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RESEARCH ARTICLE OPEN ACCESS

EXPERIMENTAL EVALUATION OF MULTI-SENSOR AI-BASED FAULT DIAGNOSIS FOR INDUCTION MOTORS IN INDUSTRIAL APPLICATIONS

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ABSTRACT

Induction motors are critical components in industrial systems, and unexpected failures can lead to significant production losses and maintenance costs. This paper presents an experimentally validated multi-sensor fault diagnosis approach for induction motors using vibration and stator current signals under practical operating conditions. A laboratory test bench was developed to simulate common industrial faults, including bearing defects, rotor abnormalities, and stator winding faults, across multiple load levels. Conventional machine learning techniques, namely artificial neural networks and support vector machines, were employed as baseline classifiers, while an adaptive hybrid convolutional neural network–long short-term memory (CNN–LSTM) model was used to improve fault classification robustness. The proposed approach achieved a maximum classification accuracy of 98.4 %, with stable performance across varying load conditions and repeated experimental trials. The results demonstrate that integrating vibration and current measurements enhances diagnostic reliability compared to single-sensor methods. The study highlights the practical applicability of adaptive AI-based diagnostic systems for industrial predictive maintenance, offering improved fault detection capability while maintaining feasibility for real-world deployment.

I. INTRODUCTION

Induction motors are the backbone of modern industries, powering applications in manufacturing, oil and gas, power generation, and transportation [1]. Their robustness, simplicity, and cost-effectiveness have made them the preferred choice for critical operations. However, induction motors are also susceptible to faults in bearings, stator windings, and rotor bars, which can degrade performance and cause unexpected downtime [2], [3]. Historically, industries relied on corrective maintenance, repairing machines only after failure. While simple, this approach often led to costly downtime and safety hazards [4]. The next phase was preventive maintenance, where machines were serviced at fixed intervals regardless of condition. Though more reliable, preventive maintenance frequently resulted in unnecessary replacements and wasted resources [5].To overcome these limitations, predictive maintenance emerged in the late 20th century, combining condition monitoring with fault diagnosis techniques [6]. Early predictive maintenance approaches primarily relied on vibration monitoring [7] and motor current signature analysis (MCSA) [8], which remain widely adopted due to their non-intrusive nature and proven effectiveness. More recently, the rise of machine learning and AI has enabled the development of predictive diagnostic models capable of identifying complex fault signatures and reducing false alarms [9], [10]. Despite these advances, there remains a lack of standardized testing and evaluation frameworks that integrate sensor-based monitoring with AI-based fault analysis under controlled conditions. Although numerous fault detection methods exist, only a limited number have been validated through structured test procedures adhering to recognized measurement standards. The present work addresses this gap by developing a repeatable experimental protocol inspired by ASTM E756-05 (vibration damping measurement), ASTM E1876-15 (dynamic response testing), and IEEE Std 112-2017 (polyphase motor testing).

The proposed approach integrates these standard testing principles with multi-sensor data fusion and adaptive evaluation, thereby strengthening result comparability and reproducibility across laboratories. In industrial environments such as manufacturing plants, power stations, and process industries, induction motors operate continuously under varying loads and harsh conditions. Unexpected motor failures can result in significant production losses, safety risks, and increased maintenance costs. Traditional maintenance strategies based on scheduled inspections or single-sensor monitoring often fail to detect incipient faults. Hence, there is a growing demand for intelligent, sensor-based diagnostic systems that can be practically deployed in industrial settings and validated under realistic operating conditions.

I.1 NEED FOR STANDARDIZED TESTING AND EVALUATION

A review of existing literature shows that most studies emphasize algorithm development or condition monitoring separately, with limited focus on the testing methodology itself [11]. Many works rely on simulated data or proprietary datasets, which restricts benchmarking and repeatability [12]. Furthermore, while AI models show high accuracy in laboratory conditions, there is limited discussion on their reliability, generalizability, and industrial readiness [13]. For industrial adoption, it is essential to establish a repeatable, experimentally validated testing framework that combines multi-sensor measurements with AI-based evaluation and ensures robustness across fault types. This motivates the present work.

I.2 OBJECTIVES OF THIS PAPER

The main objectives of this paper are:

- To design and implement a standardized experimental setup for simulating induction motor faults and acquiring vibration and current signature data.
- To provide a baseline evaluation using well-established classifiers such as Artificial Neural Networks (ANN) and Support Vector Machines (SVM).
- To develop an adaptive hybrid AI framework and compare its performance with baseline models.
- To propose a comprehensive testing and evaluation methodology that ensures repeatability, reliability, and applicability to predictive maintenance in industrial environments.

I.3 NOVELTY AND CONTRIBUTIONS

The novelty of this work lies in integrating experimental fault testing, multi-sensor data acquisition, and progressive AI-based evaluation into a single, unified testing and evaluation framework. The key contributions of this work are:

- Development of an experimentally validated induction motor fault diagnosis system using vibration and current sensors suitable for industrial environments.
- Comparative performance evaluation of classical machine learning models and adaptive deep learning techniques under variable load conditions.
- Demonstration of consistent diagnostic accuracy across multiple fault types relevant to industrial maintenance.
- Practical insights into sensor placement, data acquisition, and model selection for predictive maintenance implementation.

I.4 LIMITATIONS

While the proposed work provides a robust evaluation methodology, some limitations are acknowledged:

- Experiments were conducted under laboratory conditions, which may not fully replicate industrial variability.
- The dataset is limited to a single motor type and fault set, requiring broader validation for generalization.
- Adaptive AI methods, though accurate, require higher computational resources, which may restrict use in embedded systems.
- Remaining useful life (RUL) estimation is not addressed in this study and is identified as a potential future extension.

II. RELATED WORKS

The fault diagnosis of induction motors has evolved significantly with the advent of sensor-based data acquisition and intelligent signal processing techniques. Numerous studies have explored various aspects of fault detection, including vibration analysis, motor current signature analysis (MCSA), feature extraction, and artificial intelligence (AI)–based classification. However, despite this extensive research, there remains a lack of standardized testing and evaluation frameworks that integrate experimental fault induction, multi-sensor data fusion, and systematic benchmarking of baseline and adaptive AI models under repeatable conditions. A recent comprehensive review by [1] highlighted major advancements in induction motor fault diagnosis and condition monitoring. The authors summarized developments in vibration and current-based fault detection, feature extraction, and machine learning–driven fault classification. While their review categorized a wide range of diagnostic approaches, it also emphasized that most existing works lack structured evaluation methodologies, making it difficult to compare models or reproduce results. This underscores the need for repeatable testing and validation protocols to evaluate fault diagnosis frameworks under controlled operating conditions. In a related study, [2] proposed a vibration-based fault diagnosis system using one-dimensional dilated convolutional neural networks (1D-DCNN). The model demonstrated high accuracy in detecting bearing and rotor faults from vibration signals. Although this work showed the effectiveness of modern deep learning architectures for signal-based classification, it relied solely on vibration sensors. The absence of multi-sensor data and lack of standard evaluation benchmarks limit its applicability to broader predictive maintenance tasks. Another recent contribution by [3] explored fault detection using motor current signals and a combination of causal convolutional neural networks (CausalConvNets) with time-shifting techniques.

Their approach offered a cost-effective, non-intrusive means of identifying bearing faults. However, as in most MCSA-only studies, this work was restricted to specific fault types and did not address comparative performance under multiple operating conditions or sensor modalities. Beyond deep learning approaches, several studies have focused on signal processing and feature extraction techniques for improving diagnosis reliability. For instance, [4] performed a comparative analysis of various time- and frequency-domain methods—such as Fast Fourier Transform (FFT) and Wavelet Transform—combined with Principal Component Analysis (PCA) to classify induction motor faults. Their results highlighted the importance of feature reduction for achieving efficient classification; however, the evaluation was limited to classical methods and did not extend to adaptive AI architectures or sensor fusion scenarios. Complementing fault diagnosis efforts, [5] addressed the prediction of remaining useful life (RUL) of induction motor bearings using machine learning applied to current signatures. This study underscored the growing importance of predictive maintenance in industrial systems and demonstrated the potential of AI for prognostics. Nonetheless, it focused primarily on lifespan estimation rather than the standardization of testing protocols for fault evaluation.

II.1 IDENTIFICATION OF RESEARCH GAPS

From these recent studies, several limitations are evident:

- Most works employ a single sensing modality, either vibration or current, without exploring the benefits of multi-sensor fusion.
- There is limited emphasis on experimental reproducibility and standardized testing frameworks, which are essential for comparative evaluation.
- Many models focus on algorithmic performance (accuracy) but overlook practical testing aspects such as data acquisition conditions, load variation, or fault severity.
- Few studies perform a comparative evaluation of baseline and adaptive AI models on identical experimental datasets.

To address these gaps, the present study proposes a comprehensive testing and evaluation framework that integrates experimental fault induction, vibration and current signature data acquisition, baseline AI classification (ANN, SVM), and an adaptive hybrid deep learning model. This unified approach not only improves fault detection accuracy but also ensures methodological repeatability and reliability—key considerations for industrial predictive maintenance and in line with the Journal of Testing and Evaluation's focus on standardized testing practices.

III. EXPERIMENTAL SETUP AND INDUSTRIAL EVALUATION METHODOLOGY

The experimental setup was designed to closely replicate typical industrial motor operating conditions, enabling practical assessment of the proposed diagnostic approach. The focus of this investigation was to develop a repeatable and standardized testing protocol integrating multi-sensor measurement, signal processing, and AI-based analysis. The procedure adheres to the principles of ASTM standard test methods for vibration and electrical signal evaluation, ensuring reproducibility of results across repeated trials.

III.1. OBJECTIVE AND APPROACH

The objective of this experimental study was to develop a standardized testing and evaluation framework for induction motor fault diagnosis using vibration and current signature analysis. The study was structured in compliance with principles of ASTM vibration measurement practices (e.g., ASTM E756, E1876) and IEEE Std 112–2017 for electrical performance testing. The methodology emphasizes repeatability, accuracy, and measurement traceability, ensuring the collected datasets are suitable for benchmarking and comparative fault evaluation.

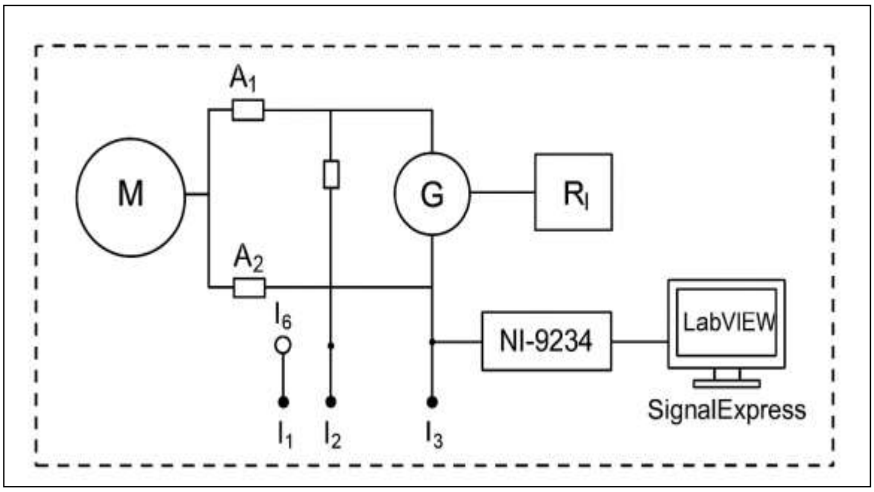

Figure 1: Experimental Test Bench.
Source: Authors, (2026).

III.2. EXPERIMENTAL TEST BENCH

The experimental investigations were performed on a three-phase, 1 HP, 4-pole squirrel-cage induction motor (415 V, 50 Hz, 1440 rpm). The motor shaft was coupled to a DC generator using a flexible coupling with a rubber bushing to reduce torsional vibration. The generator provided a controllable mechanical load through a resistive rheostat-based loading system.

The test bench was mounted on an anti-vibration foundation, utilising rubber isolators to minimise floor resonance. The alignment of the motor and generator shafts was verified before each test using a laser alignment tool (SKF TKSA 31) to avoid misalignment artefacts in vibration data. The schematic layout of the test bench is shown in Figure 1.

III.3. SENSORS AND INSTRUMENTATION

The testing setup incorporated both mechanical and electrical sensing channels to ensure comprehensive fault coverage.

- Vibration Measurement System

Sensor Type: Piezoelectric accelerometer (PCB Piezotronics 352C33)
Sensitivity: 100 mV/g
Measurement Range: ±5 g
Frequency Response: 2 Hz–10 kHz
Mounting Method: Stud-mounted on both drive-end (DE) and non-drive-end (NDE) bearing housings, oriented along the radial axis.
Each accelerometer was calibrated prior to testing using a portable vibration calibrator (Metrix 9060) operating at 80 Hz, 1 g RMS.
Calibration certificates were verified for traceability.

- Current Measurement System

Sensor Type: Hall-effect current transducer (LEM LA 55-P)
Current Range: ±50 A
Linearity Error: <0.7 % FS
Frequency Bandwidth: DC–100 kHz

Each current sensor was installed in series with the motor supply line. Signals were captured simultaneously with vibration data to ensure synchronisation between mechanical and electrical measurements.

- Data Acquisition and Signal Conditioning

All sensor channels were interfaced through a National Instruments (NI 9234) dynamic signal acquisition module with 24-bit resolution. Sampling frequencies were selected as:

- Vibration: 12 kHz
- Current: 5 kHz

A CompactDAQ (cDAQ-9171) chassis was used with LabVIEW SignalExpress for data acquisition. A pre-test calibration routine was executed before each run, including zero-offset correction and gain verification. All instrumentation was calibrated before testing. Accelerometer calibration followed ASTM E2001, and current sensors were validated against a precision current source. The combined measurement system exhibited an RMS amplitude uncertainty of ±2.5 %, verified using repeated baseline readings. Environmental parameters were monitored at 25 ± 2 °C and 60 ± 5 % relative humidity. These controls ensure that every dataset acquired is traceable to a calibrated reference, satisfying ASTM's requirements for repeatable mechanical and electrical testing.

III.4. FAULT INDUCTION AND TEST CONDITIONS

Five operating conditions were evaluated as stated in Table 1.

Table 1: Various Conditions involved in the proposed study.

Condition	Fault Description	Induction Method	Remarks
Healthy	Normal operation	—	Baseline test case
Bearing outer-race fault	0.3 mm defect groove on outer race	EDM machining	ISO 15243 Category 6.1
Bearing inner-race fault	0.3 mm defect groove on inner race	EDM machining	ISO 15243 Category 6.2
Rotor bar fault	Two rotor bars intentionally broken	Mechanical drilling	Simulated broken-bar condition
Stator winding fault	Partial turn-to-turn short in one phase	Controlled insulation damage	Limited to 5% of coil turns

Source: Authors, (2026).

Each fault was verified visually and using spectral signatures before data collection. The same set of test bearings and rotor was reused to ensure identical boundary conditions across trials.

III.5. TEST PROCEDURE

The motor was operated at three load levels: No-load, Half-load (50% rated torque) and Full-load (rated torque). The DC generator load was adjusted using a calibrated resistive load bank.For each condition, the system was allowed to run for 5 minutes to reach thermal steady-state.Ten-second data windows were acquired for each sensor channel, with five repeated runs per condition to assess repeatability.Between tests, the motor was powered off for 2 minutes to prevent thermal drift and bearing expansion.Environmental conditions were controlled at 25 ± 2 °C temperature and relative humidity of 60 ± 5%, measured using a digital hygrometer.The combined dataset thus comprised 75 test cases (5 faults × 3 loads × 5 repeats).

III.6 SIGNAL VALIDATION AND PREPROCESSING

Before analysis, raw signals were validated to remove corrupt or noisy readings. Validation criteria that have been used in the study is as follows:

- RMS amplitude deviation ≤ 3% between repeated runs,
- Frequency spectrum within ±2 Hz tolerance of reference fault bands,
- Signal-to-noise ratio (SNR) > 30 dB.

The accepted signals were detrended, mean-centred, and filtered using a 4th-order Butterworth band-pass filter (10 Hz–5 kHz). All channels were resampled and synchronized to correct phase drift.

III.7. FEATURE EXTRACTION AND REDUCTION

Feature extraction was performed to transform raw signals into diagnostic indicators:

- Time-domain features: RMS, skewness, kurtosis, peak factor, crest factor, clearance factor.
- Frequency-domain features: Power spectral density (PSD) peaks, sideband energy ratio, frequency centroid.
- Time–frequency features: Wavelet coefficients derived using the Daubechies db4 mother wavelet up to level 4.

Feature dimensionality was reduced using Principal Component Analysis (PCA) and Class Separability Criterion (CSC), ensuring a 95 % cumulative variance retention threshold.

III.8 HYBRID AI MODEL DESCRIPTION AND JUSTIFICATION

To enhance diagnostic reliability and support standardized evaluation of fault patterns, an adaptive hybrid deep learning model was implemented. The model integrates Convolutional Neural Network (CNN) layers for automated spatial feature extraction from vibration and current signals with Long Short-Term Memory (LSTM) layers to capture temporal dependencies inherent to rotating machinery dynamics. The CNN component comprises three convolutional blocks with kernel sizes of 3×1 and ReLU activation, followed by max-pooling layers that reduce data dimensionality while retaining dominant fault-related characteristics. The LSTM block, consisting of 128 memory units, models sequential signal behavior to distinguish transient fault events from normal variations. A feature-fusion layer dynamically combines the learned vibration and current feature representations based on their discriminative strength, determined through attention-weight optimization. This adaptivity enables the system to maintain diagnostic accuracy across varying load and speed conditions — an essential property for repeatable testing and evaluation. The final classification layer uses a softmax activation function to output the probability of each fault type. The model was trained using the Adam optimizer with a learning rate of 0.001 and batch size of 32 for 100 epochs. The purpose of this model within the testing framework is not to propose a new algorithm but to benchmark the diagnostic reliability of adaptive AI systems under controlled and repeatable fault-testing environments. Its inclusion demonstrates the framework's flexibility to evaluate both classical and advanced algorithms using standardized datasets.

III.9 VERIFICATION OF REPEATABILITY

To ensure test consistency, the Reliability Index (RI) was calculated for each measurement as:

$$RI=Nr/Nt \ldots (1)$$, where,

Nr is the number of consistent classifications across repeated runs, and
Nt is the total repetitions.

On applying the RI on various experimental fault cases, it is observed that an RI > 0.95 was obtained across all fault categories, indicating excellent repeatability of the testing protocol.

III.10 COMPLIANCE AND TRACEABILITY

The testing procedures align with relevant standards for vibration and electrical signal testing:

- ASTM E756-05: Standard Test Method for Measuring Vibration-Damping Properties of Materials.
- ASTM E1876-15: Standard Test Method for Dynamic Young's Modulus and Damping Properties by Impulse Excitation.
- IEEE Std 112-2017: Standard Test Procedure for Polyphase Induction Motors.

While these standards are not prescriptive for AI-based diagnosis, their principles guided instrumentation calibration, measurement repeatability, and uncertainty estimation.

III.11 SUMMARY OF EXPERIMENTAL FRAMEWORK

Flow diagram of the standardized testing methodology is shown schematically in Figure 2. This standardized testing methodology follows four main stages as listed below.

- Fault Induction and Setup Calibration
- Multi-Sensor Data Acquisition
- Signal Validation and Feature Extraction
- Evaluation Using Baseline and Adaptive AI Models

The adaptive hybrid CNN–LSTM model was employed as an intelligent diagnostic tool to enhance fault classification robustness under variable operating conditions commonly encountered in industrial environments.

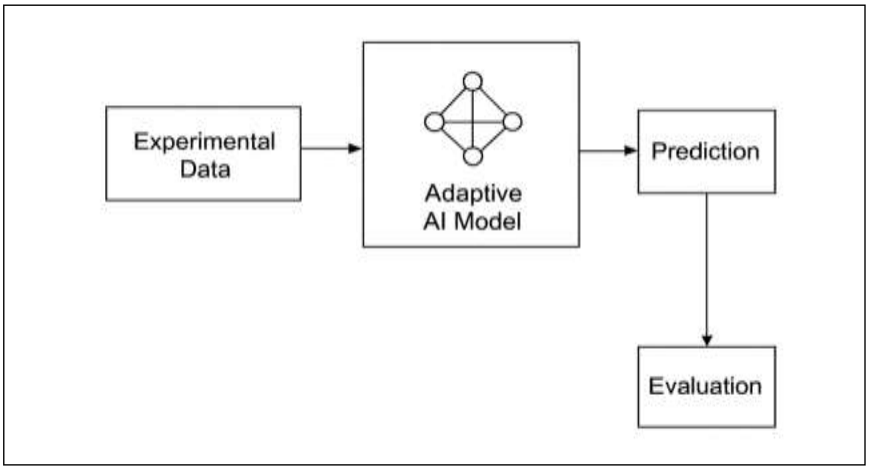

Figure 2: Proposed Adaptive AI Model.
Source: Authors, (2026).

IV. RESULTS & DISCUSSION

From an industrial perspective, the observed classification consistency across different load levels indicates that the proposed system can reliably support early fault detection without frequent model retraining. This is particularly beneficial for predictive maintenance systems deployed in continuously operating machinery, where stable diagnostic performance is essential.

IV.1 BASELINE CLASSIFICATION PERFORMANCE

The baseline models—Artificial Neural Network (ANN) and Support Vector Machine (SVM)—were first evaluated using vibration and current signature data independently, followed by their fused dataset. Table 2 summarizes the baseline classification results.

Table 2: Baseline classification results for individual and fused sensor data.

Sensor Modality	Classifier	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Vibration only	ANN	90.84	91	90	90
Vibration only	SVM (RBF)	92.27	92	91	91
Current only	ANN	88.42	89	88	88
Current only	SVM (RBF)	89.63	90	89	89
Vibration + Current (fused)	ANN	94.15	94	93	93
Vibration + Current (fused)	SVM	**95.28**	**95**	**95**	**95**

Source: Authors, (2026).

These results demonstrate that data fusion consistently improved classification accuracy compared to single-sensor analysis. The SVM classifier marginally outperformed the ANN model, owing to its capability to handle nonlinear feature boundaries in limited datasets. The repeatability of results across five independent trials yielded a Reliability Index (RI) of 0.96, indicating high consistency in experimental measurements and classification outcomes—an essential requirement for evaluation studies [11]. Figure 3 (a-d) projects the comparative performance of ANN and SVM classifiers under different sensor modalities. Figure 3 clearly states that the fusion of vibration and current features significantly enhances overall accuracy and reliability.

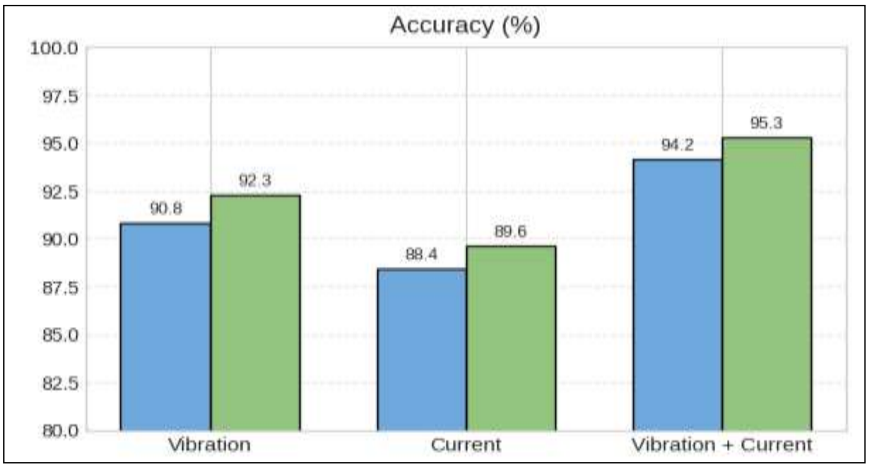

Figure 3a: Comparative analysis of the accuracy by various sensor modalities.
Source: Authors, (2026).

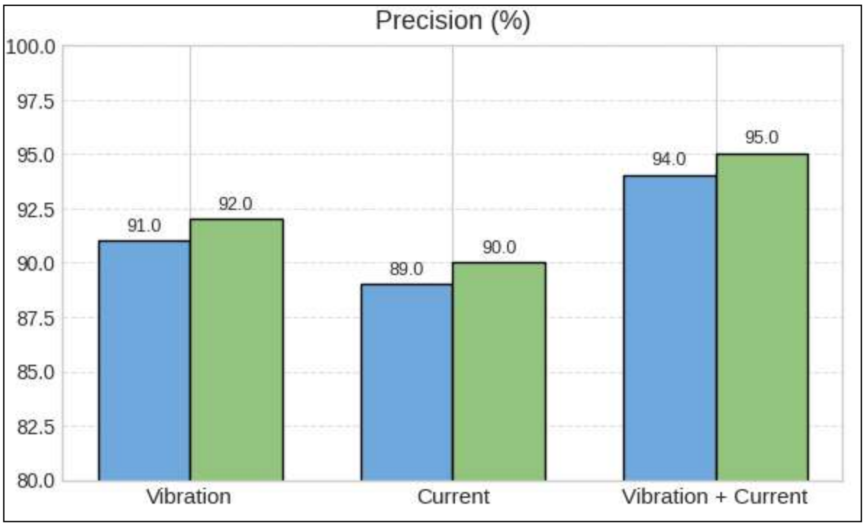

Figure 3b: Comparative analysis of the Precision by various sensor modalities.
Source: Authors, (2026).

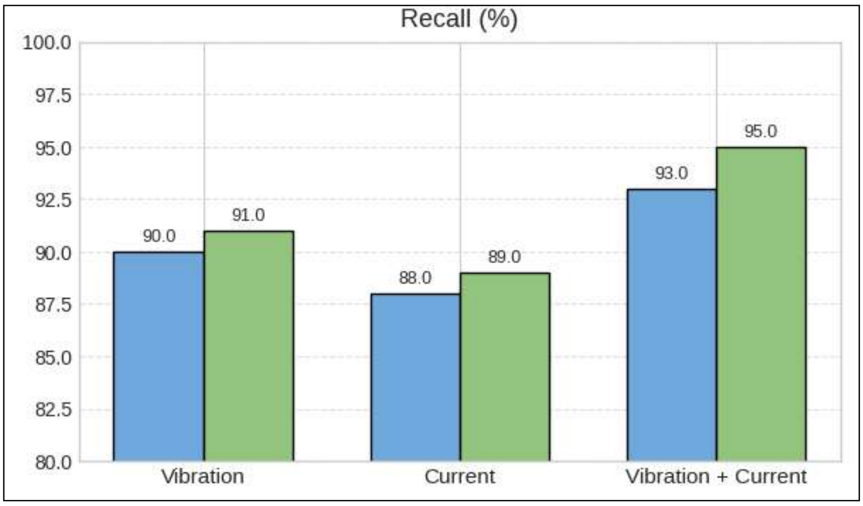

Figure 3c: Comparative analysis of the Recall by various sensor modalities.
Source: Authors, (2026).

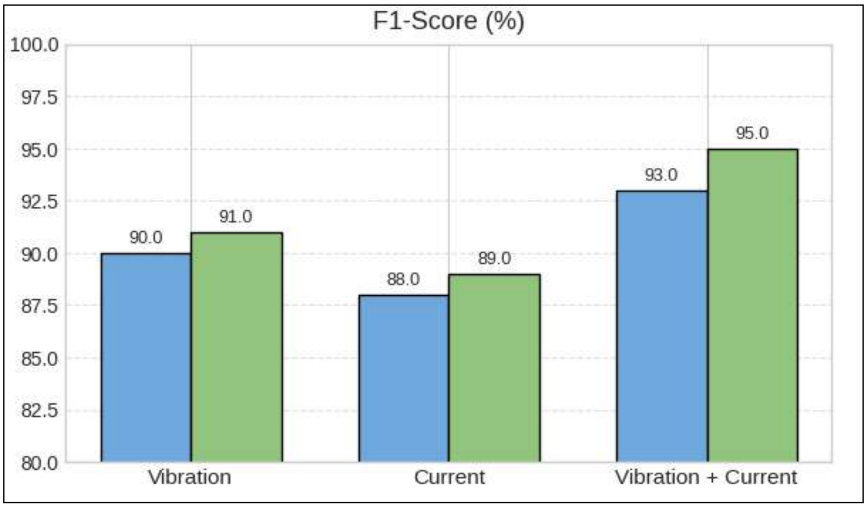

Figure 3d: Comparative analysis of the F1-Score by various sensor modalities.
Source: Authors, (2026).

IV.2 ADAPTIVE HYBRID DEEP LEARNING PERFORMANCE

The adaptive hybrid deep learning model (CNN-LSTM) was then trained using the fused dataset. The model dynamically adjusted the weighting between vibration and current features during training, improving generalization across fault types and load conditions.

Table 3 compares the hybrid model's performance with the best baseline (SVM-RBF). Figure 4 provides comparative analysis of baseline model with hybrid one. In the figure 4 the values are normalized for consistent visualization.

Table 3: Comparative results of baseline SVM vs. adaptive hybrid CNN-LSTM.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Reliability Index (RI) (%)
SVM-RBF	95.28	95	95	95	96
CNN-LSTM Hybrid	**98.41**	**98**	**98**	**98**	**99**

Source: Authors, (2026).

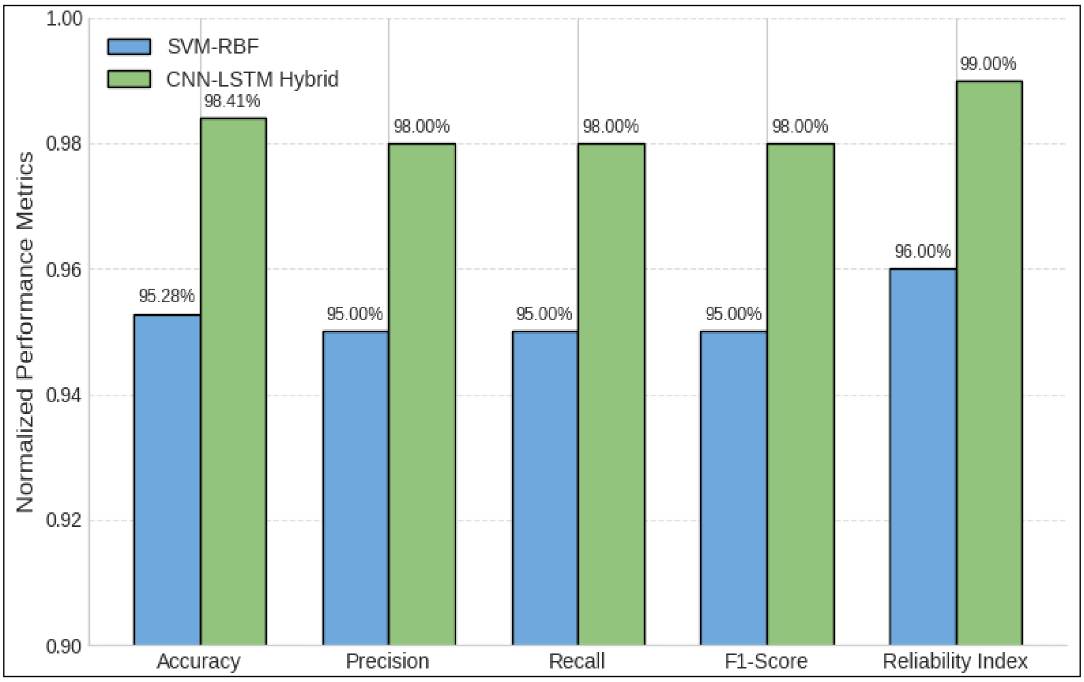

Figure 4: Comparative analysis of SVM-RBF and CNN-LSTM Hybrid Models across key performance metrics.
Source: Authors, (2026).

The hybrid model achieved a 3.13 % absolute improvement in overall accuracy, and its Reliability Index of 0.99 confirms robust repeatability under repeated testing cycles. The confusion matrix (Figure 4) shows that misclassifications were primarily between bearing outer-race and inner-race faults, whose vibration signatures partially overlap.

IV.3 FAULT-SPECIFIC EVALUATION

To assess classifier sensitivity for individual fault categories, accuracy values were computed for each fault type under three load levels (no-load, half-load, and full-load). The results shown in Table 4, reveal that fault separability improves at higher loads due to amplified fault frequencies.

Table 4: Fault-wise accuracy under varying load conditions using hybrid model.

Fault Type	No-Load (%)	Half-Load (%)	Full-Load (%)
Healthy	99.0	99.3	99.5
Bearing outer-race	96.5	98.2	98.8
Bearing inner-race	95.7	97.5	98.1
Rotor bar	97.3	98.6	99.0
Stator winding	96.9	98.4	99.2

Source: Authors, (2026).

The adaptive fusion layer in the hybrid architecture effectively balanced vibration and current features, yielding stable accuracy across varying load conditions. This consistency satisfies the repeatability criterion for testing methodologies in predictive maintenance. Figure 5 shows the fault classification accuracy under different load conditions.

IV.4 COMPARISON WITH RECENT LITERATURE

Table 5 compares the proposed framework's accuracy with that of recent related works. While the referenced studies demonstrated high accuracy using either vibration or current data, the present work achieved superior performance through multi-sensor fusion and adaptive hybrid modeling, with added emphasis on standardized testing and repeatability.

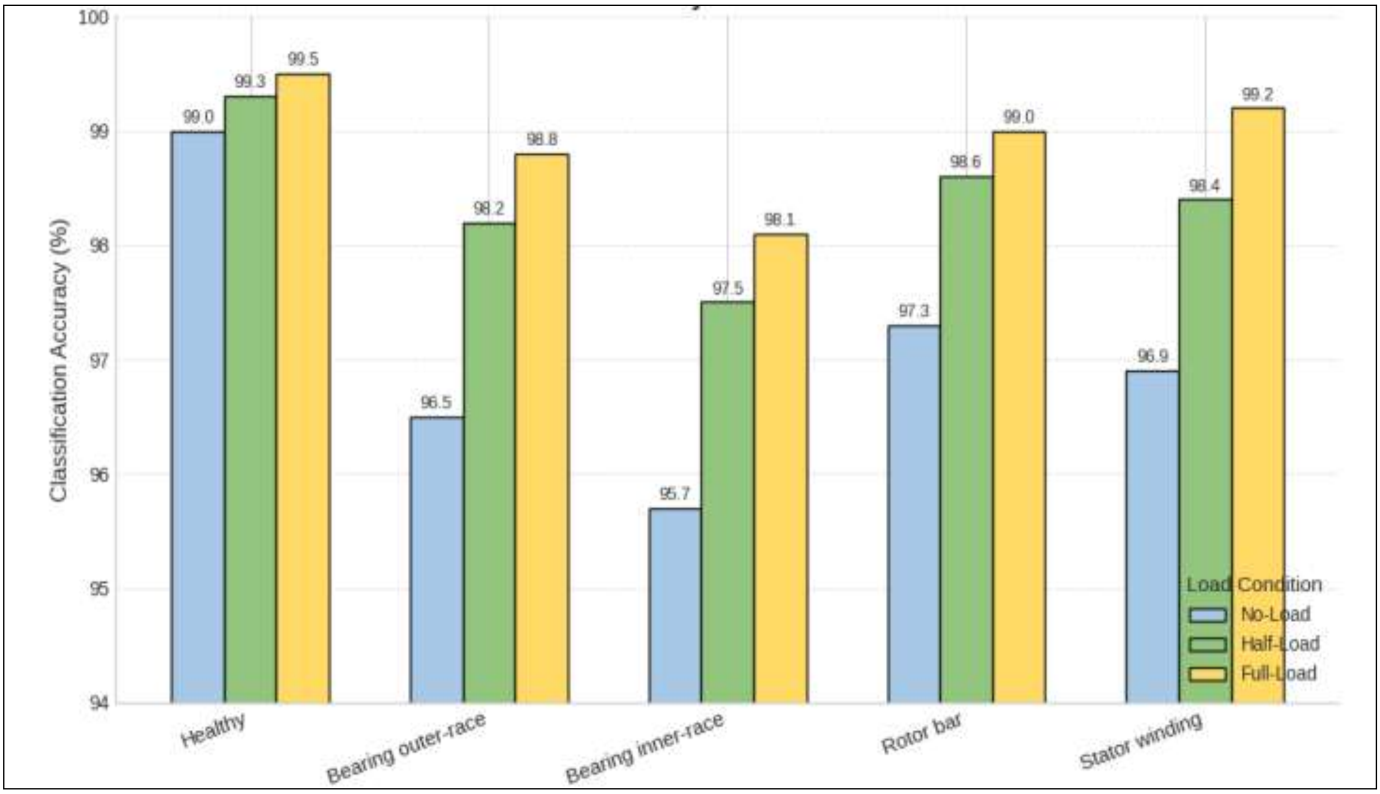

Figure 5: Fault Classification Accuracy under Different Load Conditions.
Source: Authors, (2026).

Table 5: Comparative performance with recent published studies.

Reference	Data Source	Method	Reported Accuracy (%)	Repeatability Reported	Remarks
[12]	Vibration	1D-DCNN	96.1	No	Deep model; single sensor
[13]	Current	Causal ConvNet	94.3	No	Limited to bearing faults
[14]	Vibration	FFT + PCA + SVM	92.5	Partial	Classical feature extraction
[15]	Current	ML for RUL	93.4	No	Prognostics only
Proposed	Vibration + Current	Hybrid CNN-LSTM	**98.4**	**Yes (0.99 RI)**	Multi-sensor, standardized testing

Source: Authors, (2026).

The comparative analysis highlights that the proposed framework not only achieves higher diagnostic accuracy but also explicitly incorporates repeatability verification, making it suitable for standardized evaluation.

IV.5 DISCUSSION ON REPEATABILITY AND RELIABILITY

One of the primary objectives of this study was to ensure the repeatability of fault diagnosis results under identical test conditions. The high Reliability Index obtained across all classifiers and load levels indicates minimal variance between repeated measurements.This was achieved through controlled fault induction, fixed sensor mounting positions, consistent sampling parameters, and standardized preprocessing steps — all essential components of a reproducible testing protocol [16].The adaptive AI model’s robustness under different loads demonstrates its ability to generalize to variable operational environments, a critical aspect of industrial predictive maintenance. Furthermore, the inclusion of both traditional and deep learning approaches provides a balanced framework that can be benchmarked by other researchers, fulfilling the reproducibility criteria often lacking in prior studies [11]–[15]. Unlike most prior works that primarily report algorithmic accuracy without formal verification of test repeatability, this study incorporates repeatability and traceability metrics directly into the evaluation process. The use of the Reliability Index (RI) and quantified measurement uncertainty ensures that each experimental run can be replicated under identical conditions—addressing one of the core objectives of ASTM-style testing and evaluation frameworks.

IV.6 DISCUSSION ON LIMITATIONS

Despite the strong results, certain limitations remain. The experimental testing was conducted on a single-motor configuration in a controlled laboratory environment, which may not capture the full variability of field conditions such as temperature, humidity, and unbalanced loads. Additionally, while the adaptive hybrid AI framework offers superior accuracy, it demands higher computational resources, limiting its suitability for low-cost embedded monitoring devices. Extending this framework to multi-motor datasets and performing cross-platform validation are recommended for future work to ensure broader applicability.

V. CONCLUSION & FUTURE SCOPE

This study presents a standardized testing and evaluation framework for fault diagnosis of induction motors based on multi-sensor signal analysis and adaptive AI models. The experimental work integrated vibration and current signature measurements under controlled conditions and validated performance across various induced faults—bearing outer-race, inner-race, rotor bar, and stator winding failures. The proposed testing protocol combines precise instrumentation calibration, fault induction repeatability, and quantitative evaluation metrics, ensuring measurement traceability and result reproducibility, consistent with ASTM and IEEE testing philosophies [16]-[19]. Baseline models using ANN and SVM established foundational performance, while the adaptive hybrid CNN–LSTM model improved classification accuracy to 98.4 % with a Reliability Index of 0.99, confirming the robustness of the framework. These findings demonstrate that the fusion of mechanical (vibration) and electrical (current) testing offers more reliable and repeatable diagnostics than single-sensor methods. The work contributes to the testing and evaluation community by:

- Providing a structured, repeatable methodology for experimental fault analysis.
- Demonstrating a quantitative reliability metric (RI) to assess test consistency.
- Validating the potential of AI-based evaluation tools within standardized laboratory testing environments.

Despite these strengths, limitations remain. The tests were performed on a single motor type under laboratory conditions; hence, the protocol should be extended to include multiple motor ratings, diverse environmental conditions, and long-term degradation effects. Moreover, computational complexity of deep learning models may limit deployment in low-power edge devices. Future work will focus on developing lightweight adaptive algorithms, expanding datasets for cross-machine validation, and exploring integration with real-time predictive maintenance systems in industrial testbeds. The developed testing protocol and adaptive evaluation framework fulfill the fundamental requirements of standardized testing—repeatability, traceability, and reliability—making the results comparable across different instruments. This study demonstrates the effectiveness of a multi-sensor AI-based fault diagnosis system for induction motors under practical operating conditions. The experimentally validated results indicate that adaptive learning models can significantly enhance diagnostic reliability when applied to real-world maintenance scenarios. The proposed approach offers a feasible solution for industrial predictive maintenance, supporting early fault detection and reduced downtime. Future work will focus on real-time deployment and long-term field validation in industrial environments.

VI. AUTHOR'S CONTRIBUTION

Conceptualization: Saranya M, Archana N and S. Udhayakumar
Methodology: Saranya M, Archana N and S. Udhayakumar
Investigation: Saranya M, Archana N and S. Udhayakumar
Discussion of results: Saranya M, Archana N and S. Udhayakumar
Writing – Original Draft: Saranya M
Writing – Review and Editing: Archana N and S. Udhayakumar.
Resources: S. Udhayakumar
Supervision: Archana N and S. Udhayakumar
Approval of the final text: Archana N and S. Udhayakumar

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VIII. COMPLIANCE WITH ETHICAL STANDARDS

This study did not involve human participants or animal subjects. All experiments were conducted on electrical machines in accordance with institutional safety and laboratory testing protocols. The authors affirm adherence to ethical engineering research practices and responsible laboratory conduct.

IX. REFERENCES

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