

3-Phase Supply Voltage	Healthy Condition	OC Fault Condition
V_{sa}	$230\angle 0^{\circ}$ V	$230\angle 0^{\circ}$ V
V_{sb}	$230\angle -120^{\circ}$ V	0 V
V_{sc}	$230\angle 120^{\circ}$ V	$230\angle 120^{\circ}$ V

A circuit breaker linked to phase B was utilized to simulate OC fault, as shown in Fig. 3. Between the beginning and the middle of the period, the motor functioned under healthy conditions for a total of one second. The fault then occurred and remained active from the middle of the simulation time until the end when the breaker was turned off and the supply voltage values will be changed as seen in TABLE II.

III. SIMULATION RESULTS AND DATA EXTRACTION

The following step is to analyze and study how the simulated defects affect the motor performance after simulating the IM in both healthy and defective situations. In order to assess how each problem affects the motor dynamic behavior, this involves looking at the fluctuations in stator currents, motor speed, and electromagnetic torque. This type of examination shows how sensitive various parameters are in reflecting the motor's operational condition and offers insightful information about the extent of deterioration brought on by the flaws.

The consequence of the UNBV fault indicates that the stator current waveforms clearly reflect this fault, showing a noticeable asymmetry and uneven distribution of the three-phase currents as depicted in Fig. 4. The overall stability and efficiency of the IM are adversely affected by this imbalance, which immediately affects the motor's performance by causing distortions in the stator current, variations in the motor speed, and oscillations in the developed torque as shown in Fig. 5 and Fig. 6. Like this, the stator current waveforms show significant drop in one or more phases and severe distortion under the OC fault situation, increasing the current stress on the healthy phases as seen in Fig. 7. This anomaly exacerbates the deterioration of motor function by producing more torque ripples, wider speed fluctuations, and even a loss of synchronism as illustrated in Fig. 8 and Fig. 9.

The following step after accomplishing the IM simulation stage is to record the data that was produced for a set of features, namely the stator currents, speed, and torque. 100,000 samples are collected for each loading scenario, and the data is methodically documented in an Excel sheets. After that, these datasets are ready for use in the next step, which involves creating and honing ML models for performance analysis and fault identification and the dataset was then divided into 70% for training and 30% for testing. The models were then evaluated to determine how well they detected faults.

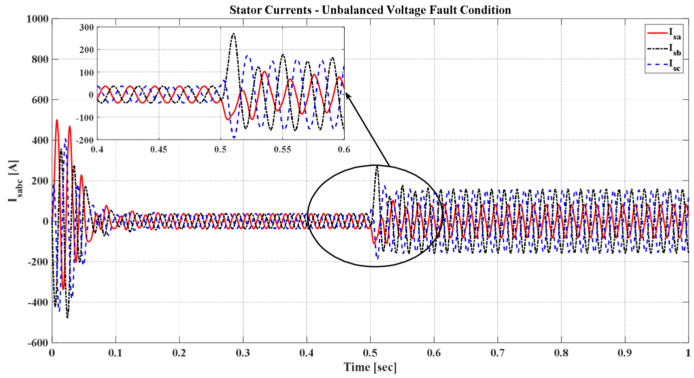

Fig. 4 Stator current waveform during UNBV fault.

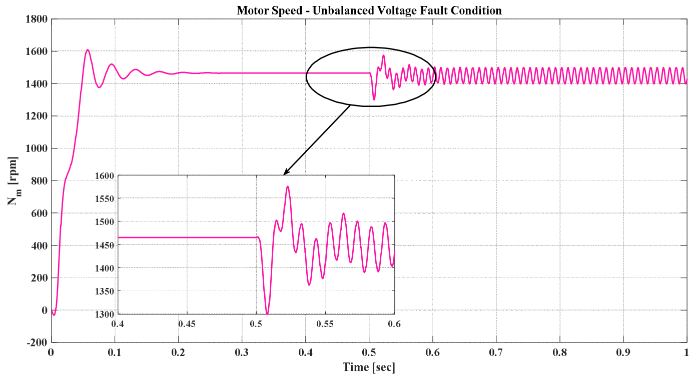

Fig. 5 Waveform of Motor Speed during UNBV fault.

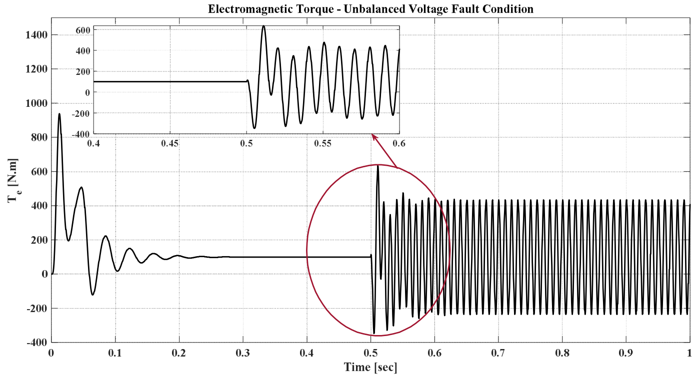

Fig. 6 Waveform of Electromagnetic torque during UNBV fault.

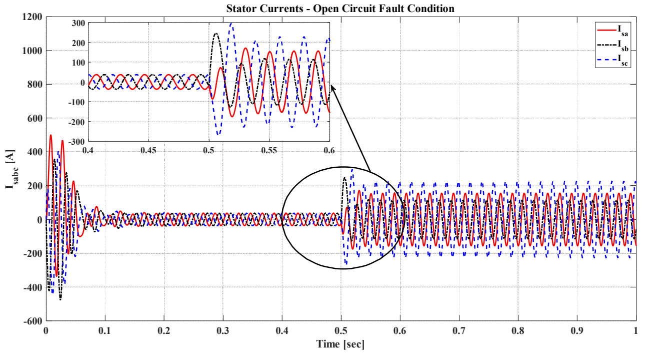

Fig. 7 Waveform of stator currents during OC fault.

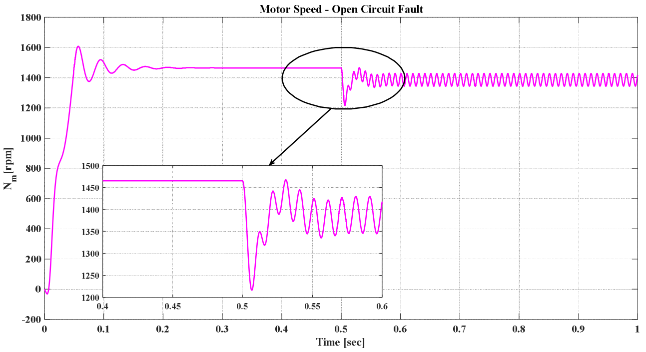

Fig. 8 Motor Speed waveform during OC fault.

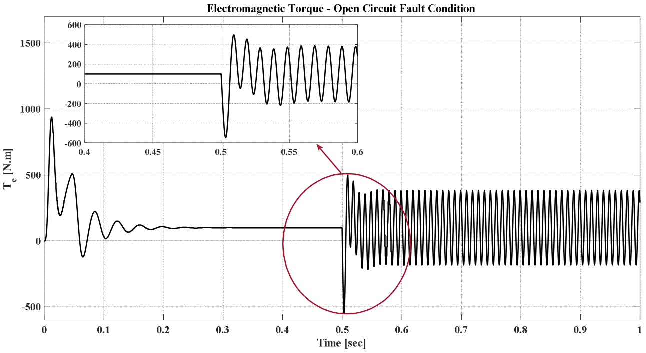

Fig. 9 Waveform of electromagnetic torque during OC fault.

IV. DEVELOPMENT OF MACHINE LEARNING ALGORITHMS

Following the meticulous preparation of the load-agnostic, multi-feature dataset, the study transitioned to the development and rigorous evaluation of the diagnostic classifiers. This phase utilized the MATLAB Classification Learner Toolbox as the foundational platform for efficient model construction and systematic optimization.

A. Selection and Initialization of Diagnostic Models

Three distinct and high-performing AI algorithms were selected based on their proven effectiveness in power system diagnostics: ANN, SVM, and KNN classifier. These models were chosen to provide a comparative analysis across different learning paradigms (deep learning, kernel-based methods, and instance-based learning).

B. *Systematic Hyperparameter Optimization*

In the field of ML, hyperparameter optimization has gained significant attention, and techniques are typically classified as either model-free or model-based algorithms. Grid search, random search, and manual search are examples of model-free methods. Although the success of manual search depends on prior knowledge, it relies on user skill to establish parameters. While it might be time-consuming, random search assesses models using random parameter combinations to find novel configurations. Although it can be computationally costly, grid search ensures a thorough investigation of the parameter space and produces dependable findings by methodically testing every combination of parameters in a preset matrix [32]. Because the grid search strategy ensures a thorough review of hyperparameter combinations, resulting in more accurate and robust model performance, we used it in our study.

A critical step in model development was the systematic tuning of model parameters to achieve peak performance and generalization capability. This was performed through Hyperparameter Optimization using the Grid Search algorithm. For each of the three classifiers (ANN, SVM, and KNN), the Grid Search technique systematically explored a predefined range of critical hyperparameters. This methodical approach guaranteed the selection of the mathematically optimal configuration for each model, ensuring the highest possible discriminatory power when faced with the combined challenge of multi-fault and multi-load classification. This optimization was instrumental in translating raw data into the robust, 100% accurate diagnostic system.

C. *Evaluation methods of machine learning models*

To validate the robustness and reliability of the optimized models, a comprehensive evaluation protocol was employed, assessing performance during both the training and independent testing stages. The evaluation relied on a multifaceted suite of standard performance metrics to provide a thorough, unbiased assessment:

- ***Confusion Matrix (CM):*** This fundamental tool was generated for both the training and testing phases to visually and quantitatively assess the true positive, true negative, false positive, and false negative rates, offering class-specific accuracy insights into the detection of Healthy, OC, and UNBV states as shown in Fig. 10 [33].
- ***Receiver Operating Characteristic (ROC) Curve:*** The ROC curve, alongside the calculated Area Under the Curve (AUC), was generated for both training and testing datasets. This analysis demonstrated the trade-off between the True Positive Rate (Sensitivity) and the False Positive Rate (Specificity), confirming the models' exceptional ability to distinguish between all fault classes across varying thresholds as illustrated in Fig. 11 [33].
- ***Key Performance Indicators (KPIs):*** The final models were quantitatively assessed using three widely accepted metrics, confirming diagnostic perfection in every aspect:
    - ***F1-Score:*** The harmonic mean of precision and recall, verifying the models' balance between false positives and false negatives [33].
    - ***Precision (Positive Predictive Value):*** The ratio of correctly predicted positive observations to the total predicted positives, ensuring a low false alarm rate [33].
    - ***Recall (Sensitivity):*** The ratio of correctly predicted positive observations to all actual positives, confirming the models' ability to detect every instance of the faults [33].

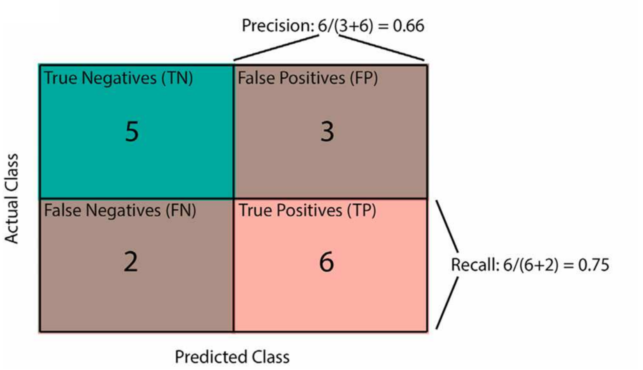

Fig. 10 Description of CM.

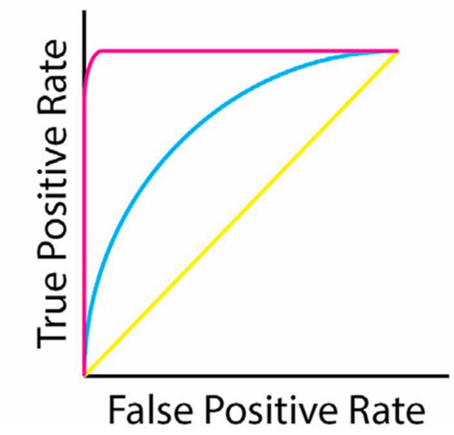

Fig. 11 Description of ROC Curve.

V. RESULTS AND DISCUSSION

The proposed defect diagnostic framework was assessed using three distinct ML algorithms: ANN, KNN, and SVM under diverse IM loading situations, such as FL, HL, and NL. Across all cases, the three models performed well, consistently achieving 100% accuracy on both the training and testing datasets. Various evaluation matrices were used for conducting a thorough performance study. The CMs proved excellent classification with no misclassifications during training phase as depicted in Fig. 12, Fig. 16, and Fig. 20 also during testing phase as shown in Fig. 13, Fig. 17, and Fig. 21, and the ROC curves showed ideal separability with an AUC of 1 as illustrated in Fig. 14, Fig. 15, Fig. 18, Fig. 19, Fig. 22, and Fig. 23. Furthermore, the precision, recall, and F1-score values for all fault categories approached unity, demonstrating the models' balanced and reliable nature as seen in TABLE III, TABLE IV, and TABLE V. The overall accuracy metric supported these findings, demonstrating the resilience of the suggested strategy. Interestingly, although operating on fundamentally distinct concepts, ANN, KNN, and SVM all converged to produce the same faultless result. This implies that the chosen features as seen in APPENDIX B had high discriminative power, allowing for reliable separation of motor problems at various load levels. These findings not only confirm the effectiveness of the suggested methodology but also highlight its high potential for use in real-world industrial fault detection applications.

Fig. 12 Training CM for ANN model.

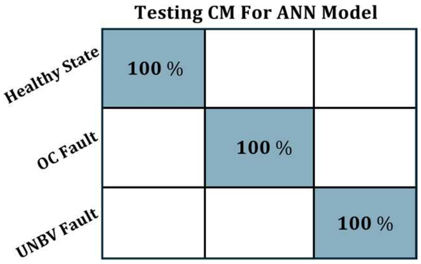

Fig. 13 Testing CM for ANN model.

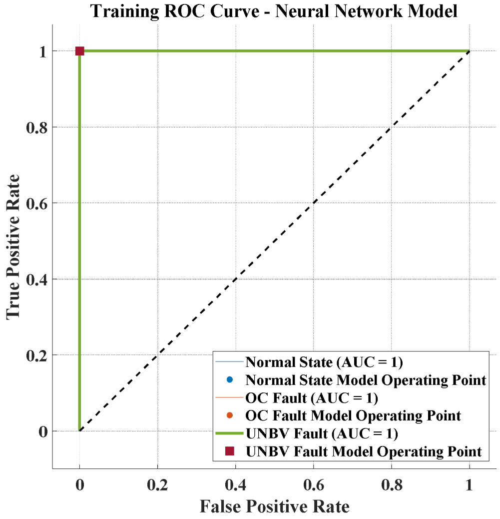

Fig. 14 Training ROC Curve for ANN model.

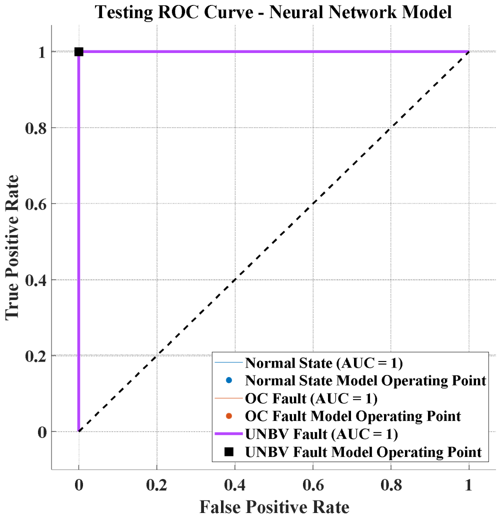

Fig. 15 Testing ROC Curve for ANN model.

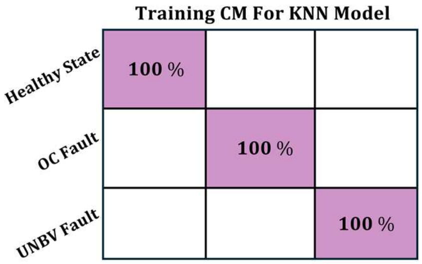

Fig. 16 Training CM for KNN model.

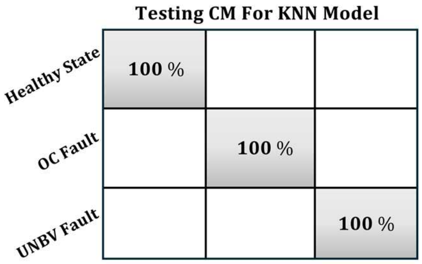

Fig. 17 Testing CM for KNN model.

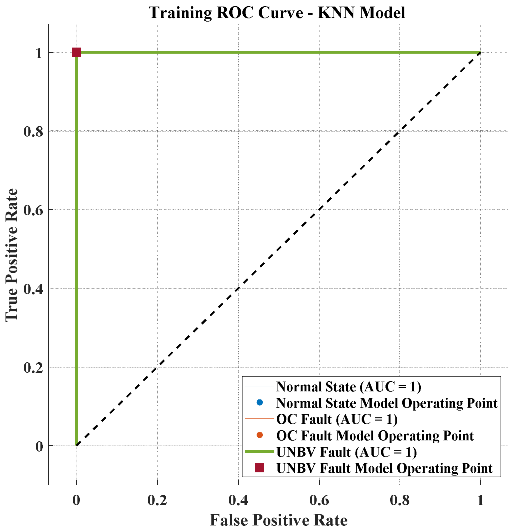

Fig. 18 Training ROC Curve for KNN model.

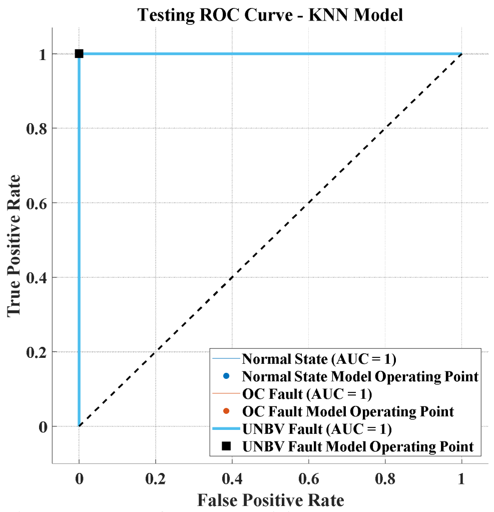

Fig. 19 Testing ROC Curve for KNN model.

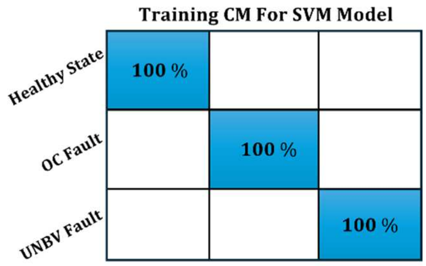

Fig. 20 Training CM for SVM model.

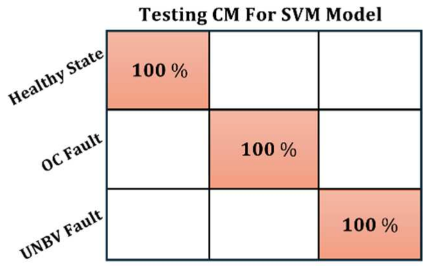

Fig. 21 Testing CM for SVM model.

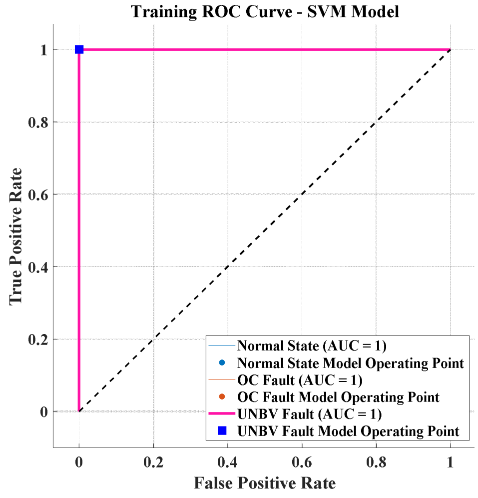

Fig. 22 Training ROC Curve for SVM model.

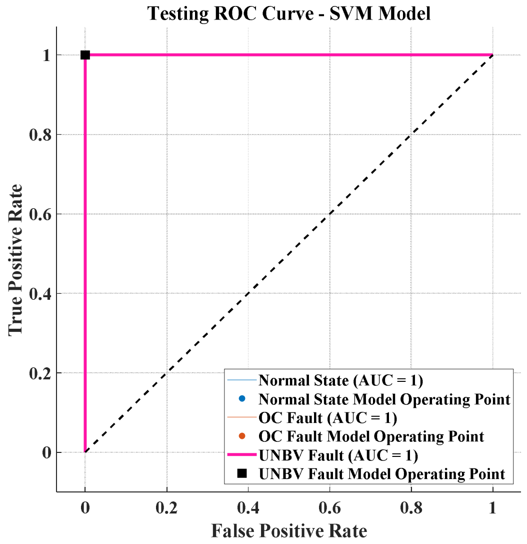

Fig. 23 Testing ROC Curve for SVM model.

TABLE III. Evaluation of ANN Model.

Fault Type	*Full load Condition*			*Half load Condition*			*No Load Condition*			*Overall Accuracy*
	Precision	Recall	F1-score	Precision	Recall	F1-score	Precision	Recall	F1-score	
Healthy State	1	1	1	1	1	1	1	1	1	100%
OC Fault	1	1	1	1	1	1	1	1	1	100%
UNBV Fault	1	1	1	1	1	1	1	1	1	100%

TABLE IV. Evaluation of KNN Model.

Fault Type	*Full load Condition*			*Half load Condition*			*No Load Condition*			*Overall Accuracy*
	Precision	Recall	F1-score	Precision	Recall	F1-score	Precision	Recall	F1-score	
Healthy State	1	1	1	1	1	1	1	1	1	100%
OC Fault	1	1	1	1	1	1	1	1	1	100%
UNBV Fault	1	1	1	1	1	1	1	1	1	100%

TABLE V. Evaluation of SVM Model.

Fault Type	*Full load Condition*			*Half load Condition*			*No Load Condition*			*Overall Accuracy*
	Precision	Recall	F1-score	Precision	Recall	F1-score	Precision	Recall	F1-score	
Healthy State	1	1	1	1	1	1	1	1	1	100%
OC Fault	1	1	1	1	1	1	1	1	1	100%
UNBV Fault	1	1	1	1	1	1	1	1	1	100%

Following the presentation and discussion of the results, the key findings can now be summarized in the form of several important points, as outlined below.

- *Perfect Classification Accuracy:* All three developed models achieved an unprecedented 100% classification accuracy for the detection of OC and UNBV faults on both training and independent testing datasets.
- *Load-Independent Robustness:* The models demonstrated absolute operational stability by

maintaining 100% accuracy across all three tested operational states: full load, half load, and no load. This success confirms the isolation of truly load-independent fault signatures.

- *Optimized Performance:* The Grid Search hyperparameter optimization successfully tuned the models to their maximum potential, highlighting the power of systematic optimization in achieving global optimum diagnostic fidelity.
- *Irrefutable Validation:* The exceptional diagnostic reliability was comprehensively validated by all evaluation metrics, with all models yielding unity scores (1.00) for Precision, Recall, and F1-Score, and an ideal AUC of 1.00 in ROC analysis.
- *New Industry Benchmark:* This outcome successfully establishes a new high-water mark for predictive maintenance systems, definitively showcasing the capability of advanced AI to deliver absolute, reliable fault diagnosis under complex, variable industrial conditions.

VI. CONCLUSION

This study successfully created a highly robust and dependable system for identifying OC and UNBV defects in IMs. A large dataset of roughly 100,000 samples was gathered under three different load scenarios (full load, half load, and no load), with important feature sets including stator currents, motor speed, and electromagnetic torque. These data were divided between 70% training and 30% testing on previously unseen new data and were then used to train and evaluate three AI classifiers: ANN, SVM, and KNN. Following rigorous hyperparameter adjustment with Grid Search algorithm, all three models displayed excellent classification performance. Each classifier achieved 100% accuracy, 100% recall, 100% precision, and an F1-score of 1.0 across both training and testing datasets under all load conditions. The ROC curve study confirmed the full separability of fault types. These numerical results conclusively verify the suggested methodology as a load-independent diagnostic tool capable of detecting faults with absolute certainty. Beyond the statistical results, the significance of these findings lies in their practical implications: they show that AI-driven diagnostic systems can operate reliably under varying industrial conditions, reducing unplanned downtime, lowering maintenance costs, and ultimately improving the overall efficiency and safety of critical motor-driven systems. Therefore, the suggested method contributes concretely to the creation of next-generation predictive maintenance methods in contemporary industry in addition to advancing the academic subject of intelligent fault detection.

APPENDIX A

TABLE VI. Parameters of Induction Motor

Parameter	**Value**
Rated Power	(20 HP)
Rated Line Voltage ($V_{line\text{-}Rms}$)	(400 V)
Number of pole pairs	(2)
Rotor Type	(Squirrel cage)
Stator Resistance (R_s)	(0.2147 Ω)
Rotor Resistance (R_r’)	(0.2205 Ω)
Inertia Constant (J)	(0.102) (kg.m^2)
Rated Speed (N_m)	(1460 rpm)
Stator Inductance (L_{ls})	(0.000991 H)
Rotor Inductance ($L_{lr'}$)	(0.009541 H)
Mutual Inductance (L_m)	(0.06419 H)

APPENDIX B

TABLE VII. Parameters of ANN Model

Parameter	**Value**
Preset	(Bilayered Neural Network)
Fully connected layers	(2)
First layer size	(10)
Second layer size	(10)
Activation	(ReLU)
Iteration limit	(1000)

TABLE VIII. Parameters of KNN Model

Parameter	**Value**
Preset	(Weighted KNN)
Number of Neighbours	(10)
Distance metric	(Euclidean)
Distance weight	(Squared inverse)

TABLE IX. Parameters of SVM Model

Parameter	**Value**
Preset	(Coarse Gaussian SVM)
Kernel function	(Gaussian)
Kernel scale	(8.9)
Box constraint level	(1)
Multiclass coding	One-vs-One

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