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Hybrid Approach for Bearing Fault Diagnosis in Induction Motors Based on Isolation Forest and Ensemble Learning

Abaiche Karima, Fouad Slaoui Hasnaoui, Abdelhak Mehadjbia

Abstract*: *Rolling element bearings are fundamental parts of rotating machinery, and their sudden breakdown may cause abnormal vibrations, an unplanned production halt, and higher maintenance costs. To address this problem, this paper presents a hybrid data-driven approach for the automatic diagnosis and classification of bearing faults using vibration signals from the IMS dataset. The proposed method first divides the raw vibration signals into fixed-length windows and computes seven statistical features to characterise the signals. An unsupervised Isolation Forest technique is then used to detect anomalous signal segments, providing an early warning of potential faults. Thus, it does not require prior knowledge of the normal condition for fault detection. Subsequently, the detected anomalies are classified using two ensemble-based supervised learning models: Extra Trees and XGBoost. The experimental results indicate that the tree-based ensemble classifiers outperform the other models tested. Specifically, XGBoost achieves an F1 score of 97. 41%, whereas Extra Trees achieves an F1 score of nearly 97%, indicating its high potential for accurately detecting different types of bearing faults. The results confirm that the proposed hybrid two-stage model is an efficient and reliable tool for bearing fault diagnosis, supporting early fault detection, and enhancing system reliability in industrial settings.

Keywords*: *Predictive Maintenance, Bearings, Anomaly Detection, Forest Isolation, Extra Trees, XGBoost, Vibration Signals.

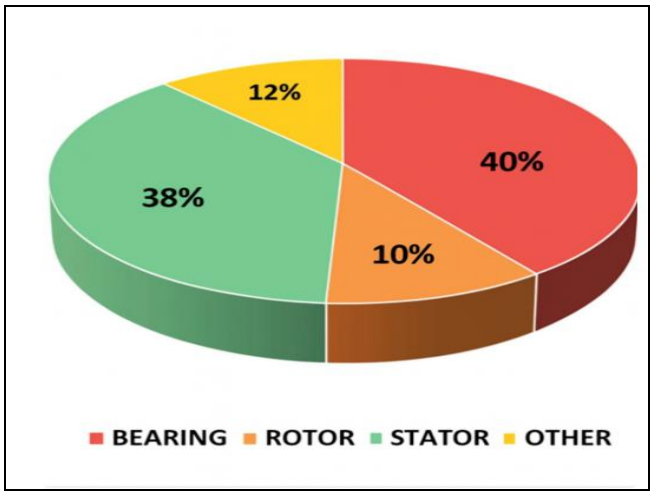
Nomenclature:
RMS: Root Mean Square
IMS: Intelligent Maintenance Systems

I. INTRODUCTION

Automation currently occupies an essential place in industry, where machines must operate continuously and reliably. Among the most heavily stressed components, bearings play a central role in the proper operation of rotating systems, and their failure is a significant cause of faults in induction motors, accounting for 40–50% of reported defects [1]. To avoid unplanned shutdowns and economic losses, it becomes essential to detect bearing faults as early as possible [2].

Numerous recent studies have proposed the use of supervised machine learning methods such as Random Forest, SVM, and ANN for bearing fault diagnosis using vibration signals [3]. Other works have shown that ensemble models such as Bagged Trees, Subspace KNN, and XGBoost achieve high fault classification performance [4]. However, these approaches rely primarily on labelled data, which is a limitation in industrial environments where anomalies are rare and often unlabeled [5].

To overcome this limitation, recent studies have explored hybrid approaches that integrate anomaly detection with supervised classification for bearing fault diagnosis [6]. Within this framework, the present work proposes a hybrid model that combines anomaly detection using the Isolation Forest algorithm with supervised classification of detected faults.



[Fig.1: Overview of the Distribution of Common Faults in Induction Motors [7]]

A simple yet effective methodology is adopted to detect and classify bearing faults using the IMS vibration dataset. The proposed approach is structured into four main stages: signal segmentation, statistical feature extraction, unsupervised anomaly detection, and supervised fault classification. During the first stage of analysis, the Isolation Forest algorithm is applied to identify abnormal signal segments.

In the subsequent stage, the segments flagged as abnormal are classified using supervised learning algorithms. Tree-based ensemble methods, particularly Extra

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*Correspondence Author(s)
Abaiche Karima, School of Engineering, University of Quebec in Abitibi-Temiscamingue, Quebec, Canada. Email ID: Karima.Abaiche@uqat.ca
Fouad Slaoui Hasnaoui, School of Engineering, University of Quebec in Abitibi-Temiscamingue, Quebec, Canada. Email ID: fouad.slaoui-hasnaoui@uqat.ca, ORCID ID: 0009-0000-2755-372X.
Abdelhak Mehadjbia*, School of Engineering, University of Quebec in Abitibi-Temiscamingue, Quebec, Canada. Email ID: abdelhak.mehadjbia@uqat.ca, ORCID ID: 0009-0001-6139-1821.

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Trees and XGBoost, demonstrate superior performance, in line with findings reported in recent studies [3].

Overall, the integration of Isolation Forest for anomaly detection with ensemble-based classifiers forms a robust and accurate hybrid framework for bearing fault diagnosis, relying on simple statistical descriptors extracted from IMS vibration signals.

II. LITERATURE REVIEW

Recent research has moved beyond traditional signal processing toward machine learning and hybrid methods for bearing fault diagnosis to address the complexity and limited availability of fault labels. Several studies have explored hybrid models that combine different learning strategies to improve diagnostic accuracy. One class of work leverages hybrid deep learning and machine learning combinations. For example, LSTM networks have been paired with Random Forest classifiers and optimised using Grey Wolf Optimisation, achieving very high multi-fault detection accuracy by combining temporal feature learning with robust classification [8]. Similarly, deep convolutional networks have been combined with random forest ensembling to automatically extract hierarchical features from vibration data, thereby improving classification robustness relative to standard models [9]. Research has also investigated ensemble-based approaches that combine multiple learners to enhance reliability. A hybrid classifier ensemble integrating Dempster-Shafer theory demonstrated improved decision fusion among deep learning, SVM, and extreme learning machine classifiers, highlighting the value of combining diverse classifiers for bearing fault identification [10]. Other studies have examined tree-based ensembles like Random Forest, XGBoost, and gradient-boosting models, finding that ensemble structures often outperform individual learners in noisy industrial environments [11].

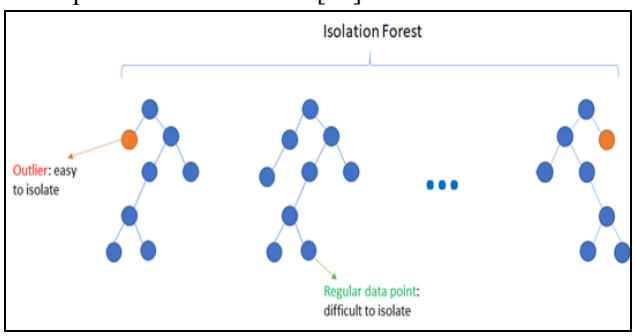
In addition to supervised ensembles, anomaly detection methods such as Isolation Forest can be effective for identifying abnormal patterns without requiring extensive labelled fault data; this has been particularly useful in scenarios where fault examples are rare. Hybrid frameworks that integrate Isolation Forest with supervised learners (e.g., XGBoost, Random Forest) further improve anomaly detection recall while maintaining classification precision [12]. Finally, broader reviews confirm a trend toward hybrid and data-efficient strategies, including meta-learning frameworks for fault diagnosis in data-scarce environments, which strengthen generalization across variable operating conditions [13]. These lines of research collectively justify hybrid approaches that combine unsupervised anomaly detection and supervised classification for practical and effective bearing fault diagnosis.

III. ESEMBLE-BASED LEARNING

In this work, machine learning techniques are employed to detect and identify bearing faults. Owing to the complex and non-stationary nature of vibration signals, relying on a single diagnostic method may be insufficient to achieve robust performance. Consequently, a multi-model approach is adopted that combines multiple learning algorithms to enhance diagnostic reliability and accuracy. The purpose of this section is to present the selected models and to justify their suitability for bearing fault diagnosis applications. These models enable both the automatic detection of abnormal behaviours in signals and the classification of fault types in the IMS dataset. In the following subsections, each model is described in a simple, straightforward manner and then integrated into the proposed hybrid methodology.

A. Isolation Forest

The Isolation Forest algorithm is an unsupervised learning method for detecting anomalies in a dataset. Its principle is that anomalous observations are easier to isolate than everyday observations. To achieve this, the algorithm generates multiple random decision trees in which anomalous points are isolated with very few splits. This ability to quickly isolate rare or unusual points makes Isolation Forest particularly effective for analysing industrial vibration signals. This model offers several advantages: it is fast, robust to noise, scalable to large data volumes, and does not require labelled data. In this work, Isolation Forest is used as the first stage of the hybrid method to automatically identify IMS signal segments exhibiting abnormal behaviour, before their supervised classification [14].



[Fig.2: Isolation Forest Model [14]]

B. Extra Trees Classifier

The Extra Trees (Extremely Randomised Trees) classifier is an ensemble model that combines multiple decision trees constructed via highly randomised sampling. Unlike conventional random forests, Extra Trees selects split thresholds at random, thereby increasing tree diversity and reducing model variance. This strong randomisation enables strong generalisation performance, even when the data are noisy or exhibit significant variation. The model is also fast to train, since it does not search for optimal thresholds but generates them randomly, making it particularly suitable for statistical descriptors extracted from vibration signals. In this work, Extra Trees is used as a classifier to distinguish the different types of bearing faults once abnormal segments have been identified. Its efficiency, stability, and simplicity make it a perfect choice for this problem [15].

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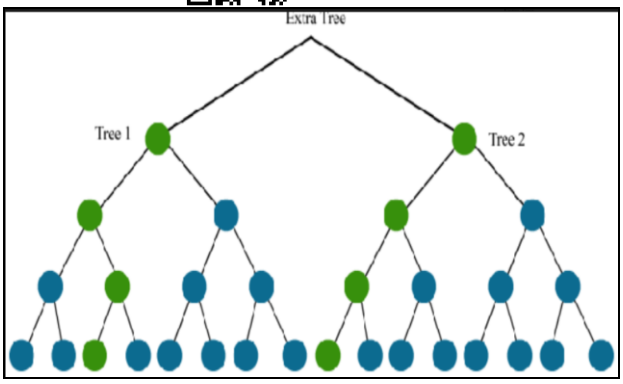
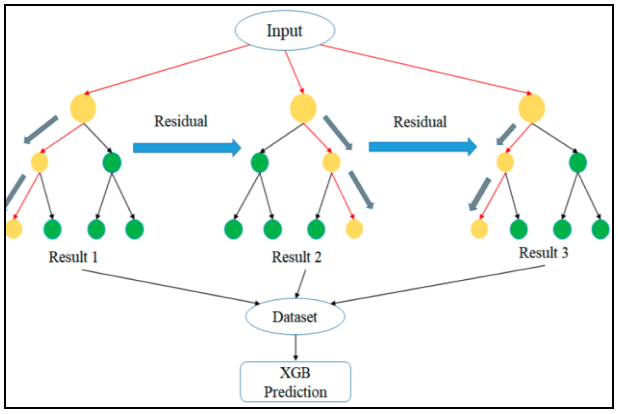


[Fig.3: Extra Trees Model [15]]

C. XGBoost Classifier

The XGBoost (Extreme Gradient Boosting) model is among the most powerful ensemble algorithms for supervised classification tasks. It is based on the boosting principle, in which multiple decision trees are built sequentially, and each subsequent tree corrects the errors of the previous trees. Through this process, XGBoost progressively learns complex patterns present in the data. This model is also well known for its high speed, regularisation capabilities, and robustness to overfitting. It efficiently handles nonlinear interactions among variables, making it a suitable choice for classifying bearing faults using vibration-based descriptors. In this work, XGBoost is employed to distinguish fault types following the detection phase, enabling accurate and stable classification [16].

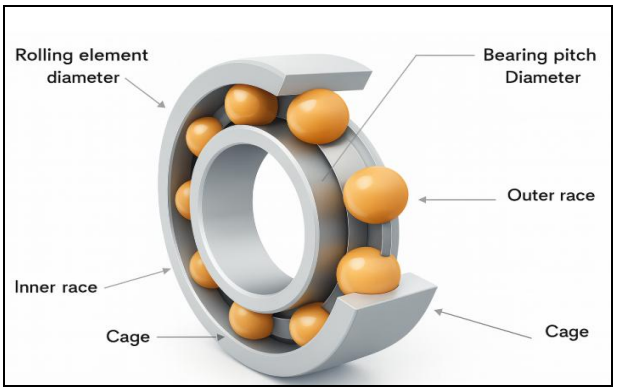


[Fig.4: XGB Model [16]]

IV. CLASSIFICATION OF BEARNING FAULTS

A. Bearing Structure

Rolling element bearings play an essential role in rotating electrical machines, particularly in induction motors, where they support the rotor and enable smooth rotational motion. For several decades, studies have shown that bearing degradation is a significant cause of induction motor failures, accounting for 30% to 50% of faults observed in industrial environments [17]. A bearing is generally composed of an inner race, an outer race, and a set of rolling elements (balls or rollers) that move along the raceways.



[Fig.5: Ball Bearing Structure]

The key point in classifying bearing faults is the location of the damage. Commonly, the main groups are: ball defect, inner race defect, and outer race defect.

Even under normal operating conditions, the root cause of bearing failures can be the initiation of subsurface fatigue microcracks under the raceways or rolling elements' surfaces. Slowly, these cracks reach the surface and increase the level of vibration. Sometimes they produce abnormal noise, which is the first indication of degradation.

Spalling is a common type of fatigue, which is manifested by the flaking of the raceway surface as a result of repeated stresses. As the defect grows, the bearing lubricant becomes contaminated, leading to local overloading along the bearing circumference; consequently, irregular operation or even complete bearing failure may occur. Additionally, other mechanical problems of a bearing include misalignment, instability, wear, excessive clearance, and abrasion, which not only cause degradation but may also accelerate it. A bearing failure will likely cause prolonged downtime, significant damage to adjacent components, and increased maintenance costs. Hence, accurate and early detection of such faults, their classification, and their treatment are vital to the trustworthiness of industrial facilities [18].

B. Description of the Used Dataset

In this study, the IMS Bearing Dataset is used, a well-known benchmark dataset jointly developed by the Intelligent Maintenance Systems (IMS) Centre and NASA to support research in bearing fault diagnosis. The data were acquired from a laboratory test rig in which four bearings were mounted on a shaft driven by an electric motor. Vibration signals were collected using piezoelectric accelerometers at a sampling frequency of 20 kHz, with each data file containing 20,480 samples.

The dataset comprises three run-to-failure experiments, enabling the observation of signal evolution from healthy operating conditions to bearing failure. This characteristic makes the dataset particularly well-suited to anomaly detection and fault classification tasks, which constitute the primary objectives of this work [19].

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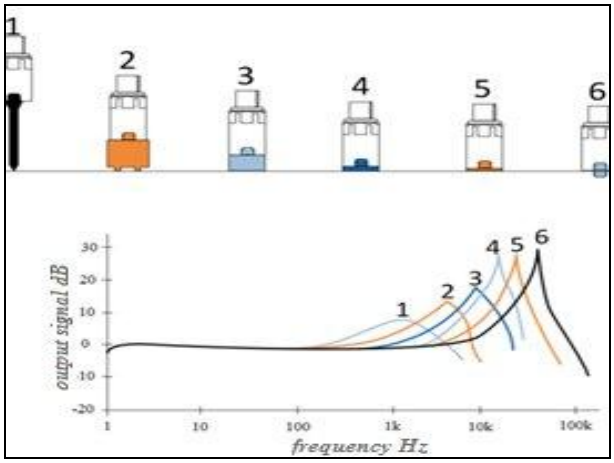


[Fig.6: Frequency Response of Vibration Sensors as a Function of Frequency]

C. Data Preprocessing

This study utilises vibration signals from the IMS dataset collected across three experimental runs (Set 1, Set 2, and Set 3) and four bearings (B1–B4). The data were first organized and subsequently preprocessed. Each raw vibration signal, consisting of 20,480 samples, was segmented into fixed-length windows, yielding multiple signal segments for analysis. From each segment, seven statistical features were extracted to characterise the signal's behaviour. These features were then assembled into a structured dataset, which served as input to the Isolation Forest algorithm for anomaly detection and to the Extra Trees and XGBoost models for fault classification.

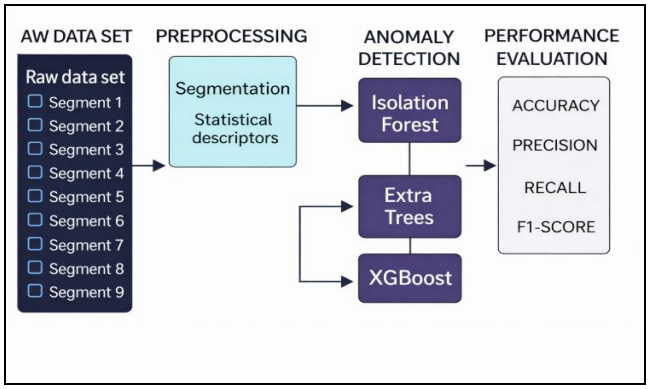
The resulting dataset comprises feature vectors derived from segmented vibration signals. Each feature vector includes a unique identifier (ID) assigned to each signal segment, root mean square (RMS) value, kurtosis, skewness, maximum amplitude, peak-to-peak value, standard deviation, entropy, and a masked label indicating the bearing health status.

V. ARCHITECTURE OF THE PROPOSED SYSTEM

The system proposed in this study is based on a hybrid architecture that integrates anomaly detection with supervised fault classification. The overall workflow consists of three main stages: data preprocessing, detection of abnormal signal segments, and fault classification. In the preprocessing stage, vibration signals from the IMS dataset are segmented into fixed-length windows to increase the number of samples and capture local variations in signal behaviour. From each segment, seven statistical features are computed to form the feature set used for model training.

The second stage focuses on the automatic detection of abnormal signal behaviour using the Isolation Forest algorithm. Owing to its ability to isolate rare observations rapidly, this method effectively identifies anomalous signal segments without requiring prior labelling. The segments identified as abnormal are subsequently classified using two supervised learning models: Extra Trees Classifier and XGBoost. These models are particularly well-suited to tabular data derived from statistical descriptors. While Extra Trees leverages a high degree of randomisation to mitigate overfitting, XGBoost employs a boosting strategy to enhance predictive performance iteratively.

Each classifier is trained and evaluated independently to assess its ability to distinguish between different fault categories. The results indicate that both models achieve high classification accuracy, with XGBoost demonstrating the best overall performance. The resulting two-stage framework, combining Isolation Forest for anomaly detection with Extra Trees and XGBoost for classification, forms an efficient and easy-to-implement system well suited to automatic bearing fault diagnosis.



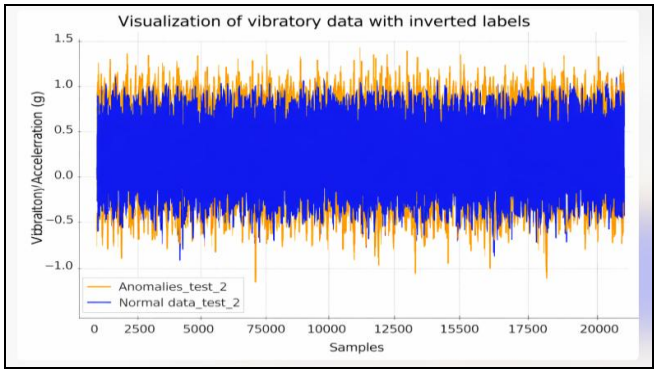
[Fig.7: General Architecture of the Proposed System]

VI. EXPERIMENTAL RESULTS

A. Anomaly Detection Using Isolation Forest

In this work, the Isolation Forest algorithm is employed to identify anomalies in bearing vibration signals. As an unsupervised learning technique, it enables the automatic detection of abnormal signal behaviour without labelled data.

Figure 8 presents the anomalies detected for Bearing No. 4 during the second experimental run. Regular signal segments remain clustered within a stable region, while anomalous segments emerge as scattered peaks, indicating irregular variations in vibration behaviour. These observations demonstrate that Isolation Forest can reveal subtle anomalies that are not easily discernible from the raw vibration signals alone. As such, anomaly detection constitutes a crucial preliminary step that enhances the effectiveness of the subsequent fault classification stage.



[Fig.8: Anomalies Detected in Bearing No. 4 During the Second Test]

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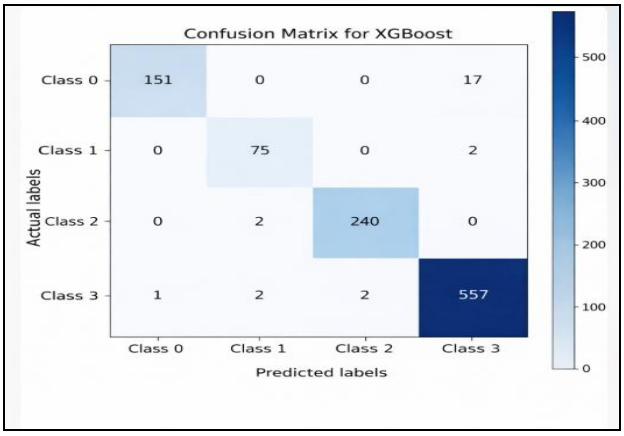
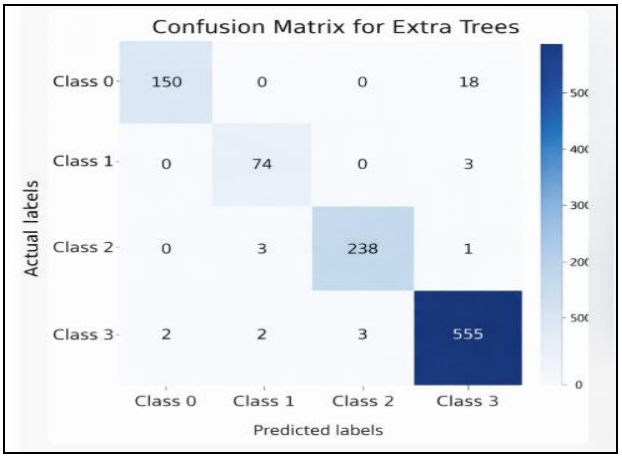
B. Classification of Anomalies

Following anomaly detection with the Isolation Forest algorithm, the abnormal signal segments are classified using the Extra Trees and XGBoost models.

Figures 9 and 10 show the confusion matrices obtained for Extra Trees and XGBoost, respectively. In both cases, most samples are correctly classified along the main diagonal, indicating strong classification performance. The Extra Trees classifier achieves an F1-score of approximately 97%, highlighting its effectiveness in distinguishing between different bearing fault types. XGBoost delivers the best overall results, with an F1-score of 97.41%, reflecting a well-balanced trade-off between precision and recall. The low misclassification rates observed for both models confirm their suitability for accurately classifying anomalous patterns in bearing vibration signals, thereby validating the effectiveness of the proposed hybrid framework.



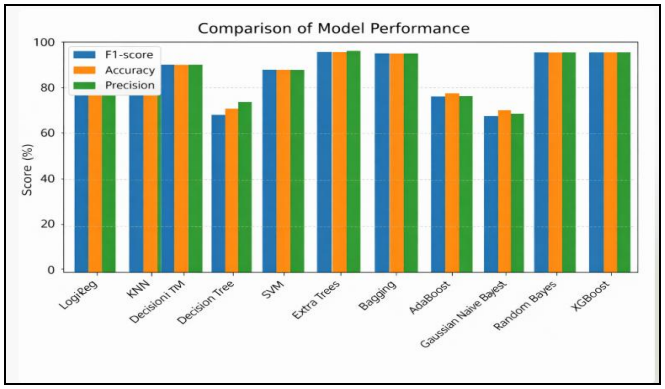
[Fig.9: Matrice Pour Xgboost]



[Fig.10: Matrice Pour Extras Trees]

C. Models Comparison

Figure 11 presents a comparative histogram of the performance of the classification models used in this research. The findings indicated that decision tree-based ensemble methods achieved the highest performance. Among these, XGBoost demonstrates superior performance, achieving an F1-score of 97. 41%, while Extra Trees achieves an F1-score of nearly 97%, showing a great precision in classifying correctly the anomalies detected. While several other classification models were considered for comparison, their performance consistently lagged behind that of Extra Trees and XGBoost. Therefore, the histogram provides a straightforward and concise representation of the comparative results and further strengthens the case for ensemble-based methods as the appropriate choice for vibration signal analysis and bearing fault diagnosis.



[Fig.11: Comparative Histogram]

VII. CONCLUSION

This study introduced a hybrid method for bearing vibration signal analysis that combines unsupervised anomaly detection with supervised fault classification. The framework proposed in this study employs the Isolation Forest algorithm to detect anomalous vibration patterns, followed by fault identification using robust ensemble classifiers, namely Extra Trees and XGBoost. All experiments, along with results, were conducted and obtained within the scope of this study using the IMS bearing dataset.

The experimental evaluation reveals that decision tree-based ensemble models outperform other classification techniques for bearing fault diagnosis. In particular, the combination of Isolation Forest and XGBoost attained the best performance with an F1-score of 97. 41%, whereas the Isolation ForestExtra Trees model produced an F1-score almost equal to 97%. These findings demonstrate that the proposed two-stage strategy is highly effective in first accurately detecting anomalies and then reliably classifying bearing defects. These findings demonstrate that the proposed two-stage strategy is highly effective in accurately detecting anomalies and reliably classifying bearing defects, confirming the robustness of the hybrid diagnostic framework built around the Isolation Forest and ensemble classifiers.

DECLARATION STATEMENT

After aggregating input from all authors, I must verify the accuracy of the following information as the article's author.

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ethical approval or consent to participate with supporting documentation.

- **Data Access Statement and Material Availability:** The adequate resources of this article are publicly accessible.
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AUTHORS PROFILE



Karima Abaiche is currently pursuing a master's degree in engineering with a concentration in Electrical Engineering at the University of Québec in Abitibi-Témiscamingue (UQAT), Canada. Her research interests include machine learning, artificial intelligence and IoT-based systems, embedded systems, and predictive maintenance of rotating machinery, with a focus on bearing fault diagnosis using vibration signals.



Fouad Slaoui Hasnaoui, received his B.Sc.A. and M.Ing. in Electrical Engineering in 1986 and 1995, respectively, from Ecole Polytechnique de Montréal. He also earned his PhD from École de technologie supérieure in Montréal, Canada, in 2003. Dr Fouad Slaoui-Hasnoui worked as a power-industrial engineer for a few years in Morocco, where he was responsible for the electrical maintenance department at one of the country's largest fish-processing industries. Then he worked in Montreal, Canada, on various research projects in power systems, grounding systems, and ground-fault distribution in substations, towers, and ground wires. He is currently a professor in power systems at the University of Quebec in Abitibi-Temiscamingue. His research interests include numerical analysis in power system stability and grounding, as well as artificial intelligence, the Internet of Things, and computer vision.



Abdelhak Mehadjbia, holds a Bachelor's degree in Computer Science, a Master's degree in Intelligent Systems Engineering, and a Master's degree in Electrical Engineering, with publications in the fields of artificial intelligence and computer vision. He is currently an Engineering Research Student pursuing a PhD at the University of Quebec at Abitibi-Témiscaming, working on various projects in intelligent systems and computer vision. He is actively involved in several research projects addressing real-world challenges, with interests in deep learning, image analysis, electrical engineering, and intelligent decision-making systems.

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