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An FEM-Informed Statistical Feature Extraction and Comparative Machine Learning Framework for Dynamic Eccentricity Fault Diagnosis in Interior Permanent Magnet Synchronous Motors

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Abstract

Interior Permanent Magnet Synchronous Motors (IPMSMs) are widely used in traction and industrial drive systems because they combine high efficiency, high power density, and excellent performance over a wide speed range. Rotor eccentricity, however, remains one of the most significant faults affecting their reliable operation; diagnosing it early is crucial for avoiding unexpected breakdowns. To achieve this, the analysis utilizes a simulation-based fault diagnosis framework that combines the Finite Element Method (FEM) with machine learning. A 550 W, 220 V IPMSM was modeled in ANSYS Maxwell to simulate dynamic eccentricity faults at three severity levels: 10%, 20%, and 40%. A fixed-length, non-overlapping window segmentation approach was used to pull statistical features from the stator current and radial air-gap flux density signals. These features were then fed into several supervised machine learning algorithms, evaluated using a consistent 5-fold cross-validation protocol across all investigated classifiers, with the Ensemble Bagged Trees classifier achieving validation accuracies of 93.12% for radial air-gap flux density and 87.86% for stator current. By integrating finite-element analysis, statistical feature extraction, and comparative machine learning, the proposed framework demonstrates the feasibility of simulation-based dynamic eccentricity severity classification in IPMSMs. The results indicate that Ensemble Bagged Trees provide the best classification performance among the evaluated classifiers, establishing a foundation for future experimental validation and real-time condition-monitoring applications.

Keywords: condition monitoring; dynamic eccentricity; fault diagnosis; finite element method; machine learning; permanent magnet synchronous motor; sliding window



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1. Introduction

The adoption of Interior Permanent Magnet Synchronous Motors (IPMSMs) in electric propulsion and industrial systems has become increasingly popular, driven by their high-power density, good torque characteristics, and rapid dynamic response [1]. Unlike surface-mounted machines, the rotor saliency in IPMSMs provides additional reluctance torque, enhancing flux-weakening capabilities, thermal stability, and overall operational robustness [2]. Despite their dependability, these motors often operate in extreme environments where they are susceptible to electrical, magnetic, and mechanical failures.

Among mechanical faults, air-gap eccentricity is one of the most significant faults reported in rotating electrical machines [3]. Eccentricity is categorized as static, dynamic, or

mixed based on the relative positioning of the stator and rotor axes. Dynamic Eccentricity (DE) occurs when the rotor's center of rotation deviates from its geometric center, leading to a "wobbling" effect [4]. This results in instantaneous airgap fluctuations that disturb electromagnetic characteristics, induced by factors such as bearing wear, frequent load variations, and improper alignment. If left undetected, the resulting unbalanced magnetic pull (UMP) can escalate into catastrophic damage to the motor's internal structure [5].

The Finite Element Method (FEM) provides a powerful analytical platform by enabling detailed electromagnetic modeling that accounts for geometric accuracy, material nonlinearity, and saturation effects [6,7]. Recent studies have successfully combined FEM with signal processing, such as wavelet transforms, to diagnose demagnetization and stator faults [8,9]. Furthermore, the integration of FEM with Machine Learning (ML) has defined a new frontier in predictive maintenance [10,11]. Recent literature showcases the efficacy of ML architectures, including Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), and Convolutional Neural Networks (CNN), in identifying short-circuit and bearing defects with high precision [12–16]. Nevertheless, most reported studies focus on a single fault type, individual diagnostic signals, or a specific classification algorithm, making it difficult to evaluate the relative effectiveness of different sensing quantities and machine learning techniques under identical operating conditions. Consequently, there remains a need for a comprehensive framework that combines high-fidelity FEM modelling with systematic feature extraction and comparative machine learning analysis for dynamic eccentricity fault severity diagnosis.

Fixed-length window-based feature extraction has emerged as an effective preprocessing technique for fault diagnosis in rotating electrical machines because it partitions continuous signals into equal-duration segments while preserving localized temporal information that may be overlooked by conventional global statistical analysis. Each signal segment is processed independently to extract representative statistical features, providing compact yet discriminative information for machine learning-based classification while reducing the influence of noise and non-stationary operating conditions. Owing to its computational simplicity and effectiveness, this approach has been widely adopted for intelligent fault diagnosis of electrical machines [17–21].

From a machine learning perspective, these localized features significantly enhance the performance of classifiers such as Random Forests and ensemble learners. Random Forest, being an ensemble of decision trees, benefits from diverse and informative feature inputs, as it aggregates predictions from multiple trees trained on varied subsets of data [22–24]. Studies demonstrate that feature extraction plays a crucial role in transforming raw high-dimensional process data into lower-dimensional yet discriminative representations, which improves both interpretability and classification accuracy [25]. Recent studies combining sliding window strategies with Random Forest models have shown significant gains in prediction accuracy by effectively capturing dynamic system parameter changes that static feature representations overlook [26].

Adaptive and optimized ensemble techniques have advanced, notably through sliding window-based ensemble pruning methods. These methods adjust the number of trees in a Random Forest by assessing performance within a moving accuracy window, which lowers computational complexity while improving predictive accuracy by keeping only the most pertinent sub-ensembles. This integration underscores the relationship between temporal feature extraction and ensemble optimization, resulting in more effective fault prediction systems [27–30].

Recent research trends are also moving toward hybrid frameworks that combine data-driven models with classical control strategies. In industrial automation and electric vehicle (EV) systems, purely data-driven approaches may lack guarantees of stability and real-time

reliability. Therefore, hybrid models integrate machine learning-based fault detection with robust or adaptive control techniques, ensuring that even when faults are detected, the system can maintain operational stability and fault tolerance. This convergence of intelligent diagnostics and control engineering is particularly critical for safety-critical applications such as smart grids, autonomous systems, and EV powertrains [31–33].

Despite the significant progress in FEM-assisted and machine learning-based fault diagnosis of PMSMs, several research areas need to be addressed. Most existing studies focus on a single diagnostic signal, such as stator current or vibration, while comparatively fewer investigations evaluate the diagnostic capability of electromagnetic quantities such as radial air-gap flux density under identical operating conditions. Furthermore, many reported approaches concentrate on fault detection rather than systematic fault severity classification across multiple eccentricity levels. Although deep learning techniques have demonstrated promising performance, they generally require large datasets and substantial computational resources, limiting their practical applicability in industrial condition-monitoring systems. In addition, comparative investigations of conventional machine learning algorithms using FEM-generated datasets for eccentricity diagnosis remain limited. These gaps motivate the development of a computationally efficient and systematic diagnostic framework capable of accurately identifying different eccentricity severities while providing insight into the relative effectiveness of multiple diagnostic signals [34–37].

This work investigates the effects of dynamic eccentricity in an IPMSM by leveraging a hybrid diagnostic framework comprising ANSYS Maxwell 2022 R2 FEM and MATLAB R2025a-based machine learning. A 550 W IPMSM model is utilized to simulate dynamic eccentricity fault severities of 10%, 20%, and 40%. Statistical features are extracted from the simulated stator current and radial air-gap flux density signals using a fixed-length, non-overlapping window segmentation technique. The extracted features are subsequently used to evaluate the performance of multiple supervised machine learning classifiers for dynamic eccentricity severity classification. The proposed framework provides a computationally efficient, simulation-based approach for intelligent condition monitoring and forms a foundation for future experimental validation and real-time implementation.

The main contributions of this paper are summarized as follows:

- A high-fidelity finite element model of a 550 W Interior Permanent Magnet Synchronous Motor was developed to simulate dynamic eccentricity faults at multiple severity levels under rated operating conditions.
- A comprehensive diagnostic dataset was generated from both radial air-gap flux density and stator current signals, enabling a comparative investigation of invasive and non-invasive condition-monitoring strategies for dynamic eccentricity diagnosis.
- A fixed-length, non-overlapping window-based statistical feature extraction framework was implemented to preserve localized electromagnetic characteristics and generate discriminative statistical features for dynamic eccentricity severity classification.
- Multiple supervised machine learning algorithms were systematically evaluated under identical training and testing conditions to identify the most suitable classifier for dynamic eccentricity fault severity classification.
- The proposed framework demonstrates that Ensemble Bagged Trees achieve the best classification performance among the evaluated machine learning algorithms while maintaining computational simplicity, highlighting their suitability for simulation-based dynamic eccentricity severity classification and providing a foundation for future experimental validation and real-time condition-monitoring applications.

The remainder of this paper is organized as follows. Section 2 reviews the related literature approaches to eccentricity faults. Section 3 presents the finite-element modelling and implementation of dynamic eccentricity in the IPMSM. Section 4 describes the feature

extraction procedure, dataset preparation, machine learning methodology, and diagnostic performance evaluation. Section 5 discusses the limitations and future scope of the present study, and Section 6 provides the conclusion.

2. Eccentricity Fault Approaches

Recent advances in condition monitoring of Permanent Magnet Synchronous Motors (PMSMs) have resulted in the development of numerous fault diagnosis techniques employing analytical modelling, finite element analysis, signal processing, and machine learning. Among these approaches, the Finite Element Method (FEM) has emerged as an indispensable tool for investigating fault mechanisms because it accurately captures electromagnetic field distributions, magnetic saturation, and geometric nonlinearities that are difficult to represent using analytical models. Consequently, FEM-generated datasets have been increasingly adopted for developing intelligent fault diagnosis algorithms, particularly in situations where experimental fault data are difficult, expensive, or unsafe to obtain.

Machine learning techniques have further enhanced the capability of PMSM fault diagnosis by enabling the automatic identification of fault patterns from measured or simulated signals. Conventional classifiers such as Support Vector Machines (SVM), k-Nearest Neighbours (k-NN), Decision Trees, Random Forests, and ensemble learning algorithms have demonstrated promising performance for detecting electrical, magnetic, and mechanical faults. More recently, deep learning approaches, including Convolutional Neural Networks (CNNs) and hybrid deep learning architectures, have been investigated for automatic feature learning and fault classification. However, these methods generally require substantially larger labelled datasets, greater computational resources, and longer training times, which may limit their practical implementation in real-time industrial condition-monitoring systems.

To improve the diagnostic capability of conventional machine learning algorithms, several studies have employed window-based signal segmentation and statistical feature extraction to capture localized fault characteristics from electrical machine signals. By partitioning continuous signals into fixed-duration segments, representative statistical descriptors such as mean, root mean square (RMS), standard deviation, peak-to-peak value, crest factor, skewness, and kurtosis can be extracted to characterize the local behaviour of the machine. This feature engineering approach provides compact yet discriminative information while maintaining low computational complexity, making it particularly suitable for intelligent fault diagnosis using conventional supervised learning algorithms.

Most existing studies focus on a single diagnostic signal, a specific fault type, or the evaluation of a limited number of machine learning algorithms. Comparatively fewer investigations have integrated high-fidelity finite element modelling with a systematic comparison of multiple conventional machine learning classifiers using statistical features extracted from both radial air-gap flux density and stator current signals. Furthermore, limited attention has been devoted to multi-level dynamic eccentricity severity classification using simulation-generated datasets under identical operating conditions.

Motivated by these research gaps, the proposed framework integrates high-fidelity finite element modelling with fixed-length, non-overlapping window-based statistical feature extraction and comparative machine learning analysis for dynamic eccentricity severity classification in an Interior Permanent Magnet Synchronous Motor. Statistical features extracted from both radial air-gap flux density and stator current signals are used to comparatively evaluate multiple supervised machine learning algorithms under identical operating conditions, enabling a systematic assessment of their diagnostic capability. The proposed framework provides a computationally efficient simulation-based methodology

for intelligent fault diagnosis while establishing a foundation for future validation using multiple independent finite-element simulations, experimental measurements, and real-time condition-monitoring applications.

The principal differences between representative recent approaches and the proposed framework are summarized in Table 1.

Table 1. Comparison of Recent Studies on PMSM Dynamic Eccentricity Diagnosis.

Reference	Diagnostic Signal	Methodology	Major Limitation/Research gap
[4]	Air-gap Flux	FEM + ML	Investigated only static eccentricity in SPMSMs.
[7]	Magnetic Field	FEM + ML	Preliminary investigation without comprehensive classifier evaluation and performance analysis.
[9]	Current & Flux	Signal Sensitive Analysis	Compared diagnostic signals but did not perform comparative machine learning-based fault classification.
[16]	Current	Ensemble Learning	Focused on current-based diagnosis without utilizing complementary flux-density information.
Proposed	Current & Radial Flux Density	FEM + Fixed Window statistical feature extraction + Comparative ML (Ensemble Bagged Trees)	Classifies multiple dynamic eccentricity severity levels using complementary diagnostic signals and comprehensive machine learning performance evaluation.

3. Finite Element Analysis of Dynamic Eccentricity Fault in Interior Permanent Magnet Synchronous Motor

3.1. IPMSM Configuration

The proposed diagnostic framework is developed using a three-phase, 0.55 kW, 220 V Interior Permanent Magnet Synchronous Motor (IPMSM) operating at a rated speed of 3600 rpm, as shown in Figure 1.

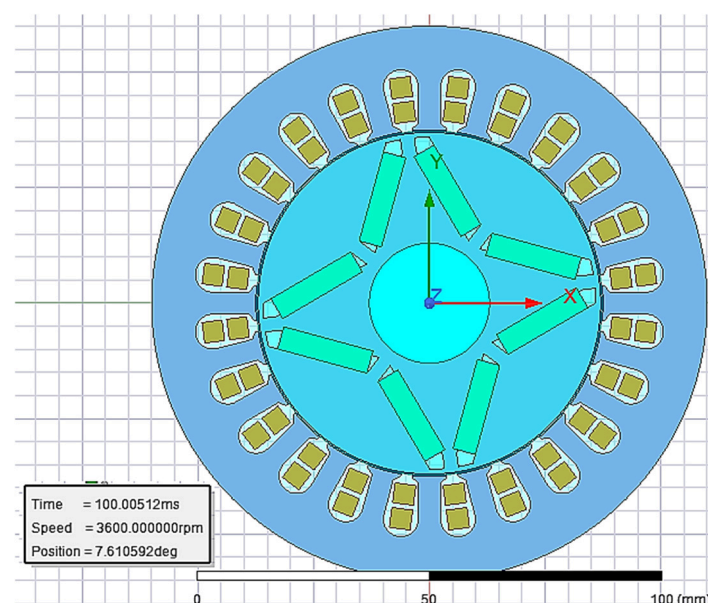


Figure 1. Finite Element Model of IPMSM.

The machine was modelled using ANSYS Maxwell to facilitate high-fidelity transient electromagnetic analysis. Initially, the healthy IPMSM was analyzed to establish baseline electromagnetic characteristics, including stator phase currents, magnetic flux distribution,

and radial air-gap flux density. These baseline results were subsequently compared with those obtained under dynamic eccentricity conditions. Table 2 lists the design specifications of IPMSM.

Table 2. IPMSM Design Specifications.

Parameters	Rated Values
Rated output power	0.55 kW
Frequency	120 Hz
Rated Voltage	220 V
Rated Speed	3600 rpm
Operating temperature	75 °C
Control-type	PWM
No. of poles	4
Rotor type	V-type
Permanent Magnet	XG196/96

3.2. Finite Element Model Development

A two-dimensional transient finite element model of the Interior Permanent Magnet Synchronous Motor (IPMSM) was developed in ANSYS Maxwell to investigate the electromagnetic behavior under healthy and dynamic eccentricity conditions. The model was established using the machine dimensions and electrical specifications listed in Table 2. A transient electromagnetic solver was employed under rated operating conditions, with balanced three-phase excitation supplied through a voltage-source inverter and the rotor rotating at its rated speed.

The developed finite element model provides a controlled and repeatable environment for systematically investigating dynamic eccentricity at different fault severity levels while maintaining identical operating conditions throughout the simulations. This approach enables the generation of consistent electromagnetic datasets for feature extraction and machine learning-based fault classification, thereby establishing a reliable simulation-based framework for the development and evaluation of intelligent diagnostic algorithms. Although the present study is limited to simulation-based validation, the proposed methodology provides the foundation for future experimental verification.

Transient electromagnetic simulations were subsequently performed in ANSYS Maxwell 2D using the transient finite-element solver under rated operating conditions. A fixed time step of 0.0002 s was employed over a total simulation duration of 0.3 s, while adaptive time stepping was disabled to maintain a uniform temporal resolution throughout the analysis. The outer computational boundary was assigned a vector potential boundary condition, and rotor motion was modelled using the Cylindrical Gap motion-band formulation. The stator and rotor cores were assigned the predefined M19_24G_2DSF0.950 electrical steel material, the permanent magnets employed the XG196/96_2DSF1.000_X material, and the windings used the predefined copper_75C material model. These simulation settings were maintained consistently for the healthy and all dynamic eccentricity models to ensure that any observed variations in the electromagnetic responses were solely attributable to the introduced fault conditions.

The IPMSM analytical model was exported to ANSYS Maxwell for transient finite-element analysis. Before introducing dynamic eccentricity faults, the analytical model performance was evaluated to verify consistency between the analytical machine design and the intended rated operating specifications. As summarized in Table 3, the baseline model exhibited a rated output power of approximately 0.55 kW, rated speed of 3600 rpm, rated torque of 1.46 Nm, RMS armature current of 3.91 A, and efficiency of 83.15%. These

results demonstrate the consistency of the baseline analytical machine design adopted for the subsequent transient finite-element simulations.

Table 3. Full-load operating characteristics of the healthy IPMSM obtained from analytical model.

Parameter	Analytical Model Characteristics
Rated Output Power	0.55 kW
Rated Speed	3600 rpm
Rated Torque	1.46 Nm
RMS Armature Current	3.91 A
Efficiency	83.15%

The transient finite-element model employed the cylindrical gap mesh operation to accurately discretize the rotating air-gap interface between the stator and rotor. Manual surface approximation was applied to improve the geometric representation of curved machine regions, with surface deviation values of 0.037 mm for the permanent-magnet regions and 0.06 mm for the remaining machine geometry. A normal deviation of 15° was specified for both surface approximation operations. The same mesh operations and discretization parameters were retained for the healthy and all dynamic eccentricity models to ensure a consistent numerical solution and to eliminate mesh-related variations in the comparative analysis.

The numerical model employed identical solver settings, material properties, boundary conditions, and mesh operations for all operating conditions to ensure a consistent comparative evaluation between the healthy and dynamic eccentricity cases. This modelling strategy was adopted to ensure that the observed variations in the electromagnetic responses were solely attributable to the introduced dynamic eccentricity under identical numerical conditions.

3.3. Dynamic Eccentricity Modelling

Dynamic eccentricity was incorporated into the finite-element IPMSM model by introducing an eccentric offset between the rotor and stator while allowing the minimum air-gap location to rotate synchronously with the rotor during transient operation. Unlike static eccentricity, where the minimum air-gap location remains fixed relative to the stator, dynamic eccentricity produces a continuously varying air-gap distribution throughout rotor rotation, resulting in periodic modulation of the electromagnetic field. These variations influence both the radial air-gap flux density and stator current, making them suitable diagnostic signals for fault detection and severity classification.

The dynamic eccentricity ratio is expressed as $E = (e/g) \times 100$, where ‘e’ represents the radial displacement of the rotor centre from its concentric position and ‘g’ denotes the nominal radial air-gap length. The existing transient Motion Setup and motion band generated for the healthy model were retained without modification to preserve the original rotor motion definition.

Figure 2 illustrates the workflow adopted for implementing dynamic eccentricity in the IPMSM using ANSYS Maxwell.

Motion Eccentricity provides two independent parameters: Motion Axis Translation and Moving Parts Translation. The Motion Axis Translation was maintained at (0, 0) mm so that the rotational axis remained coincident with the stator geometric centre, whereas the Moving Parts Translation was specified as (0.05, 0) mm, (0.10, 0) mm, and (0.20, 0) mm to represent 10%, 20%, and 40% dynamic eccentricity, respectively.



Figure 2. Workflow of dynamic eccentricity in ANSYS Maxwell, from the healthy model to the transient dynamic-eccentricity finite-element model.

The rotor components enclosed within the existing motion band were assigned the prescribed Moving Parts Translation, while the motion band continued to govern the transient rotational motion of the rotor. During transient simulation, the rotor position was continuously advanced according to the prescribed rotational speed, while the electromagnetic field solution was recomputed at each time step for the corresponding eccentric rotor position.

Since the eccentricity vector remains fixed relative to the rotating rotor, the location of the minimum air gap revolves synchronously with the rotor throughout each mechanical revolution. As illustrated in Figure 3, the displaced rotor centre (O_r) follows a circular trajectory about the fixed motion axis (O_s) while maintaining a constant eccentricity magnitude e throughout the transient simulation. This rotating air-gap characteristic distinguishes dynamic eccentricity from static eccentricity, in which the minimum air-gap location remains fixed relative to the stator.

Figure 4 presents an analytical illustration of the theoretical air-gap variation over one mechanical revolution to further clarify the adopted dynamic eccentricity modelling approach.

Three dynamic eccentricity severity levels corresponding to rotor displacements of 0.05 mm, 0.10 mm, and 0.20 mm were investigated, representing 10%, 20%, and 40% eccentricity, respectively. Apart from the specified Moving Parts Translation used to introduce the eccentricity, all other machine dimensions, material properties, inverter configuration, and operating conditions remained identical to those of the healthy model. The machine was supplied through a three-phase DC–AC voltage-source inverter employing sinusoidal pulse-width modulation (PWM), as illustrated in Figure 5. Consequently, any observed variations in the electromagnetic responses were solely attributable to the imposed dynamic eccentricity.

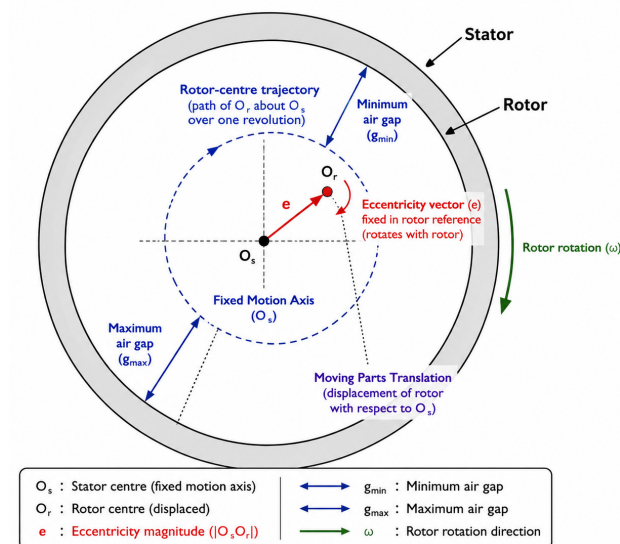


Figure 3. Schematic representation of dynamic eccentricity. The stator centre O_s and rotor centre O_r are separated by the eccentricity vector e ; because the Motion Axis remains fixed at O_s while the Moving Parts Translation displaces the rotor geometry, O_r traces a circular rotor-centre trajectory (dashed) about O_s once per mechanical revolution. The dotted reference lines indicate the radial directions associated with the minimum and maximum air-gap locations, which revolve within the stator reference frame.

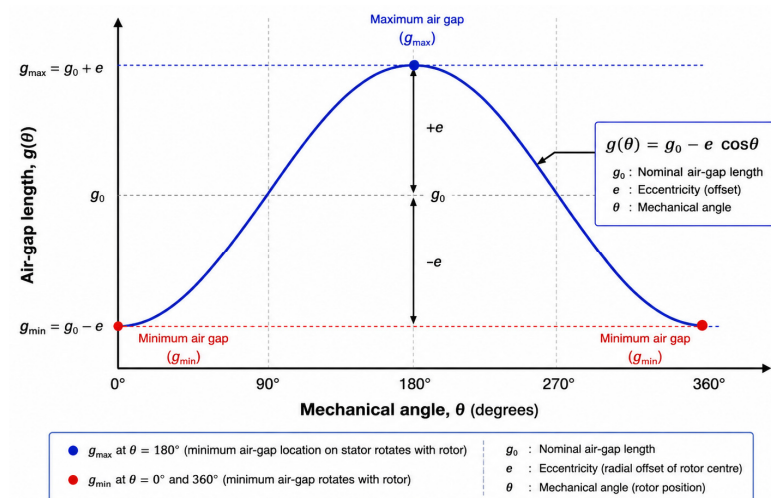


Figure 4. Analytical illustration of the air-gap variation $g(\theta) = g_0 - e \cos\theta$ with mechanical angle θ over one rotor revolution, where g_0 is the mean air-gap length and e is the eccentricity offset.

3.4. Electromagnetic Analysis Under Dynamic Eccentricity

The developed finite-element model was evaluated under rated operating conditions at a rated speed of 3600 rpm and a load torque of 1.45 Nm. The influence of dynamic eccentricity on the electromagnetic behavior of the IPMSM was analyzed using stator current, magnetic flux distribution, and radial air-gap flux density. These quantities were selected because they provide complementary information regarding the electrical and magnetic responses of the machine under different fault severity levels.

Figure 6 compares the stator phase currents of the healthy IPMSM with those obtained under the 40% dynamic eccentricity condition. The time-domain waveforms indicate that the peak current magnitudes remain nearly identical for both operating conditions. Although a 40% dynamic eccentricity corresponds to a rotor displacement of only 0.20 mm, the resulting variation in current magnitude remains relatively small. This observation

suggests that conventional threshold-based current monitoring techniques may not be sufficiently sensitive for the early detection of dynamic eccentricity faults. Nevertheless, subtle waveform variations introduced by the fault can be effectively captured through statistical feature extraction and subsequently exploited by machine learning algorithms for reliable fault classification.

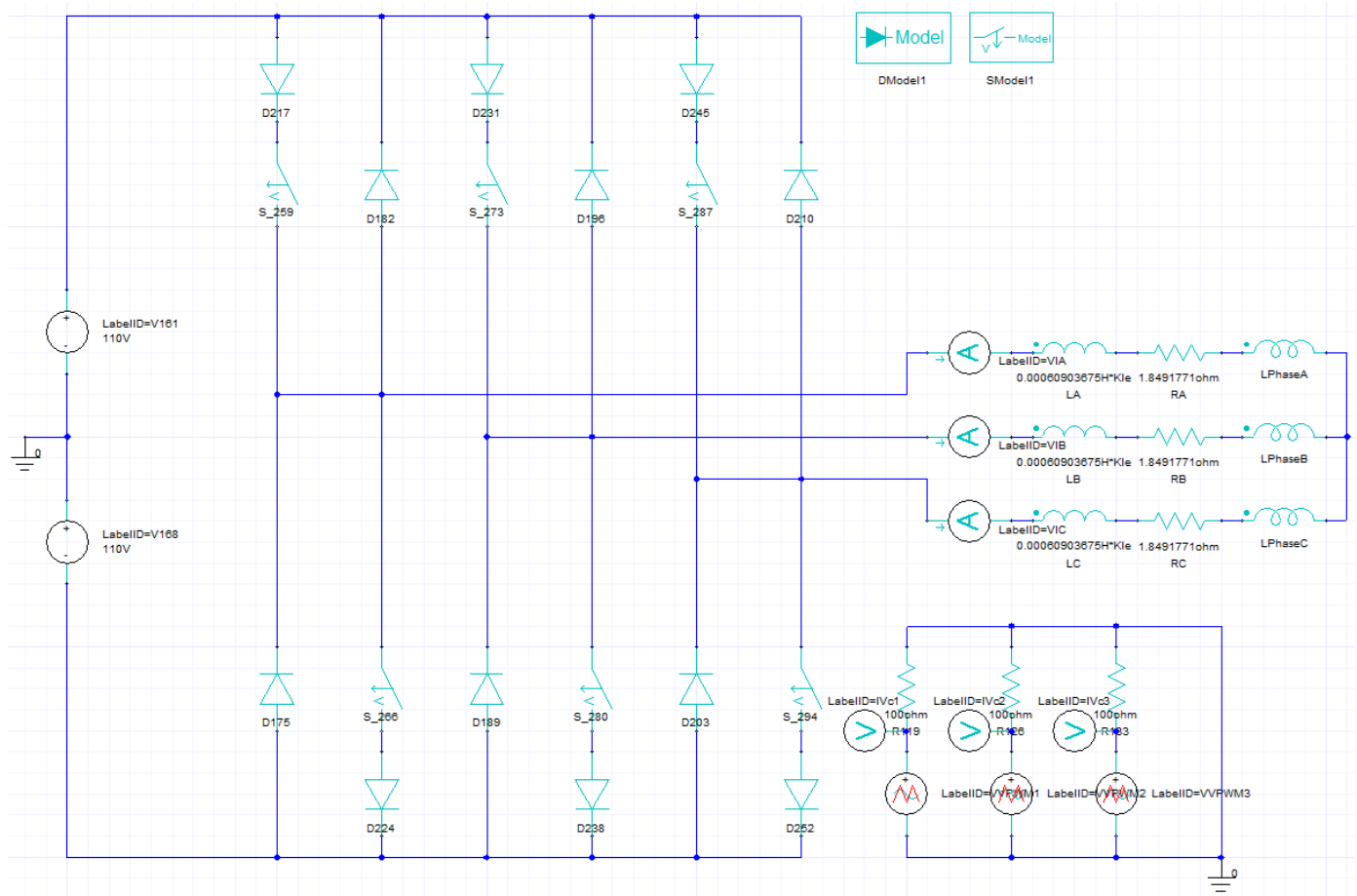


Figure 5. IPMSM Converter and Control.

Table 4 summarizes the RMS values of the stator phase current under healthy and dynamic eccentricity conditions.

Table 4. Variations in the RMS Values of Stator Phase Current.

IPMSM Condition	RMS Value
Healthy	7.1594
10% Faulty	7.1732
20% Faulty	7.2040
40% Faulty	7.2118

Figure 7 illustrates the magnetic flux distribution of the healthy IPMSM and the machine operating under 40% dynamic eccentricity. Under healthy conditions, the magnetic flux lines exhibit a nearly symmetric magnetic flux distribution across the four-pole structure. In contrast, dynamic eccentricity introduces a non-uniform air-gap reluctance, causing the magnetic flux to concentrate in regions where the air gap is reduced while weakening in regions with an increased air-gap length. This magnetic asymmetry becomes progressively

more pronounced with increasing fault severity and provides a distinctive electromagnetic signature suitable for fault diagnosis.

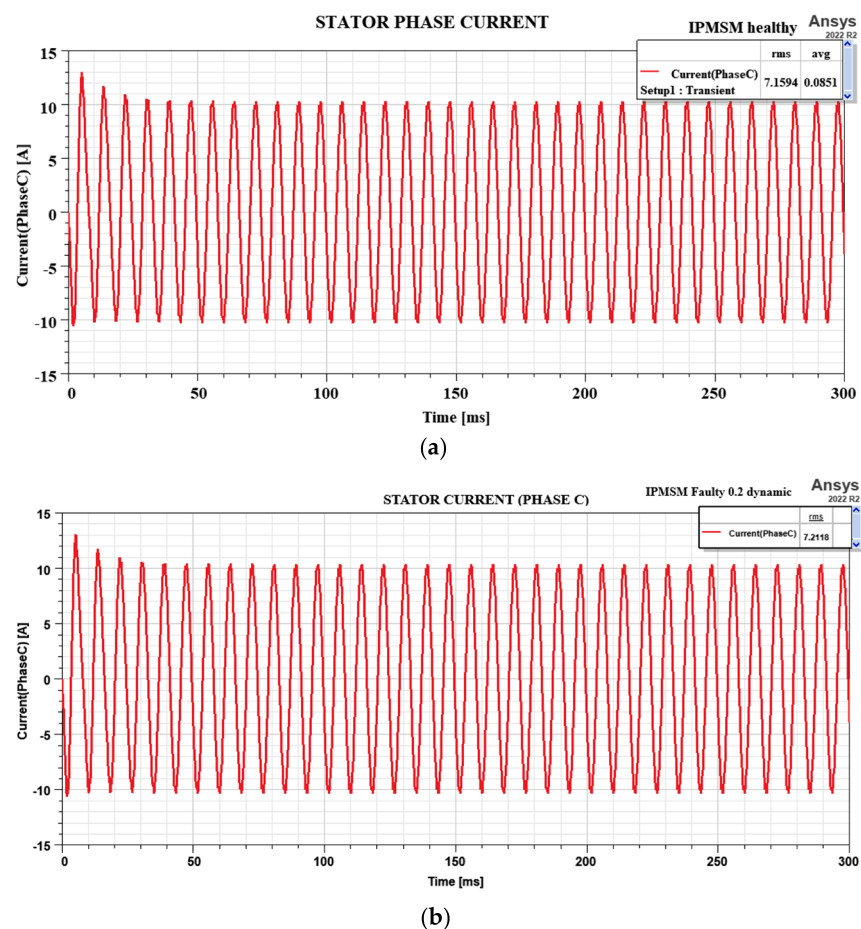


Figure 6. Stator Phase Current. (a) Healthy IPMSM. (b) 40% Eccentric IPMSM.

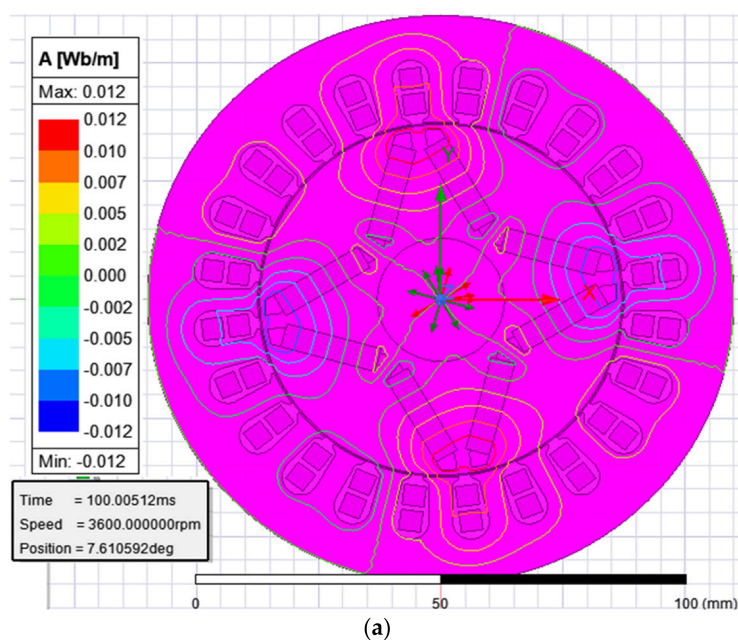


Figure 7. Cont.

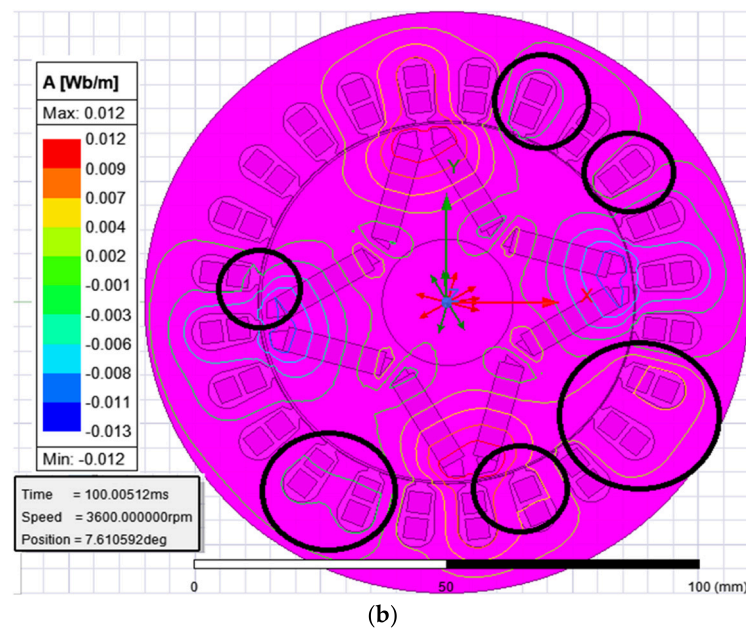


Figure 7. Flux Distribution over IPMSM. (a) Healthy Motor. (b) 40% Eccentric Motor. The black circles highlight regions exhibiting pronounced asymmetries in the magnetic flux distribution associated with increasing fault severity, while the arrows indicate the direction of rotation.

Figure 8 presents the radial air-gap flux density of the IPMSM under healthy and dynamic eccentricity conditions. The healthy machine exhibits a periodic and symmetric waveform, whereas the eccentricity faults introduce localized distortions, waveform asymmetry, and increased harmonic distortion arising from variations in the air-gap reluctance, slotting harmonics, and rotor–stator interactions. As the fault severity increases from 10% to 40%, these distortions become progressively more evident, demonstrating the high sensitivity of radial air-gap flux density to dynamic eccentricity. Consequently, radial air-gap flux density, together with stator current, provides complementary diagnostic information for statistical feature extraction and subsequent machine learning-based fault severity classification.

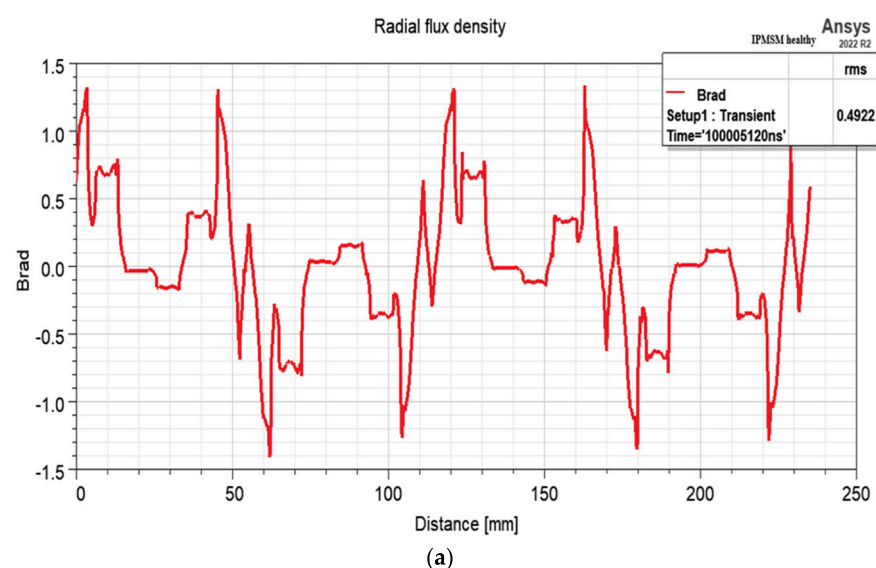


Figure 8. Cont.

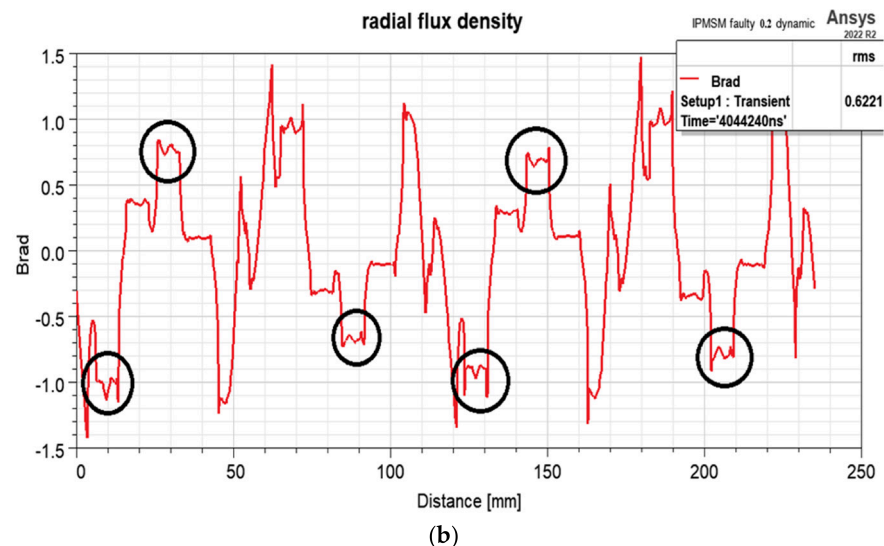


Figure 8. Radial flux density of IPMSM. (a) Healthy motor. (b) 40% Eccentric motor. The black circles indicate the regions of distortion in the radial flux density waveform resulting from variations in fault severity.

Table 5 summarizes the RMS values of the radial air-gap flux density for healthy and faulty operating conditions. The results indicate a gradual increase in RMS value with increasing eccentricity severity, reflecting the progressive distortion of the magnetic field distribution. Although the variations associated with 10% eccentricity are relatively small, they demonstrate the onset of electromagnetic asymmetry. At 40% eccentricity, the increase becomes considerably more pronounced, indicating significant magnetic field distortion. These observations indicate that the RMS value alone is insufficient for reliable early-stage fault diagnosis and should therefore be complemented by additional statistical features and machine learning techniques to improve fault sensitivity and classification accuracy.

Table 5. Variations in the RMS Values of Radial Flux Density.

IPMSM Condition	RMS Value
Healthy	0.4922
10% Dynamic Eccentricity	0.4972
20% Dynamic Eccentricity	0.5014
40% Dynamic Eccentricity	0.6221

4. Feature Extraction, Dataset Preparation, and Machine Learning Framework

4.1. Feature Extraction

Figure 9 illustrates the proposed workflow. The simulated radial air-gap flux density and stator current signals obtained from the finite element analysis were processed to extract representative statistical features for machine learning-based fault severity classification. The two diagnostic signals were extracted using different procedures according to their physical characteristics. The stator phase current was obtained from the transient finite-element simulation performed over 0–300 ms. To avoid start-up transient effects, only the steady-state interval between 30 ms and 230 ms was exported for analysis, resulting in 100,001 uniformly sampled data points. In contrast, the radial air-gap flux density was extracted along a predefined air-gap path extending from 0 mm to 230 mm with a spatial resolution of 0.002 mm, yielding 115,001 uniformly spaced samples. These exported

datasets formed the basis for the subsequent statistical feature extraction and machine learning analysis.

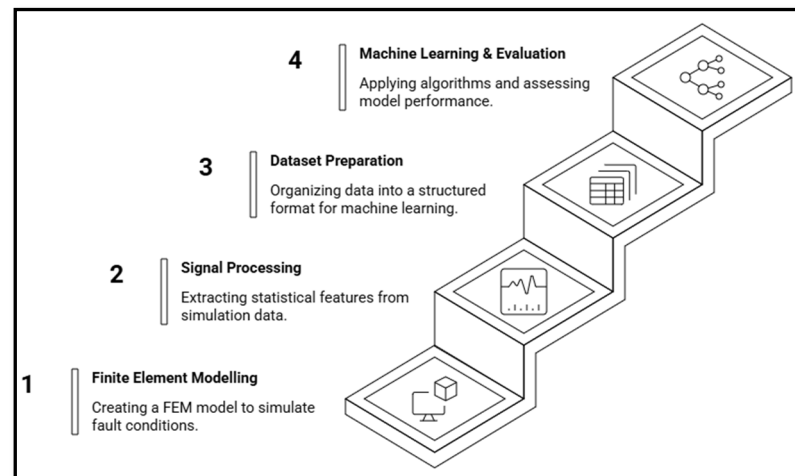


Figure 9. Workflow of the proposed finite element-based machine learning framework for dynamic eccentricity severity classification in IPMSM.

Although both diagnostic signals were segmented using a fixed-length strategy, the segmentation criterion differed according to the signal domain. The radial air-gap flux density represents a spatial distribution of the magnetic field along the air gap and was therefore divided into consecutive segments containing 10 samples each. In contrast, the stator current represents a time-domain electrical signal and was segmented using a fixed temporal duration of 0.05 ms. The number of samples contained in each current segment depends on the segment duration and the sampling frequency of the exported waveform.

For both diagnostic signals, the segmentation interval was equal to the segment length, resulting in fixed-length, non-overlapping segmentation. Consequently, each feature vector was extracted from a unique portion of the simulated waveform without sharing samples with adjacent segments. This approach provides localized signal characterization while avoiding the redundancy associated with overlapping window techniques.

It should be noted that one transient finite-element simulation was performed for each operating condition (Healthy, 10%, 20%, and 40% dynamic eccentricity). Consequently, the extracted feature vectors originate from four independent simulated waveforms and should be regarded as feature vectors derived from the corresponding simulated waveforms rather than statistically independent experimental observations.

4.2. Statistical Feature Computation

Each segmented waveform was characterized using seven statistical features commonly employed in electrical machine fault diagnosis, namely Mean, Root Mean Square (RMS), Standard Deviation, Peak-to-Peak Value, Crest Factor, Skewness, and Kurtosis. These features collectively describe the average signal level, energy content, dispersion, waveform amplitude, impulsiveness, asymmetry, and distribution characteristics associated with dynamic eccentricity. The selected features were chosen because they provide complementary information regarding the local electromagnetic behaviour of the machine. Mean and RMS quantify the average signal level and energy content; Standard Deviation reflects signal variability, Peak-to-Peak Value and Crest Factor capture localized waveform distortions, whereas Skewness and Kurtosis describe higher-order statistical variations associated with dynamic eccentricity.

The statistical features were computed for each non-overlapping signal segment using MATLAB. Each feature vector consisted of the seven statistical descriptors listed above,

and the resulting feature vectors were subsequently used to construct the labelled dataset for machine learning classification.

4.3. Dataset Preparation

Following feature extraction, every feature vector was assigned a class label corresponding to its operating condition, namely Healthy (Class 0), 10% Dynamic Eccentricity (Class 1), 20% Dynamic Eccentricity (Class 2), and 40% Dynamic Eccentricity (Class 3). Feature vectors extracted from all operating conditions were subsequently combined to form the dataset used for supervised machine learning. Each feature vector corresponds to one non-overlapping signal segment extracted from the respective finite-element waveform, with all feature vectors generated independently within each operating condition before being combined into a single labelled dataset for classifier development.

The resulting dataset comprised exactly 11,500 feature vectors for each operating condition (Healthy, 10%, 20%, and 40% dynamic eccentricity), yielding a total of 46,000 labelled feature vectors. The dataset was therefore perfectly balanced across the four fault classes, thereby eliminating class-imbalance effects during classifier training and evaluation. Since the feature vectors within each operating condition were extracted from the corresponding transient finite-element simulation, the reported classification results demonstrate the effectiveness of the proposed framework within the available simulation dataset.

4.4. Machine Learning Classification

The labelled feature dataset was imported into the MATLAB Classification Learner to comparatively evaluate multiple supervised machine learning algorithms for classifying the severity of dynamic eccentricity faults in the IPMSM. The classifiers were trained using the default training configurations provided by the MATLAB Classification Learner, and validation performance was estimated using the built-in 5-fold cross-validation procedure. The classifiers investigated include Decision Trees, Linear Discriminant Analysis, Logistic Regression, Naïve Bayes, Support Vector Machines, k-Nearest Neighbours, Artificial Neural Networks, and Ensemble Bagged Trees.

For performance evaluation, the labelled dataset was randomly partitioned into training (70%) and testing (30%) subsets. Multiple supervised machine learning classifiers were trained using identical feature sets and evaluation procedures to ensure a fair comparative assessment of their diagnostic performance. Classification accuracy, precision, recall, F1-score, confusion matrices, and receiver operating characteristic (ROC) curves were employed to evaluate and compare the predictive capability of the investigated classifiers. Since one transient finite-element simulation was available for each operating condition, the adopted evaluation protocol provides a comparative assessment of classifier performance within the dataset of available simulations. More comprehensive validation using multiple independent simulations and grouped cross-validation strategies will be considered in future work. All classifiers were trained and evaluated using identical training and validation protocols to ensure a fair comparative assessment of their relative classification performance. Among the evaluated classifiers, the Ensemble Bagged Trees algorithm achieved the highest classification performance under the adopted evaluation protocol and was therefore selected for detailed performance analysis. The classification performance of each model was evaluated using overall classification accuracy, confusion matrices, precision, recall, F1-score, and receiver operating characteristic (ROC) curves with the corresponding area under the curve (AUC). These complementary performance metrics provide a comprehensive assessment of the classification capability of the investigated machine learning algorithms.

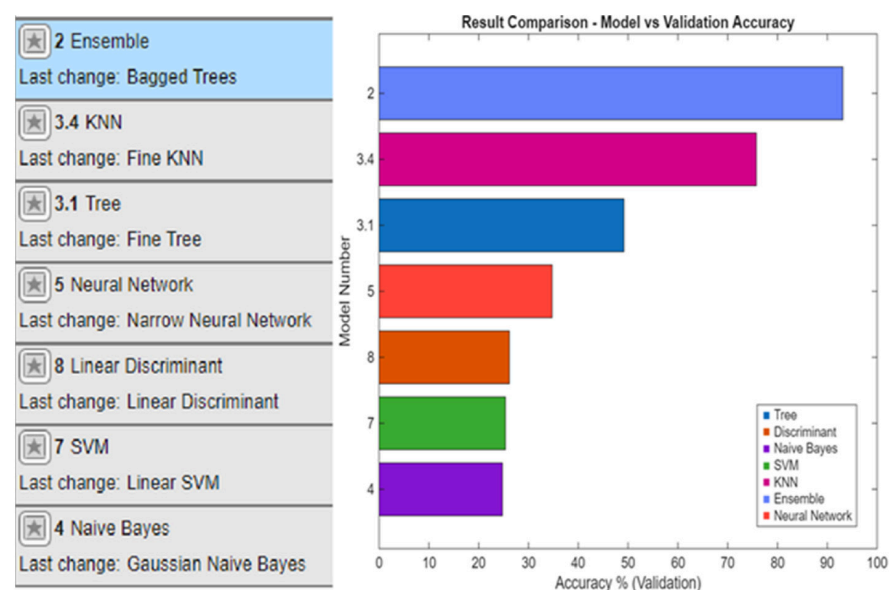
4.5. Comparative Performance of Machine Learning Classifiers

The extracted statistical feature vectors were used to evaluate the capability of multiple supervised machine learning algorithms for distinguishing healthy and dynamic eccentricity conditions. All classifiers were trained and evaluated using the same feature dataset and identical evaluation protocol to enable a fair comparison of their diagnostic performance. The classification results obtained using radial air-gap flux density and stator current features are presented in the following subsections.

Figure 10 and Table 6 compare the diagnostic performance of the evaluated supervised machine learning classifiers using identical feature sets and a common 5-fold cross-validation protocol. Among the investigated classifiers, Ensemble Bagged Trees consistently achieved the highest validation and testing accuracies for both the radial air-gap flux density and stator current datasets, recording validation accuracies of 93.12% and 87.86%, respectively, with corresponding testing accuracies of 94.36% and 88.76%. The superior performance of Ensemble Bagged Trees demonstrates its ability to effectively exploit the statistical information contained in the extracted features for distinguishing between healthy and different dynamic eccentricity severity levels within the available simulation dataset.

Table 6. Performance comparison of machine learning classifiers using 5-fold cross-validation for radial air-gap flux density and stator current datasets.

Classifier	Radial Flux Density Validation Accuracy (%)	Radial Flux Density Test Accuracy (%)	Stator Current Validation Accuracy (%)	Stator Current Test Accuracy (%)
Ensemble Bagged Trees	93.12	94.36	87.86	88.76
K-Nearest Neighbour (KNN)	75.74	75.48	83.83	84.21
Decision Tree	49.17	48.27	29.94	29.51
Neural Network	34.75	36.34	26.62	27.36
Discriminant Analysis	26.17	26.72	25.21	25.22
Support Vector Machine (SVM)	25.36	24.46	25.09	24.90
Naïve Bayes	24.78	24.68	25.17	25.05



(a)

Figure 10. Cont.

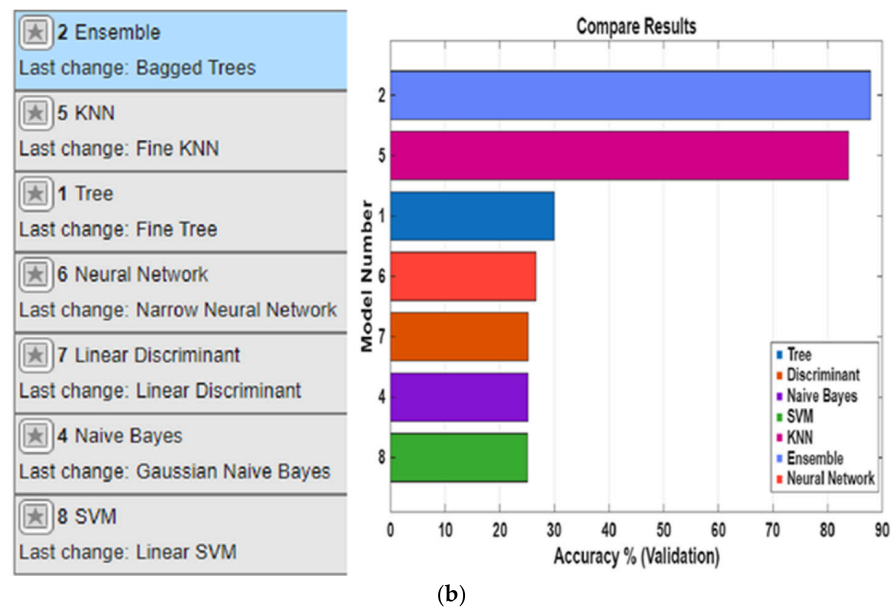


Figure 10. Model vs. Validation Accuracy. (a) Radial Flux Density dataset. (b) Stator Phase Current dataset.

Among the evaluated classifiers, the Ensemble Bagged Trees algorithm consistently achieved the highest validation and testing accuracies for both diagnostic signals. This superior performance can be attributed to the bootstrap aggregation of multiple decision trees, which reduces prediction variance while effectively capturing the nonlinear relationships among the extracted statistical features. Consequently, Ensemble Bagged Trees provided the most reliable classification performance within the available simulation dataset.

4.6. ROC Analysis

The diagnostic performance of the evaluated machine learning classifiers was further assessed using Receiver Operating Characteristic (ROC) analysis for both the radial air-gap flux density and stator current datasets, as illustrated in Figure 11. The ROC curves were generated from validation results obtained via 5-fold cross-validation. Among the evaluated classifiers, the Ensemble Bagged Trees model demonstrated the best classification performance, achieving Area Under the Curve (AUC) values of approximately 0.99 for both datasets. These near-unity AUC values indicate excellent discrimination between the investigated operating conditions and further confirm the effectiveness of the extracted statistical features for dynamic eccentricity severity classification. The high true-positive rates combined with low false-positive rates confirm the strong discriminative capability of the proposed diagnostic framework within the available simulation dataset. These results further confirm that the extracted statistical features provide strong discriminatory information for distinguishing the investigated dynamic eccentricity severity levels, with the Ensemble Bagged Trees classifier exhibiting the most consistent diagnostic performance among the evaluated machine learning algorithms.

4.7. Confusion Matrix Analysis

The classification performance of the Ensemble Bagged Trees classifier was further analyzed using validation and testing confusion matrices for both the radial air-gap flux density and stator current datasets, as presented in Figures 12 and 13. Unlike overall accuracy, confusion matrices provide class-wise insight into the distribution of correct classifications and misclassifications, thereby enabling a detailed assessment of the classifier's capability to distinguish the four operating conditions.

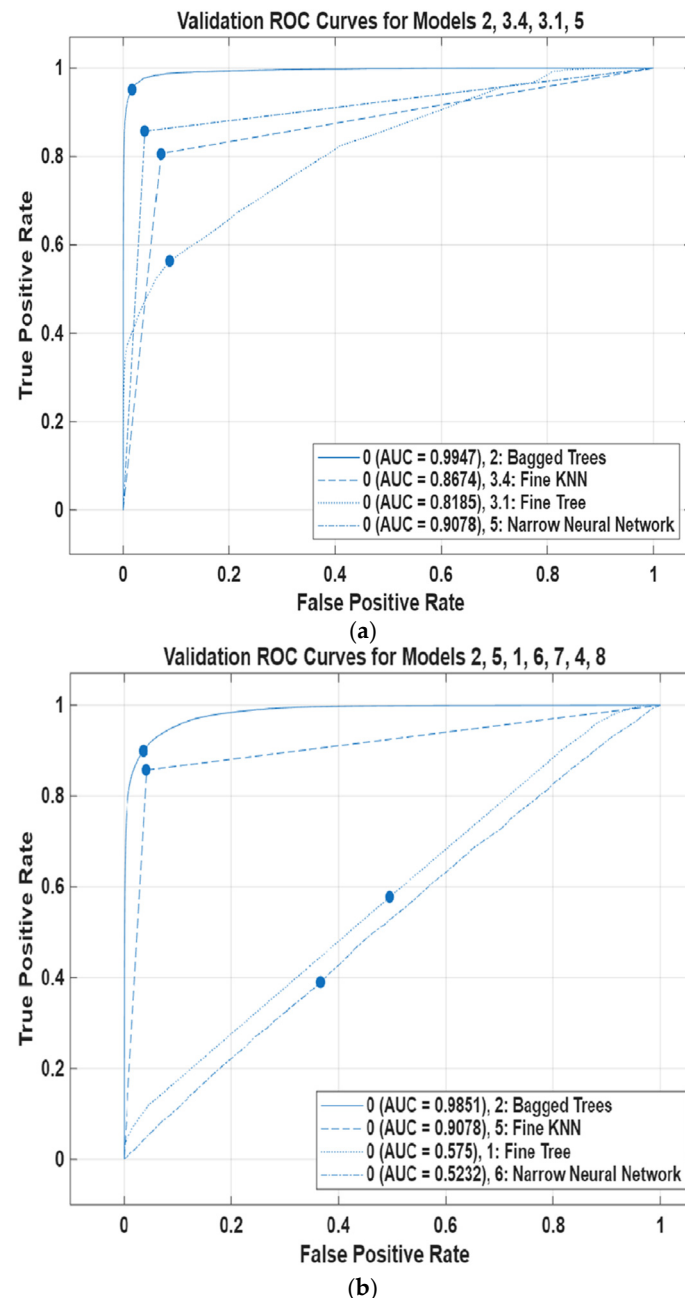


Figure 11. Validation ROC curve. (a) Radial Flux density dataset. (b) Stator Phase current dataset.

Figures 12 and 13 present the validation and testing confusion matrices obtained using the Ensemble Bagged Trees classifier for radial air-gap flux density and stator current, respectively. In both cases, the majority of the samples are concentrated along the principal diagonal, indicating high classification accuracy of the healthy condition and all three dynamic eccentricity severity levels. Only a limited number of samples appear in the off-diagonal elements, demonstrating minimal confusion between adjacent fault classes. The close agreement between the validation and testing confusion matrices demonstrates consistent classification performance within the available simulation dataset of the proposed classifier. Furthermore, the excellent classification performance supports the effectiveness of the proposed fixed-length, non-overlapping statistical feature extraction methodology, which provides sufficient discriminatory information for reliable dynamic eccentricity severity classification in IPMSMs.

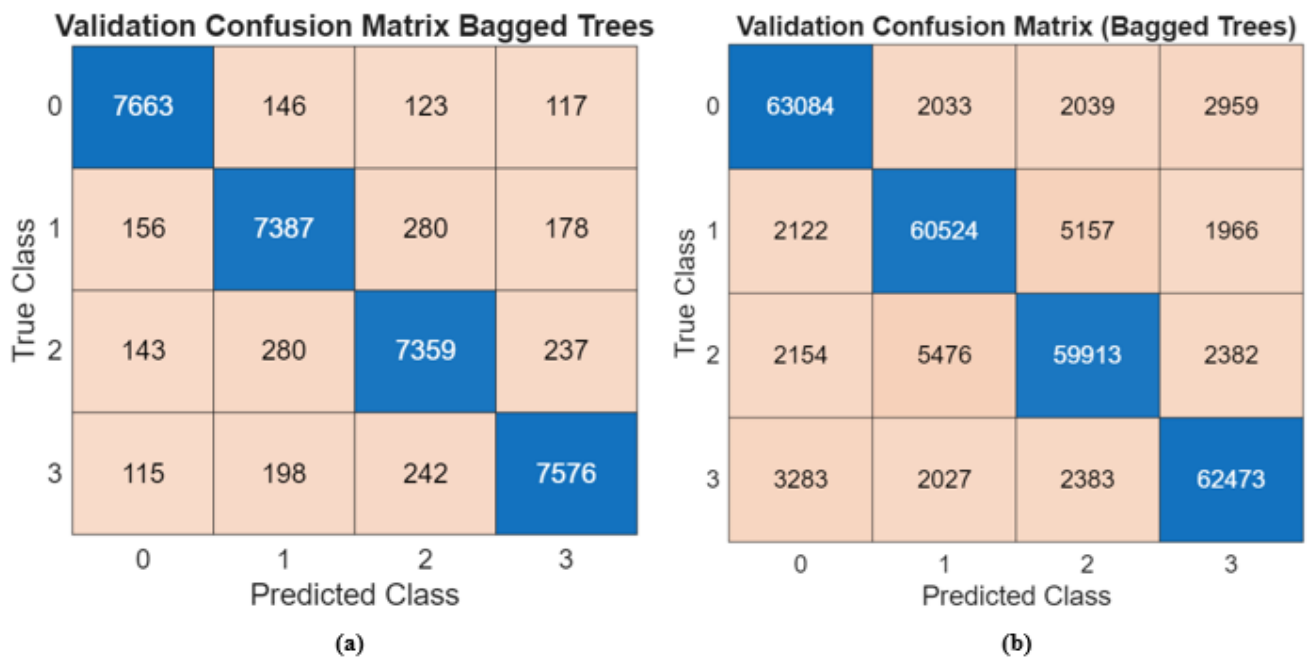


Figure 12. Validation Confusion Matrix. (a) Radial Flux density dataset. (b) Stator Phase current dataset.

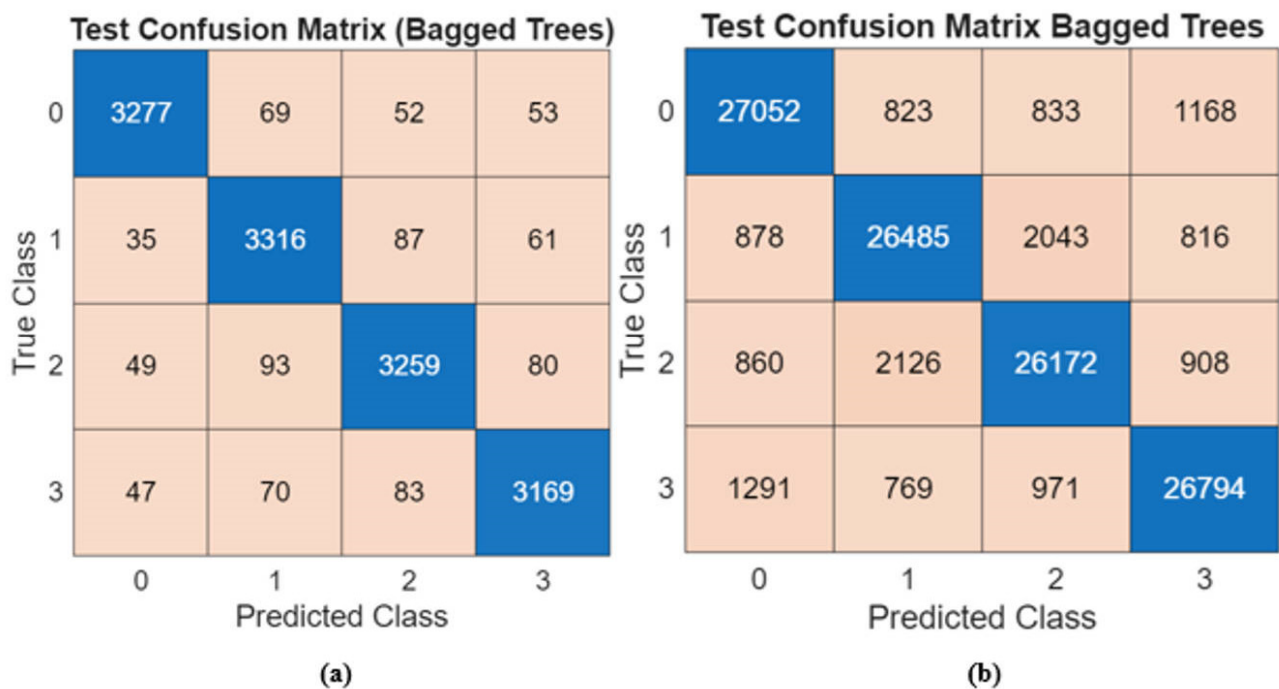


Figure 13. Test Confusion Matrix. (a) Radial Flux density dataset. (b) Stator Phase current dataset.

4.8. Precision, Recall and F1-Score Analysis

To provide a more comprehensive evaluation of the proposed diagnostic framework, the performance of the Ensemble Bagged Trees classifier was further assessed using Precision, Recall, and F1-score for each operating condition. Unlike overall classification accuracy, these performance metrics evaluate the classifier's ability to correctly identify each fault class while minimizing false-positive and false-negative predictions. The evaluation was performed for both the radial air-gap flux density and stator current datasets using the results obtained from the 5-fold cross-validation procedure.

The results presented in Table 7 demonstrate the consistent performance of the Ensemble Bagged Trees classifier across all operating conditions. For the radial air-gap flux density dataset, Precision, Recall, and F1-score values exceed 91% for every class, indicating excellent discrimination between healthy and faulty operating conditions. Similarly, the stator current dataset achieved values greater than 85% for all evaluation metrics, indicating consistent classification performance despite the comparatively lower fault sensitivity of stator current signals.

Table 7. Precision, Recall, and F1-score of the Ensemble Bagged Trees classifier for radial air-gap flux density and stator current datasets.

Operating Condition	Radial Flux Density			Stator Current		
	Precision (%)	Recall (%)	F1-Score (%)	Precision (%)	Recall (%)	F1-Score (%)
Healthy	94.9	95.2	95.0	89.3	90.0	89.6
10% Dynamic Eccentricity	92.2	92.3	92.3	86.4	86.7	86.6
20% Dynamic Eccentricity	91.9	91.8	91.9	86.2	85.7	85.9
40% Dynamic Eccentricity	93.4	93.2	93.3	89.5	89.0	89.3

The balanced performance observed across all fault severity levels indicates that the proposed fixed-length, non-overlapping feature extraction strategy effectively captures the fault-related characteristics required for accurate classification. Furthermore, the close agreement between Precision, Recall, and F1-score demonstrates that the classifier maintains a favorable balance between false-positive and false-negative predictions, thereby supporting the effectiveness of the proposed diagnostic framework for dynamic eccentricity fault diagnosis in IPMSMs.

4.9. Histogram of Stator Current and Flux Density

The statistical distribution of the extracted feature dataset is illustrated by the histograms presented in Figure 14 for the radial air-gap flux density dataset and Figure 15 for the stator phase current dataset. The continuous class labels are grouped into discrete intervals (bins), where the interval $[-0.5, 0.5]$ represents the Healthy condition (Class 0), while the intervals $[0.5, 1.5]$, $[1.5, 2.5]$, and $[2.5, 3.5]$ correspond to the 10% (Class 1), 20% (Class 2), and 40% (Class 3) dynamic eccentricity conditions, respectively.

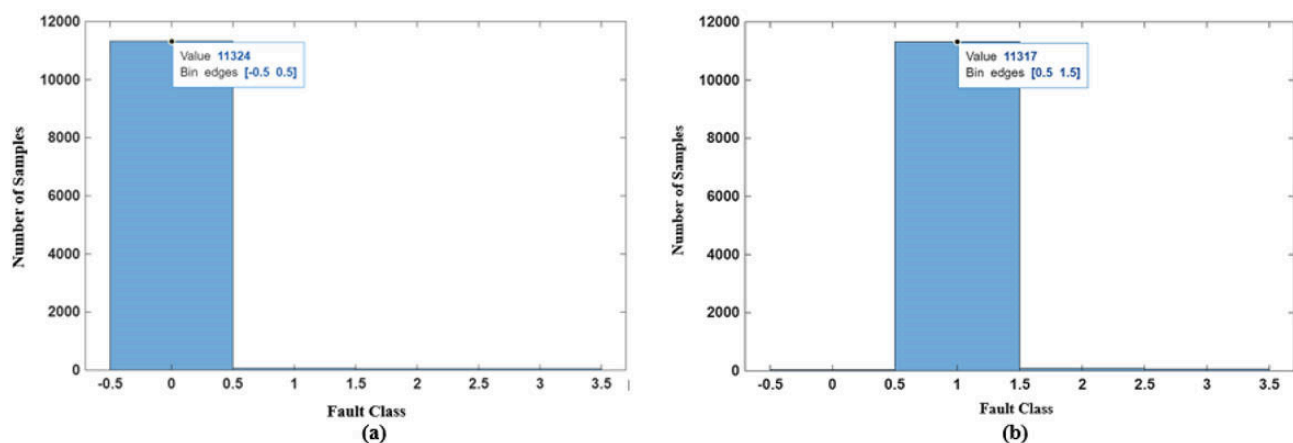


Figure 14. Cont.

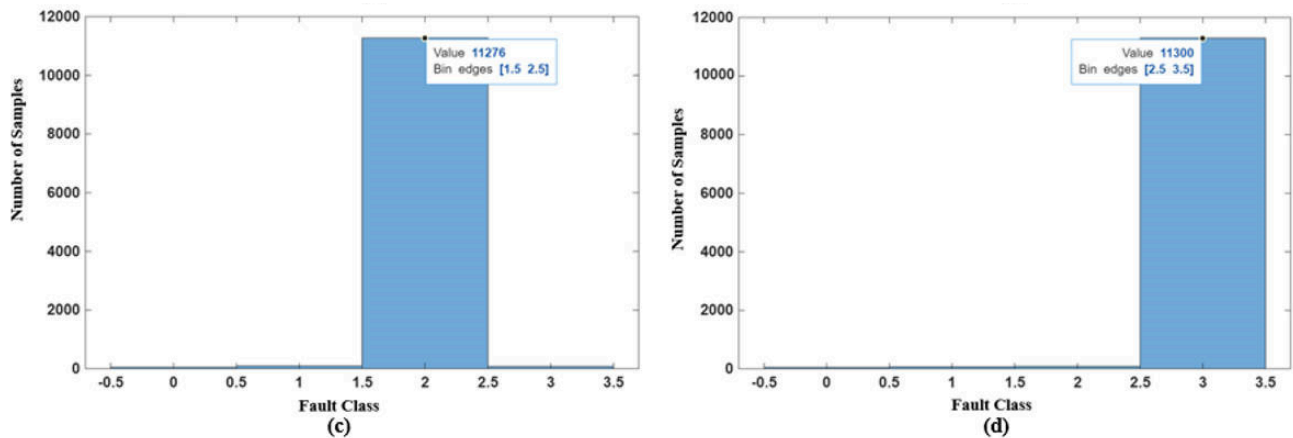


Figure 14. Histograms of the radial air-gap flux density dataset for (a) healthy, (b) 10% dynamic eccentricity, (c) 20% dynamic eccentricity, and (d) 40% dynamic eccentricity conditions.

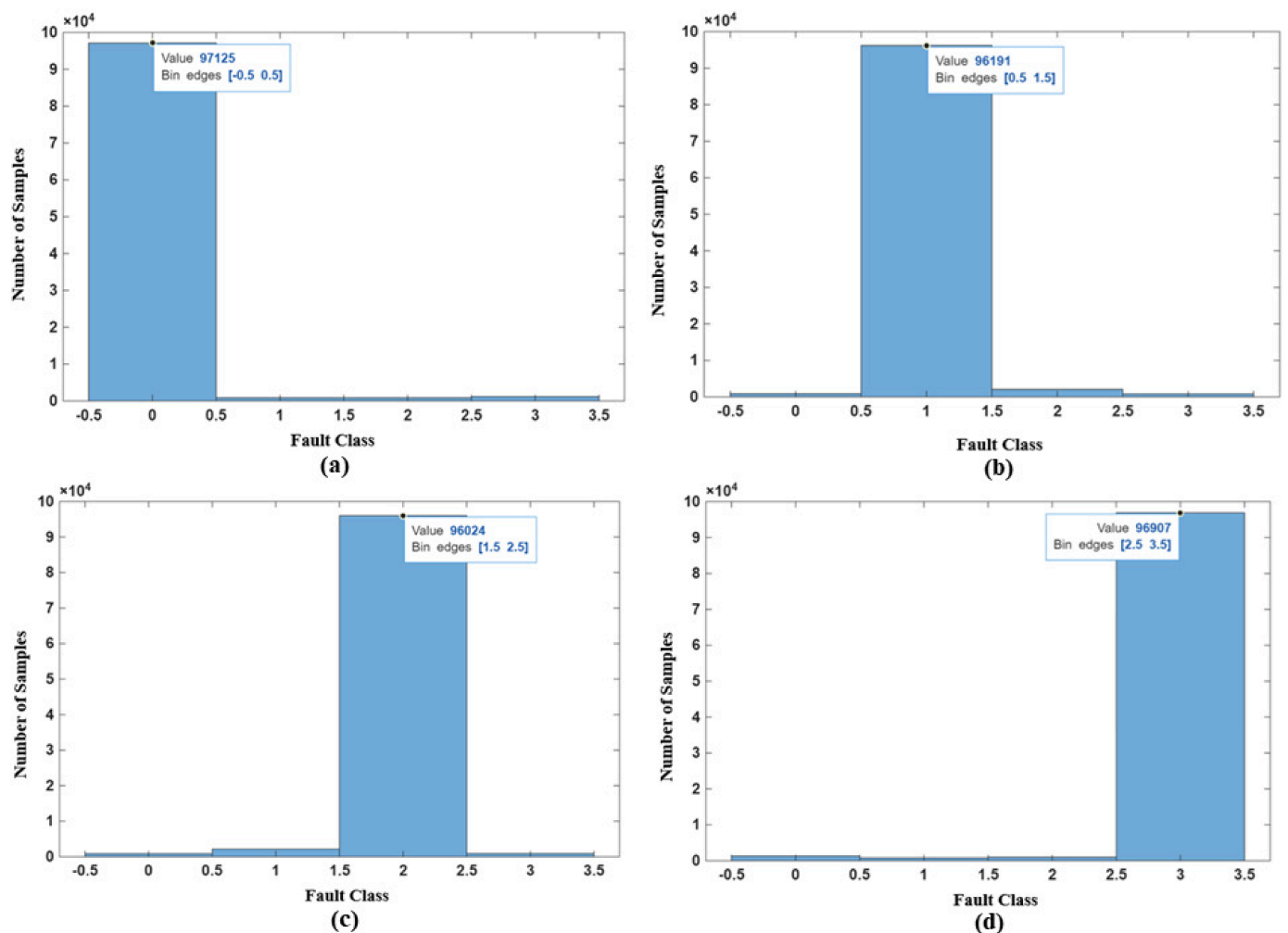


Figure 15. Histograms of the stator phase current dataset for (a) healthy, (b) 10% dynamic eccentricity, (c) 20% dynamic eccentricity, and (d) 40% dynamic eccentricity conditions.

Figure 14 demonstrates a nearly uniform distribution of feature vectors across the four operating conditions, with approximately 11,500 feature vectors generated for each class through fixed-length, non-overlapping segmentation of the corresponding finite-element simulated radial air-gap flux density waveform. This balanced distribution minimizes class imbalance during classifier training and enables an unbiased comparison of classification

performance across the investigated operating conditions. The balanced class distribution ensures that classifier performance is not influenced by class imbalance, thereby enabling an equitable comparison of the investigated machine learning algorithms.

Similarly, Figure 15 illustrates the distribution of feature vectors extracted from the stator phase current signal. A comparable class distribution is observed, indicating that the dataset is well balanced for supervised machine learning training. The uniform distribution across the four operating conditions reduces learning bias and facilitates a fair evaluation of classifier performance for dynamic eccentricity severity classification.

The balanced distributions observed for both diagnostic signals demonstrate that the proposed feature extraction procedure provides comparable numbers of feature vectors for each operating condition, thereby supporting an equitable assessment of the investigated machine learning classifiers within the available simulation dataset.

5. Future Scope

This study presents a simulation-based framework developed using a high-fidelity finite-element model in ANSYS Maxwell to investigate dynamic eccentricity faults in an IPMSM. The proposed framework enables systematic analysis of fault-induced electromagnetic behaviour under controlled operating conditions and provides simulation-generated datasets for machine learning-based fault diagnosis. Although the present investigation is limited to simulation-based validation, the methodology establishes a foundation for future experimental verification using laboratory-scale IPMSM test platforms. Furthermore, while radial air-gap flux density demonstrated higher diagnostic sensitivity than stator current, its practical implementation requires dedicated magnetic sensors, whereas stator current can be measured non-invasively.

The present investigation was conducted under rated operating conditions to isolate the influence of dynamic eccentricity on the electromagnetic behaviour of the machine. Accordingly, the performance of the proposed framework under different operating speeds, load torques, inverter operating conditions, temperature variations, measurement noise, parameter uncertainties, and multiple simultaneous fault conditions remains to be investigated.

One independent transient finite-element simulation was performed for each operating condition (Healthy, 10%, 20%, and 40% dynamic eccentricity). Statistical features extracted from fixed-length, non-overlapping signal segments were used to construct a balanced dataset for classifier evaluation. Consequently, the reported classification performance demonstrates the effectiveness of the proposed framework within the available simulation dataset. Further assessment of model generalization using multiple independent simulations and grouped validation strategies will be considered in future work.

Future work will focus on experimental validation using a laboratory-scale IPMSM test bench, generation of multiple independent simulation and experimental datasets, evaluation under different operating speeds and load conditions, investigation of multi-sensor fusion strategies, assessment of classifier robustness under practical operating conditions, and validation using grouped cross-validation protocols to provide a more comprehensive evaluation of model generalization.

6. Conclusions

This study presented an integrated finite-element and machine learning framework for the diagnosis of dynamic eccentricity faults in an Interior Permanent Magnet Synchronous Motor (IPMSM). A transient finite-element model developed in ANSYS Maxwell was employed to simulate healthy operation together with three dynamic eccentricity severity levels (10%, 20%, and 40%). Statistical features extracted from fixed-length, non-overlapping

segments of radial air-gap flux density and stator current signals were subsequently used to train and comparatively evaluate multiple supervised machine learning classifiers.

Among the investigated classifiers, the Ensemble Bagged Trees algorithm achieved the highest diagnostic performance, yielding validation accuracies of 93.12% for the radial air-gap flux density dataset and 87.86% for the stator current dataset. Complementary ROC-AUC, confusion matrix, Precision, Recall, and F1-score analyses further confirmed the effectiveness of the proposed framework for distinguishing healthy operation from different dynamic eccentricity severity levels within the generated simulation dataset. The results also demonstrate that radial air-gap flux density provides higher diagnostic sensitivity than stator current for simulation-based dynamic eccentricity diagnosis.

The proposed framework integrates high-fidelity finite-element modelling, statistical feature extraction, and comparative machine learning analysis into a systematic methodology for dynamic eccentricity severity classification in IPMSMs. The study demonstrates the potential of combining finite-element simulations with machine learning techniques for intelligent electrical machine fault diagnosis and provides a simulation-based foundation for future experimental validation, evaluation under diverse operating conditions, and further development toward practical condition-monitoring systems for electric-drive applications.

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Abbreviations

The following abbreviations are used in this manuscript:

IPMSM	Interior Permanent Magnet Synchronous Motor
FEM	Finite Element Method
RMS	Root Mean Square
ROC	Receiver Operating Characteristics
AUC	Area Under Curve
DE	Dynamic Eccentricity

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