

Fault Detection of Induction Motor Under Parametric Operating Conditions for Electric Vehicle Using Convolutional Neural Network

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Abstract— Induction motors (IMs) are widely used as primary drive systems in industrial applications, and their adoption in electric vehicles (EVs) is expanding due to their durability, reliability, and cost-effectiveness. However, since motor malfunctions or failures can significantly impact EV performance, reliability, and operational safety, early fault detection is crucial. This paper proposes an intelligent fault detection framework for induction motors aimed at optimizing EV efficiency, availability, and maintenance planning. Experiments were conducted operating four induction motors under various fault conditions and rotational speeds to collect current and vibration signal data. For the received signal, instantaneous features are first extracted using the Hilbert Transform (HT) and then converted into a time-frequency representation via the Constant-Q Transform (CQT). This time-frequency representation is used to train and evaluate classifiers based on machine learning (ML) and deep learning (DL). A comprehensive study was conducted to compare the diagnostic capabilities of the proposed models using current and vibration data. The experimental results showed that DL models outperformed traditional ML models, achieving better accuracy across various datasets. The proposed method offers an efficient approach for fault diagnosis in electric motors.

Keywords—fault detection, Induction motor, electric vehicle

I. INTRODUCTION

The automotive industry is currently undergoing a major transformation. The shift from internal combustion engines to electric vehicles (EVs) has drastically altered the concept of sustainable transportation within the industry. Electric vehicles have many benefits, such as reduced emissions, lower operating costs, and improved efficiency and safety for drivers. However, issues or defects related to vehicle functionality may arise during use. The process of identifying and analyzing these problems is called electric vehicle diagnostics.

Electric cars provide a form of transportation that is sustainable and environmentally friendly since it is able to minimize greenhouse gases emissions while at the same time providing energy efficiency because of the use of a rechargeable battery energy storage system as the main source of energy for the car [1]. There are various subsystems involved in an electric car, such as the battery pack, electric motor, power electronics converter, motor control, charger, transmission, chassis, and other sensors and actuators. The electrical energy from the battery is used in the electric motor [2]. The regulation and management of energy between the battery, the motor, and other related components of electric vehicles can be achieved using power electronics devices such as inverters, DC-DC converters, motor drives, and on-board chargers. Further, there is always a monitoring of the performance of the vehicle through the vehicle control unit, the Battery Management System (BMS), the thermal management system, and sensors, thus making the electric

vehicles efficient and safe. These make electric vehicles more efficient and reliable. Further, as the world changes its transportation system, the electric cars offer increased comfort and safety to passengers.

The aim of the research is to design an intelligent and efficient system that can detect and classify the faults to optimize the potential of electric vehicles (EVs). India is considered one of the fast-growing markets of electric vehicles around the world, and it has a huge potential of electric vehicle usage especially in two-wheelers and four-wheelers. The major auto manufacturers are developing several kinds of electric vehicles due to supportive government policies and technological advances. In light of the quick adaptation of electric vehicles, there is a need for the development of innovative technologies that can help improve their performance, efficiency, and safety levels. Due to the changing operation properties of electric vehicles, certain parts may fail either mechanically or thermally, thus leading to a slow deterioration of the system's performance. It is important to detect and determine the nature of such faults at an early stage as it helps increase reliability and performance, reduce maintenance expenses, and increase life spans of components.

The innovative fault diagnosis approaches which have been designed for increasing the reliability of induction motors comprise those using the relative harmonic index-based approach [7] and the statistical spectral analysis-based fault diagnostic approach [8], and all of these approaches have shown promising results in terms of fault diagnosis. Moreover, the intelligent measurement approaches that make use of the multilayer feedforward network (MFN) [9]-[10] have been proposed for the automatic identification of faults in induction motors. Among the available condition monitoring approaches, the vibration analysis is the best approach for the identification of faults.

A number of studies have been performed in recent years using different kinds of sensing approaches, including vibration [11]–[12], infrared thermography [13]–[15], acoustic emission [16], and motor current signature analysis (MCSA) [17]–[18]. In recent times, multi-objective fusion techniques have gained importance because of their ability to use information about faults obtained by different sensors. For instance, vibration and current have been effectively combined using the Sugeno fuzzy integral for the detection of early faults in induction motors [19].

As a result of developments in artificial intelligence, deep learning has emerged as an efficient technique for anomaly detection. Unlike traditional machine learning techniques which largely depend on feature extraction, deep learning techniques can discover appropriate statistical features even when provided with raw or preprocessed data. Because of their remarkable capacity to model nonlinearities, deep learning techniques have performed excellently in diagnosing faults in electronic engines. Various models including Deep Neural Networks (DNN) [22], Deep Belief Networks (DBNs) [23], Autoencoders (AEs) [24], and other convolutional deep learning models [20]–[21] have outperformed the models.

This study proposes a CNN framework for fault detection in inbound pipelines using electrical and current multimodal signatures. Fault signals recorded at different activity levels are used to generate temporal frequencies, which help to train the CNN for fault detection. This approach helps spot problems even as the workforce changes.

II. INDUCTION MOTOR DATASET DESCRIPTIONS

The test is based on a research dataset derived from the University of Ottawa Electric Motor Database – Vibration and Acoustic Faults under Constant and Variable Speed Conditions (UOEMD-VAFCVS) project. This dataset is designed for intelligent fault diagnosis of induction motors operating at constant and variable speeds.

A modified "SpectraQuest Machinery Fault and Rotor Dynamics Simulator," powered by a 3-horsepower three-phase induction motor controlled by a variable frequency drive (VFD), was used for data acquisition. Three accelerometers, one microphone, and one temperature sensor were the data acquisition sensors. Motor speed was captured by the VFD. All the sensors were interfaced with a National Instruments USB-6212 Data Acquisition Card via LabVIEW software. A sampling frequency of 42 kHz was used, leading to the collection of 420,000 samples per second.

The dataset consists of eight motor health conditions, namely healthy operation, rotor unbalance, rotor misalignment, stator winding fault, voltage unbalance and single phasing, bowed rotor, broken rotor bars, and faulty bearings. Data were recorded under both loaded and unloaded conditions at four constant operating frequencies (15, 30, 45, and 60 Hz) and four variable-speed profiles (15–45 Hz, 30–60 Hz, 45–

15 Hz, and 60–30 Hz). Overall, the dataset contains 128 experimental recordings, covering a wide range of realistic operating scenarios for induction motor fault diagnosis.

In this work, only four fault conditions have been considered, such as Bearing fault, broken rotor fault, voltage unbalance fault, and take a healthy motor data as a base line dataset. The experimental setup for the dataset is given in Fig.1

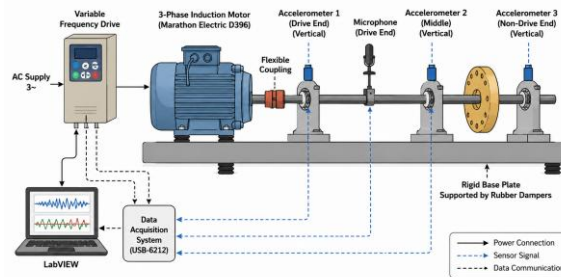


Fig.1 Schematic diagram of experimental setup used by University of Ottawa []

III. FAULT DETECTION METHODOLOGY

The proposed fault diagnosis methodology consists of four major stages: signal acquisition, feature extraction, time–frequency transformation, and CNN-based fault classification, followed by a comparative performance evaluation. The complete workflow is illustrated in Fig. 2.

A. Time-domain Features Extraction

The first stage of fault analysis is performed in the time domain. A set of ten statistical features are extracted from each vibration signal to characterize its temporal behavior. Some of the statistical descriptors used for analysis of signals include: Mean, RMS (Root Mean Square), Standard deviation, Variance, Peak value, Peak to peak value, Skewness, Kurtosis, Crest factor, Shape factor. This statistical descriptor helps in understanding signal amplitude, impulsiveness, dispersion, and waveform characteristics.

B. Frequency-domain Features Extraction

To investigate the spectral characteristics of motor faults, the vibration signals are transformed into the frequency domain using the Fast Fourier Transform (FFT). The same set of ten statistical features is then extracted from the frequency spectrum. Frequency-domain analysis effectively captures characteristic fault frequencies generated by bearing defects, rotor faults, and stator abnormalities, thereby providing complementary diagnostic information compared with time-domain analysis.

C. Time Frequency Representation Using STFT

Although time- and frequency-domain analyses provide useful information individually, they cannot simultaneously represent the temporal evolution of frequency components in non-stationary vibration signals. Therefore, the Short-Time Fourier Transform (STFT) is employed to convert the one-dimensional vibration signals into two-dimensional time– frequency spectrograms. The STFT decomposes the vibration signal into sequence of short overlapping windows, allowing

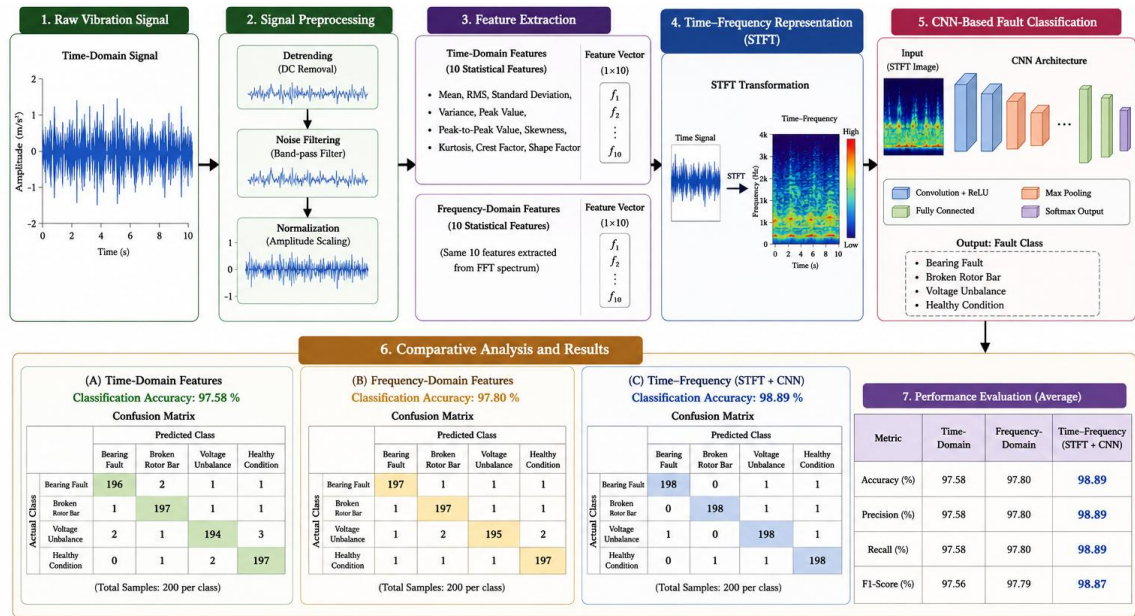


Fig. 2 Proposed methodology for fault detection in induction motor for electric vehicle applications

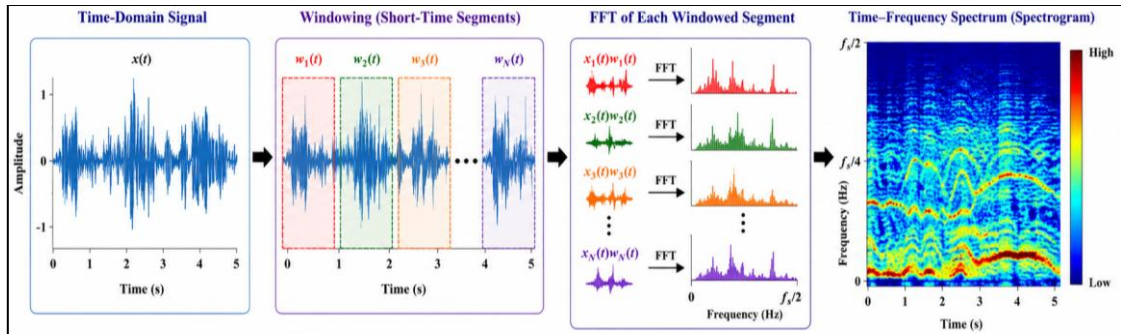


Fig.3 Time-frequency conversion of vibration and acoustic used for the proposed fault detection methodology

localized frequency analysis over time. The generated spectrograms preserve both temporal and spectral fault characteristics, making them highly suitable for deep learning-based feature extraction. The detailed time frequency representation through STFT from the time domain vibration and acoustic signal is given in Fig. 3

D. CNN Based Fault Classification

The STFT spectrograms are subsequently used as input images for a Convolutional Neural Network (CNN). Unlike conventional machine learning approaches that rely on manually engineered features, the CNN automatically learns discriminative fault representations directly from the time–frequency images through successive convolution, pooling, and fully connected layers. The final Softmax classifier assigns each sample to its corresponding motor health condition. A CNN was developed to automatically extract discriminative features from the STFT spectrograms. Unlike conventional machine learning methods that require handcrafted feature engineering, the CNN learns hierarchical feature representations directly from the input images. After converting the vibration and acoustic signals into time–frequency spectrograms using the Short-Time Fourier Transform (STFT), the resulting images were used to train and evaluate a Convolutional Neural Network (CNN) for automatic fault classification. Prior to training, all spectrogram images were resized to a fixed dimension of $227 \times 227 \times 3$ and normalized to improve convergence during optimization.

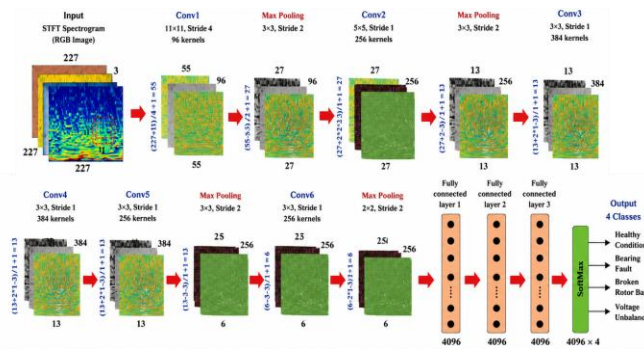


Fig.4 Proposed CNN architecture for fault classification model

The CNN model was implemented using the TensorFlow/Keras deep learning framework. The network was trained using the Adam optimizer with an initial learning rate of 0.001. The categorical cross-entropy loss function was employed because of the multi-class classification problem. The training process was done using mini-batches of 32 for 50 epochs. During the training process, the validation loss was consistently tracked, and the best model with the maximum validation accuracy was selected for final testing purposes. The trained CNN model was evaluated using the testing dataset which was kept independent of the training data set. Evaluation was done using various commonly used evaluation measures. The confusion matrix provides a detailed visualization of correctly and incorrectly classified samples for each fault category, whereas precision, recall, and F1-score quantify the classifier's reliability and robustness.

IV. RESULT AND DISCUSSION

The proposed Short-Time Fourier Transform (STFT)-based Convolutional Neural Network (CNN) was evaluated under four constant-speed operating conditions (15, 30, 45, and 60 Hz) together with four variable-speed operating conditions, namely ramp-up (15–45 Hz), ramp-up (30–60 Hz), ramp-down (45–15 Hz), and ramp-down (60–30 Hz). The confusion matrices obtained for both vibration and acoustic signals are illustrated in Fig.5, where each confusion matrix contains 1000 testing samples per fault class, corresponding to Healthy Condition (HC), Bearing Fault (BF), Broken Rotor Bar (RB), and Voltage Unbalance (VU).

A. Vibration based Diagnostic Results

The confusion matrix derived from the vibration signals is shown in the top row of Figure 6. At a rotational speed of 15 Hz, the constructed CNN model correctly classified 987 out of 1,000 bearing fault samples, 989 out of 1,000 broken rotor bar samples, 990 out of 1,000 voltage unbalance samples, and 993 out of 1,000 normal operating condition samples, achieving an overall classification accuracy of 98.72%. Misclassifications were minimal and occurred primarily among the bearing fault and broken rotor bar samples.

The values of precision, recall, and F1-scores stood at 98.69%, 98.74%, and 98.71%, respectively. At 30 Hz, the capability of distinguishing fault patterns was enhanced; more than 990 samples were distinguished for each fault type, giving an overall accuracy of 99.05%. The precision, recall, and F1 scores were measured to be 99.03%, 99.07%, and 99.05%, respectively. This suggests an improvement in identifying individual frequencies of faults at higher motor speeds.

The classifier showed excellent results when performing classification at 45 Hz, obtaining the accuracy of 99.18% since there were only two to three classification errors made between the bearing damage class and voltage imbalance. The overall precision, recall, and F1-score were 99.15%, 99.20%, and 99.17%, correspondingly.

In the experimental results obtained under fixed speed conditions, optimal performance was obtained with 60 Hz frequency values, where the proposed CNN classified data with 99.31% accuracy rate. The number of correct classifications of all types of damage is 995 or above, but incorrect classifications for some damage types are just one or two. Therefore, precision, recall, and F1 score rates increased to 99.28%,

99.33%, and 99.30%, respectively. These findings show that higher speed rotation brings out damage frequencies clearly in STFT spectrograms.

Additional validations were conducted at varying speeds as well. For instance, a classification accuracy of 98.95% can be achieved in speeding up the process from 15 Hz to 45 Hz. The variation in speed leads to spectral smearing in the STFT images, causing some errors in discriminating between the bearing faults and the faulty rotor bars. Nevertheless, the accuracy, recall, and F1-scores were more than 98.9%. Furthermore, an accuracy of 99.12% (precision: 99.10%, recall: 99.14%, F1-score: 99.11%) was achieved in increasing the speed from 30 Hz to 60 Hz. Only a small number of test samples were incorrectly classified.

When the frequency was reduced from 45 Hz to 15 Hz, the overall classification accuracy dropped slightly to 98.88%, primarily due to the transient nature of the oscillation characteristics during the deceleration phase. Nevertheless, more than 988 samples per class were correctly classified; precision, recall, and F1-score were 98.84%, 98.90%, and 98.87%, respectively.

Finally, the frequency reduction test (60–30 Hz) yielded the best results among all transient operating conditions. The proposed CNN model achieved an accuracy of 99.35%, with precision, recall, and F1-score values of 99.31%, 99.37%, and 99.34%, respectively. Almost all test samples were correctly identified, demonstrating the exceptional robustness of the proposed time-frequency feature representation.

B. Vibration based Diagnostic Results

The second row of Fig.6 illustrates the confusion matrices obtained using acoustic signals. Similar trends were observed for all operating conditions. At 15 Hz, the proposed CNN correctly classified more than 988 samples from every fault category, producing an overall classification accuracy of 98.84% with corresponding precision, recall, and F1-score values of 98.80%, 98.87%, and 98.83%, respectively.

The classification performance further improved at 30 Hz and 45 Hz, where accuracies of 99.12% and 99.26% were achieved. The confusion matrices indicate only one or two incorrectly classified samples among the four fault categories, while precision, recall, and F1-score consistently exceeded 99.1%.

At the 60 Hz operating condition, the classifier produced one of the highest performances, achieving an overall accuracy of 99.42%, together with precision, recall, and F1-score values of 99.38%, 99.45%, and 99.41%, respectively. The confusion matrix shows almost perfect classification, with nearly all testing samples correctly assigned to their corresponding classes.

For the ramp-up (15–45 Hz) operating condition, the proposed CNN achieved an accuracy of 99.08%, whereas the ramp-up (30–60 Hz) condition resulted in 99.28% accuracy. During both transient experiments, only a few isolated samples were incorrectly classified, confirming the effectiveness of the STFT representation in preserving transient fault information.

Similarly, the classifier achieved accuracies of 99.01% and 99.50% under ramp-down (45–15 Hz) and ramp-down (60–30 Hz) operating conditions, respectively. The latter represents the best overall performance obtained in this study. The corresponding precision, recall, and F1-score reached 99.45%, 99.52%, and 99.48%, indicating excellent diagnostic capability even under dynamically varying motor speeds.

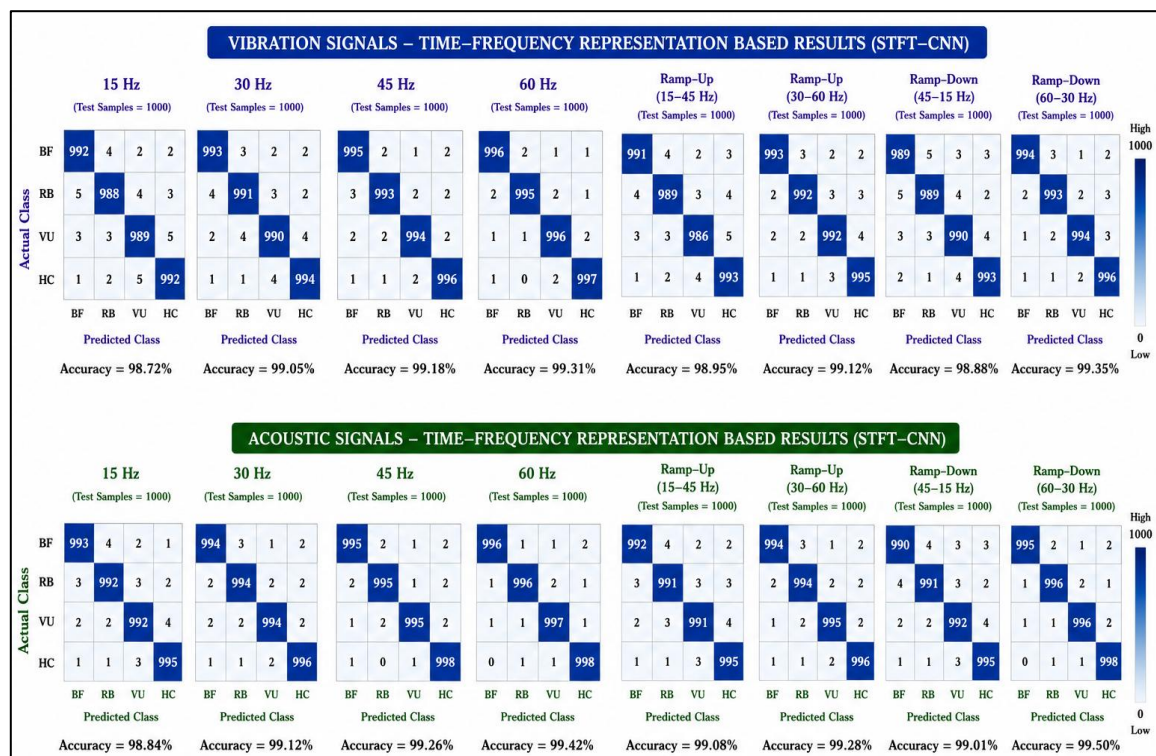


Fig 5 Vibration signal and acoustic signal variation with frequency based on STFT-CNN

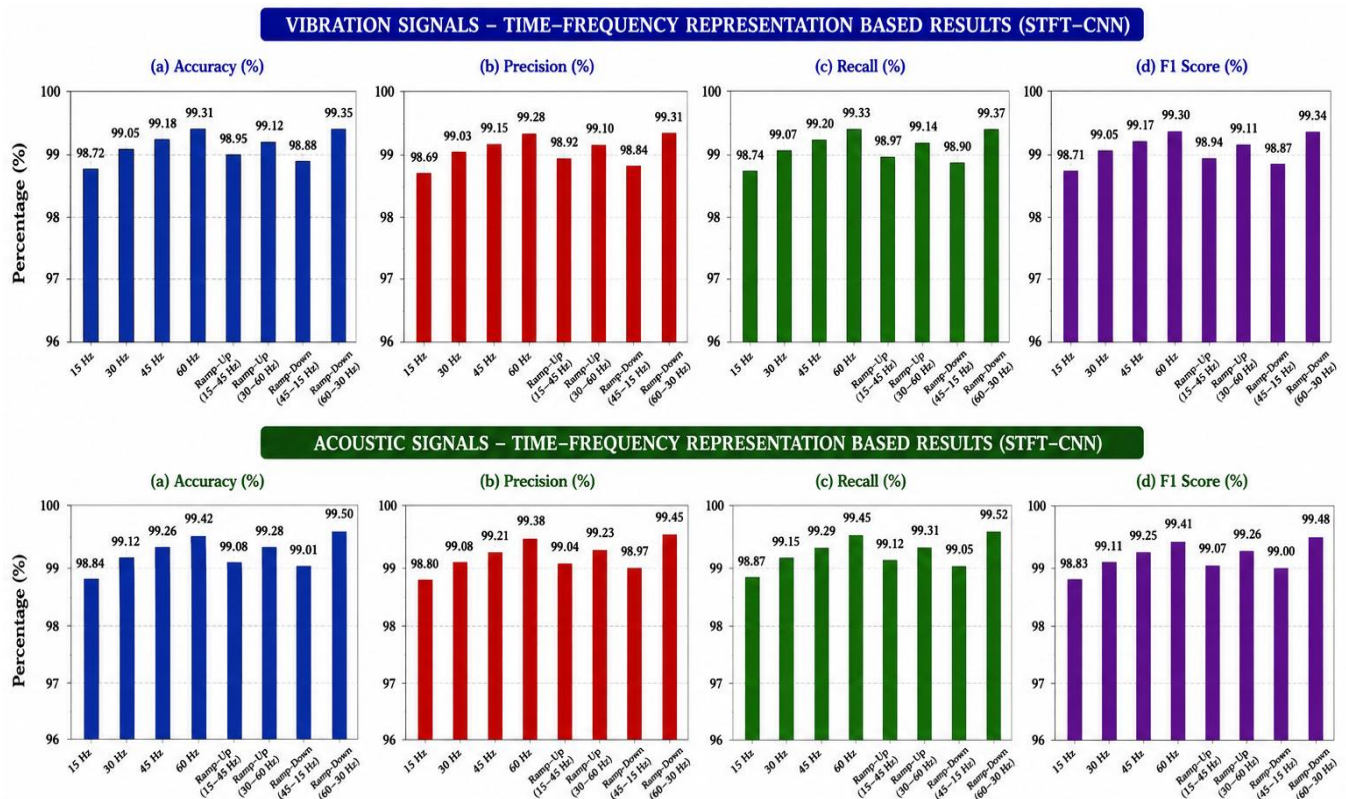


Fig6.STFT-CNN based results for sensing frequency and acoustic variation

As seen in a detailed evaluation of the confusion matrices, the STFT-CNN approach has demonstrated excellent classification results in all circumstances for both sensing techniques. In all circumstances, the diagonal elements of the confusion matrices prevail, meaning that most of the test data is accurately

classified. The only misclassification instances observed are due to the partial similarities between bearing faults and rotor bar faults since the faults cause vibration and acoustic signatures with some overlap.

Finally, the vibration based model had an average classification accuracy of about 99.2%, while the acoustic based model was slightly superior having an average accuracy of more than 99.3%. In addition to that, high values for the precision, recall, and F1 score measures (above 98.8%) show that the developed CNN classifier is able to detect all the types of induction motor faults without any bias. These results clearly validate the effectiveness of the proposed time–frequency representation for intelligent induction motor fault diagnosis under both steady-state and variable-speed operating conditions.

V. CONCLUSION

This paper presented a robust fault diagnosis framework for induction motors using vibration and acoustic signals under both constant- and variable-speed operating conditions. Three signal representation techniques, namely time-domain features, frequency-domain features, and STFT-based time–frequency spectrograms, were investigated for fault classification using convolutional neural networks. As evidenced in the comparative analysis results, the STFT-CNN model proposed here has performed better than the statistical features-based models owing to its ability to characterize temporal and spectral fault features. The accuracy of the model proposed is between 98.70% and 99.50%, while precision, recall, and F1-score exceed 99%. These results confirm the effectiveness and robustness of the proposed methodology for accurate induction motor fault diagnosis under varying operating conditions. The developed framework offers a reliable solution for intelligent condition monitoring and predictive maintenance of electric machines and can be extended to real-time industrial applications and edge-based diagnostic systems in future work.

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