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Predictive maintenance for induction motors: a novel synergy of deep learning and machine learning techniques

V. Rajini[1], Karunya Harikrishnan[2], Krismadinata[3]
[1]Department of Electrical and Electronics Engineering, Sri Sivasubramaniya Nadar College of Engineering, Chennai, India
[2]Department of Computer Science and Engineering, Shiv Nadar University, Chennai, India
[3]Department of Electrical Engineering, Faculty of Engineering, Universitas Negeri Padang, Padang, Indonesia

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ABSTRACT

Condition monitoring of induction motors is vital for preventing unexpected downtimes and minimizing the maintenance costs in industrial settings. A predictive maintenance model for early detection of faults is proposed. The motor current, flux, vibration, thermal and acoustic emission signatures are commonly used for fault detection as these signals reveal fault specific frequency components. Signal processing techniques like wavelet transform and Hilbert transform are used to identify faults at incipient stages. Machine learning and deep learning models are used nowadays to extract features and classify the faults accurately. The current and flux signals from healthy and faulty motors for inter turn faults were analyzed in this work and features were extracted through various signal processing methods. These features were then used to train models, including deep learning architectures, to classify motor faults. While the classical machine learning models provided a reasonably accurate fault classification, the convolutional neural network provided a very good classification accuracy. The findings show that deep learning models excel in detecting faults, especially under noisy and varying operational conditions, outperforming the traditional methods. These models offer a scalable, real-time solution for improving the reliability and efficiency of induction motor and facilitate more reliable assessments and contribute towards energy efficiency and extended lifetime of equipment.

Corresponding Author:

V. Rajini
Department of Electrical and Electronics Engineering, Sri Sivasubramaniya Nadar College of Engineering
OMR Road, Kalavakkam, Chennai, Tamil Nadu, India
Email: rajiniv@ssn.edu.in

1. INTRODUCTION

In most industrial environments, monitoring the health of machines is important to improve productivity. An appropriate maintenance strategy is important to avoid the failure of machinery so that the cost of production and time can be minimized. The maintenance of machines can be responsive, preventive, or predictive in nature. While the responsive maintenance is a reactive approach where fix-on failure happens, the preventive maintenance is a pre-planned approach. The predictive approach is based on forecasting strategy. This approach offers a cost and time advantage as compared to responsive and preventive approaches, respectively. A combination of various intelligent models can be used for a robust forecast and better prediction accuracy. It is essential to have a robust methodology for fault detection so that they can be identified at an incipient stage and can be mitigated at the earliest. Hence, developing a reliable intelligent model for monitoring the health of the most widely used induction motor is the main motivation of this work.

Various physical signatures like vibration, temperature, acoustic emission, current, voltage, power, and magnetic flux are generally used. These methods require sensors and devices for data acquisition. The motor current based condition monitoring is a non-invasive method requiring only low-cost current sensors with a simple implementation. It has the ability to detect electrical and mechanical faults, including bearing faults. The flux based condition monitoring requires a flux coil to be inserted in the machine during design and measuring the induced voltage across this coil. This research uses current and flux signatures for fault classification.

Amid various approaches proposed in the literature, the performance of model-based approach is mostly dependent on the exclusive motor models. Knowledge-based approaches using statistical and deep learning algorithms are gaining increasing interest among the scientific community for condition monitoring of machines. The features derived from various acquired signatures are used in these algorithms. Fourier transform, wavelet transform (WT), and convolutional neural networks (CNN) are used for this purpose by some researchers. A hybrid approach based on empirical and adaptive features were used for bearing fault classification of by Xie *et al.* [1] using vibration signatures. Bazan *et al.* [2] have used current signatures with information theoretic measurements and intelligent tools such as multi-layer perceptron- artificial neural network, k-nearest neighbours (KNN), and support vector machines (SVM) for the detection of abrasive wear in the bearings of induction motor. Hoang and Kang [3] have used the information fusion on current signatures. A fault diagnosis framework based on a CNN, which integrates domain knowledge and broad learning system was proposed by Feng *et al.* [4] for bearing faults. The approach proposed by Zhao *et al.* [5] used a multi sensor device for collecting the time domain-based vibration signals. A multimanifold deep extreme learning machine was used for feature extraction and fault diagnosis. Wavelet decomposition and artificial neural networks were used by Sadeghian *et al.* [6] for rotor fault detection of induction motors. Rezende *et al.* [7] have demonstrated the viability of the combined use of CNN techniques with thermal analysis for detection of failures in electric motors. A data driven deep learning model is investigated by Sohaib *et al.* [8] and Theissler *et al.* [9]. A detailed review of literature in predictive maintenance for industry 4.0 is done [10]-[13]

The digital twin concept is picking up momentum in industrial sector. Falekas and Karlis [14] have investigated a detailed review in this area. As most of the industrial drives use power electronic devices, a review of the application of AI techniques in industrial drives was written by Zhao *et al.* [15].

Rajini *et al.* [16] have investigated the classification of induction motor faults with machine learning and wavelet feature extraction techniques. The purpose of this study was to demonstrate the applicability of the proposed CNN model along with the performance of the existing machine learning models. Various deep learning architectures applied to induction motor fault diagnosis are given by Sikinyi *et al.* [17]. Rajapaksha *et al.* [18] compared supervised machine learning algorithms using features derived from the fast Fourier transform (FFT) of acoustic data for condition monitoring of induction motors. A case study where the FFT is used to extract energy features, feeding in to ML models for diagnosis is done by Khalil and Rostam [19].

A framework based on deep learning for health monitoring of was given by Ganguly *et al.* [20]. Two powerful deep learning architectures, CNN and LSTM, to extract both spatial (local) and temporal (sequence) features from vibration signals for fault diagnosis are done by Sun *et al.* [21]. The digital twin and industrial IoT for monitoring, a key trend showing the practical deployment of condition monitoring systems are done by Santos *et al.* [22]. For monitoring the electrical drives, a simulation-assisted neural network was used by [23]. Motor current signature analysis combined with autoregressive spectral estimation (an alternative to FFT) for high-resolution fault diagnosis, focusing on non-invasive sensing was done by [24]. A study focusing on improving diagnostic accuracy and robustness by fusing data from multiple using an advanced Deep Learning framework was given by [25].

This paper aims to demonstrate the viability of a hybrid approach that combines FFT with machine learning (ML) and deep learning (DL) models using the current and flux signatures of electric motors to understand and diagnose failures. This joint approach is a highly effective, cutting-edge method in the field of predictive maintenance (PM) for electric motors. This methodology is crucial for Industry 4.0 applications, enabling prognostics and health management (PHM) systems that maximize motor lifespan and minimize unplanned downtime.

2. METHOD

2.1. Experimental setup

The dataset was curated by conducting experiments. The test setup consists of two motors, one is taken as the healthy motor and faults are simulated in the other motor called test motor. It also has a dynamometer which can be coupled to any one of the two identical induction motors. Two identical motors have the following specification: three-phase, 1 HP, 415 V, 50 Hz, 4 pole, and 1500 rpm. Flux coil with

80 turns is also inserted in both the motors for the flux measurement. The test motor is provided with an external tapping to create stator inter turn short circuit fault. Provision is given for the replacement of rotor/bearing with punched rotor/bearing to create rotor/bearing fault, respectively. Dynamometer rating is 0.75 kW, 1500 rpm, 0.5 kg-m, excitation of 85 volts. By adjusting the excitation voltage of the dynamometer setup, the load of the induction motor can be varied. Data acquisition card with measurement computing USB 1208FS – Plus is used to acquire the stator current signal under healthy and various faulty conditions. The data acquisition was done using a USB-1208FS with 8 configurable analog inputs for 11-bit single-ended eight inputs or four 12-bit differential inputs and two 12-bit analog output channels. Analog input channels are used to get the signal from the 2:1 ratio current sensor and the load torque signal from the dynamometer. DSO-X 3024A MY54020518 - 200 MHz is used for acquiring the stator current and flux signals. Figure 1 shows the experimental setup used for the present investigation. The overall approach is depicted in Figure 2. This test bench was meticulously set up to enable the emulation of stator winding inter-turn short-circuits. This involved provision on the stator circuit to facilitate the insertion of short circuits at various levels, ranging from subtle defects to severe situations.

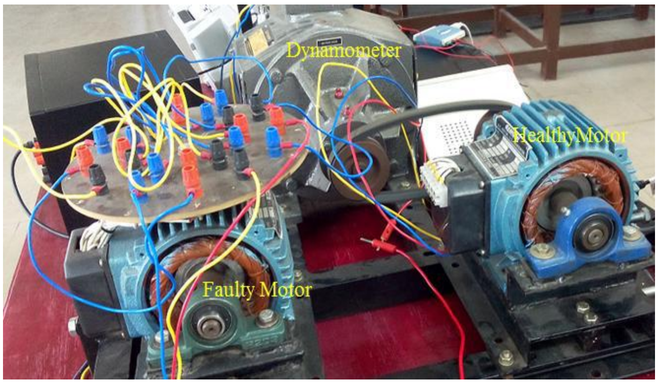


Figure 1. Experimental setup

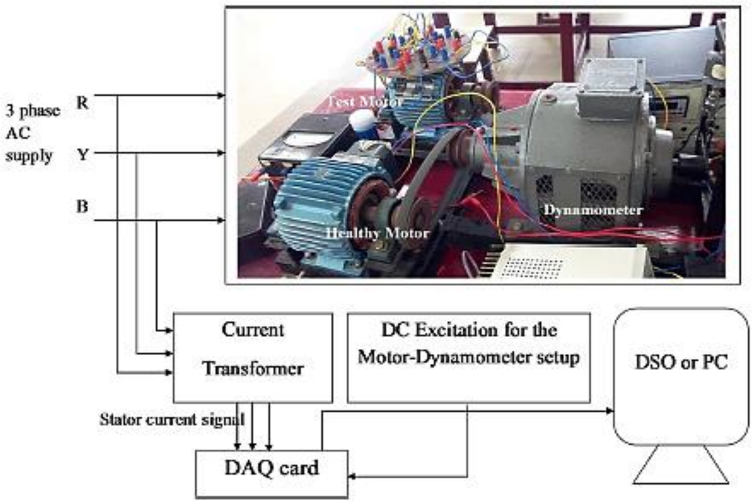


Figure 2. Overall block diagram

2.2. The data set and data exploration

The data set has the flux and current signatures for no load, half load and full load applied to the motor. The drive frequency is also adjusted from 25 Hz to 50 Hz with 5 Hz increments. A sample current and flux spectra recorded is shown in Figure 3. Ch1 represents the flux and Ch2, 3, and 4 are the three phase currents. Consequently, a decision was made to leverage these two sets of measurements independently to construct distinct predictive models, each focused on identifying the corresponding fault classes. This separation of data was intended to assess the individual correlations between current values and fault classes, as well as between flux and fault classes.

2.3. Feature extraction

The FFT was employed to extract viable features from the measured current and flux data and transform the extracted features as deemed efficient for the model to learn and reproduce. The FFT, commonly abbreviated as FFT, is a common yet effective technique employed in signal processing to analyze and represent signals in the frequency domain. The FFT accomplishes this by decomposing a signal into its constituent sinusoidal components of varying frequencies and amplitudes as shown in Figure 4. Therefore, it is particularly useful for identifying dominant frequencies and periodic components within a signal. FFT is deployed for the given flux and current signals to capture the constituent frequency components.

The dataset initially consisted of 100,000-time domain samples collected over a 10-second interval. To facilitate efficient processing firstly, infinite values were removed from the dataset. Subsequently, FFT was used for frequency domain conversion.

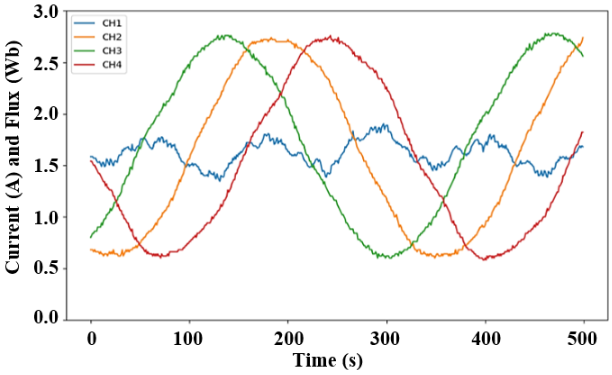


Figure 3. Sample current and flux signatures

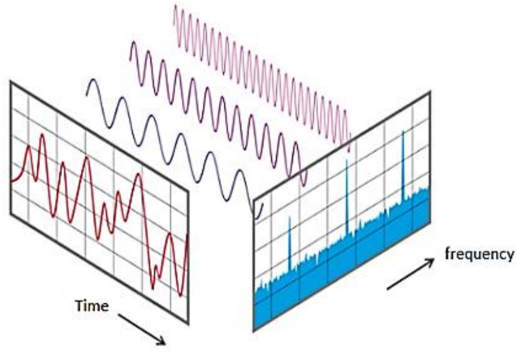


Figure 4. Time and frequency domain spectra

The FFT operation generated 100,000 samples in the frequency domain. To avoid redundant data, a down-sampling step was introduced by taking advantage of the symmetry in signal magnitude around discontinuities. This allowed for the removal of one half of the values while retaining the relevant information. From the 100,000 frequency domain samples, only 50,000 samples were retained for further analysis.

During our ablation studies, we identified that sampling frequencies at 5 Hz intervals provided the optimal performance for our model. This finding was pivotal as it allowed us to significantly reduce the data dimensionality without compromising the model's efficacy. Initially, our dataset consisted of 50,000 samples, each representing a comprehensive range of frequencies.

To further streamline the dataset an additional reduction step was implemented. Specifically, every 10th sample from the original set of 50,000 samples was selected. This strategic down-sampling resulted in a final dataset where each data point consisted of 5,000 features in the frequency domain. By applying these two key steps, sampling at 5 Hz intervals and then reducing the total number of samples by a factor of 10, the critical frequency information necessary for the models' performance was retained while significantly reducing the dataset size. A sample FFT for current and flux signals is given in Figure 5.

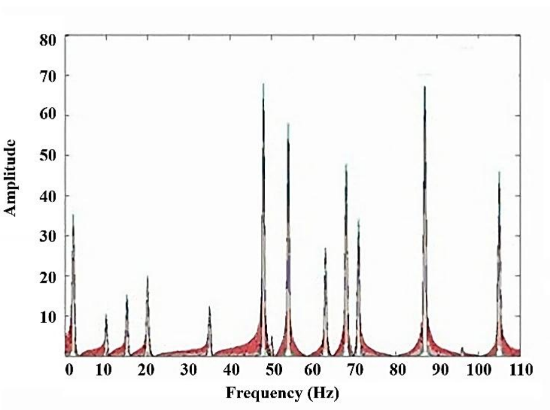


Figure 5. Sample FFT spectra for current and flux signals

To further understand the pattern of faults in the data, spectrograms of each channel were generated separately and subsequently used to predict faults in an induction motor. For each channel, a spectrogram was computed using the short-time Fourier transform (STFT) with a segment length of 1024 samples, an overlap of 512 samples, and 1024 FFT points. The spectrogram, which converted the time-series data into the frequency domain, was then rescaled to a 0-255 range to facilitate image representation. These rescaled spectrograms were saved as PNG images in designated directories, allowing for visual analysis and further processing in fault prediction models.

3. FAULT CLASSIFICATION METHODS AND RESULTS

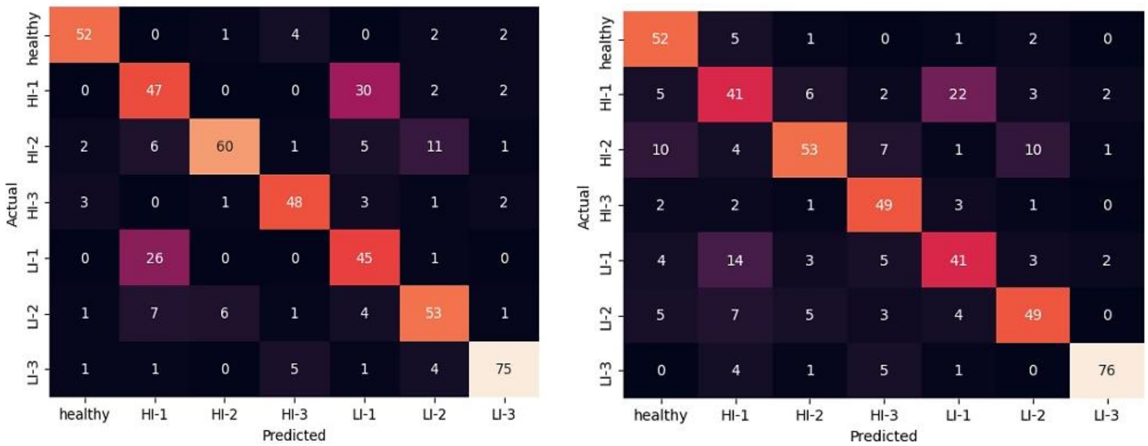
The parametric classifiers, such as maximum likelihood classification (MLC) provide high accuracy when the data has a normal distribution. Their performance drastically falls when the data has a non–normal distribution. Non parametric alternatives like decision tree, random forest, and artificial neural network (ANN) classifiers are becoming popular for data which do not have normal distributions.

3.1. Decision tree

A decision tree (DT) is a flowchart-style model in which each internal node tests an attribute, each edge corresponds to an outcome of that test, and each leaf stores a class label. To classify an unlabeled instance XXX, the attribute tests are evaluated from the root to a single leaf; the label at that terminal node is returned as the prediction. DTs are highly interpretable and often achieve competitive accuracy. It has an inherent feature of handling mixed data types with an ability of accommodating missing features. However, a small change in the training data can result in a different prediction. DTs support multi-class classification natively and can also be configured for regression tasks. After training, inference is computationally inexpensive.

A decision tree classifier learns a hierarchy of axis-aligned rules that partition the input space into regions with (ideally) homogeneous class labels. The model is non-parametric: it does not assume a fixed functional form or require iterative weight updates as in parametric models.

Initially, upon deploying the algorithm on the current dataset, two key observations emerged. Firstly, the decision boundaries are very shallow, indicating that only a few frequency bins are genuinely useful for predictions. Secondly, most of these significant bins are in the high-frequency region. This suggests that the crucial fluctuations necessary for effective fault prediction are primarily found in higher frequencies, thus requiring a concentrated focus on these regions. Figures 6(a) and 6(b) show the confusion matrix of DT with current and flux, respectively.



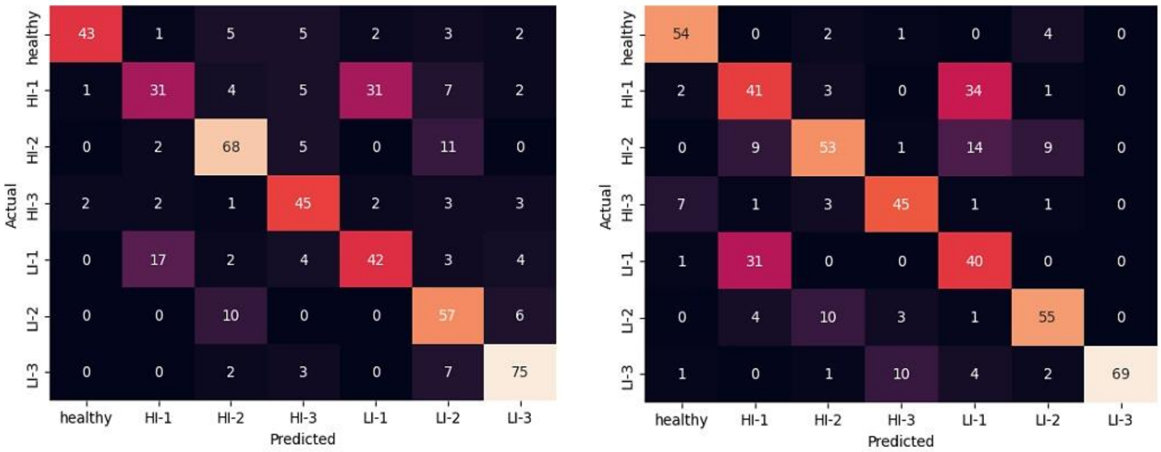
(a) (b)

Figure 6. Confusion matrix of decision tree with (a) current and (b) flux signature

Given these observations, it was clear that more sophisticated techniques were necessary to improve the model's performance and handle the inherent non-linearity in the data. This realization led us to explore ensemble learning techniques, particularly random forest, which offered a more robust and flexible approach to capturing the complexity of the data.

3.2. Random forest classifier

The RF classifier is an ensemble-based approach using multiple decision tree classification and regression trees. Random multiple trees and resampled training data are used to improve the performance. Individual tree predictions are used for final model prediction. Implementing the random forest classifier did not lead to significant improvements in the fault detection. Figures 7(a) and 7(b) show the confusion matrix of the random forest algorithm with the current and flux signatures, respectively.



(a) (b)

Figure 7. Confusion matrix of random forest: (a) flux and (b) current signature

The performance metrics like F1 score, precision, recall, and fault accuracy for stator current and flux are compared in Figure 8. While both decision trees and random forest classifiers demonstrated decent performance, achieving an average of 71% accuracy, for current signatures, we further investigated deep learning techniques to achieve better performance with current signatures. As a result, an experiment with a simple neural network was built.

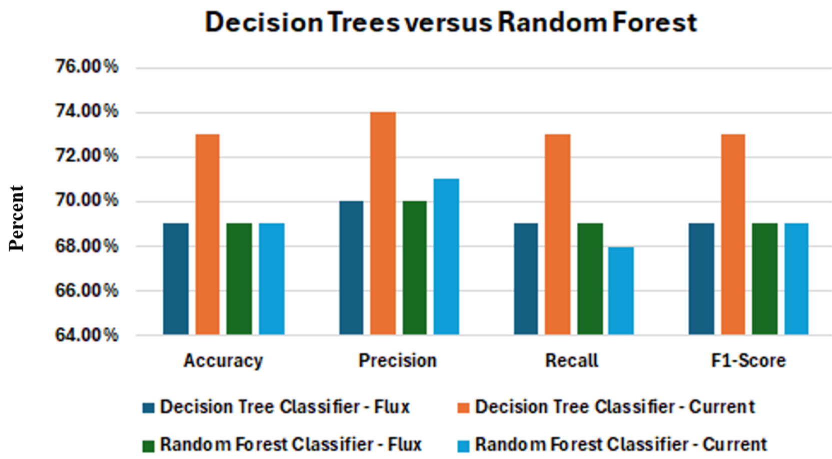


Figure 8. Evaluation scores of fault detection

3.3. Artificial neural network

An ANN, represents a fundamental class of machine learning models inspired by the human brain. ANNs consist of interconnected layers of artificial neurons that process and transform input data to capture the underlying nonlinearity. A perceptron, the fundamental unit of ANN, accepts multiple inputs, and the weighted sum of each input is added up. The weights enhance or inhibit a signal. A bias value is then added to the weighted sum before it is passed to an activation function to introduce non-linearity to the outputs. Hence, the model learns complex and nonlinear patterns [9], [10]. Perceptrons are stacked together in parallel (in a layer) and sequentially over multiple layers, where input data goes through repetitive transformations, ultimately producing an output or prediction. Figure 9 depicts a single perceptron. The equation for a single perceptron is given in (1).

$$yi = \Phi(\Sigma Wi\ xi + bi) \tag{1}$$

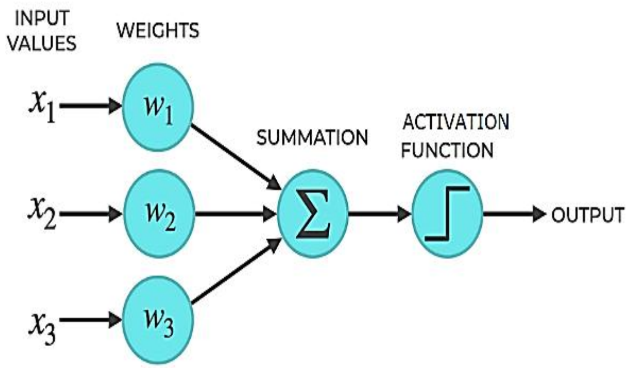


Figure 9. Single perceptron

The densely connected ANN with 8 layers is used for this study. Each layer employs ReLU activation functions. The output layer uses a Softmax activation function. To prevent overfitting, a dropout rate of 0.2 is applied to each layer. The ANN performed comparatively well, achieving an accuracy of 82%. Figure 10 shows the confusion matrix of ANN with current signatures. It is evident from Figure 10 that the ANN slightly outperformed the random forest classifier due to its capability to capture the non-linearities and higher-order interactions within the data, which are crucial for accurate flux prediction.

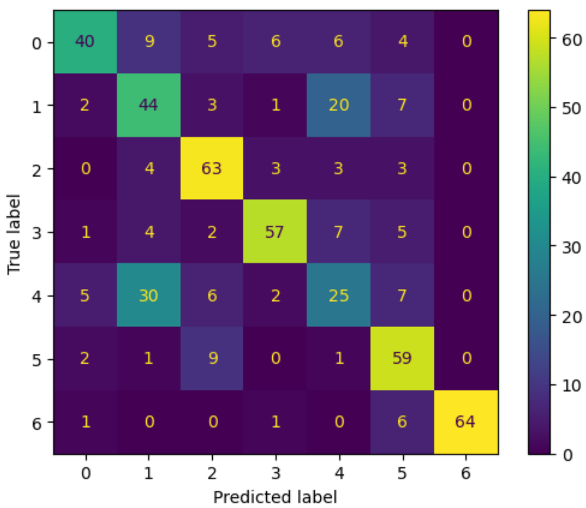


Figure 10. Confusion matrix of ANN for current signature

Given the complexity of the current data, a decision was made to further explore deep learning techniques for fault classification using the three different current channels. To leverage the temporal patterns and sequential nature of the data, we decided to implement a 1D CNN. Both the spectrograms of a single channel of current and the raw signal were input separately for comparisons.

3.4. The proposed CNN

A straightforward 1D CNN was implemented in PyTorch, specifically designed for classification tasks. The architecture consists of a series of convolutional layers, each followed by the Gaussian error linear unit (GELU) activation function, and culminates in a linear layer for final classification. A set of filters to the input data are applied by each layer and feature maps capturing various aspects of the input signal are captured. The GELU activation function is applied after each convolutional layer. The decision to use GELU over other activation functions, such as ReLU or sigmoid, was driven by its superior performance in handling complex data distributions and its ability to provide a smooth transition for negative inputs. This contributes to improved gradient flow and more stable training. GELU combines the advantages of ReLU with the smoothness of a Gaussian distribution, enabling it to better approximate the input distribution and enhance the model's learning capability. The final linear layer maps the high-level features extracted by the convolutional layers to the desired output classes, which in this case is set to seven.

Understanding the receptive field of convolutional layers is essential for interpreting the spatial context captured by the network. The receptive field determines the extent of the input space that affects the output of a neuron. In the context of CNN, a larger receptive field allows each neuron to incorporate more global information, while a smaller receptive field focuses on more localized patterns. Accurate calculation of the receptive field helps in designing networks that can effectively capture the necessary features for a given task. The receptive field calculator function computes the receptive field for the entire network architecture, layer by layer. This function iterates through the list of layers, calculating and accumulating the receptive field size at each step based on the corresponding layers' kernel size, stride, and dilation. Each successive layer expands the receptive field according to its parameters.

The receptive field R_{out} after a convolutional layer can be computed iteratively. For a 1D convolutional layer with input receptive field size R_{in}, kernel size K, stride S, and dilation D, the receptive field R_{out} is given in (2).

$$R_{out} = R_{in} + (K - 1) \times D \quad (2)$$

The CNN performed better with spectrogram inputs with 7 layers of convolution with an accuracy of 86%. The confusion matrices given in Figure 11 are a testament to this fact. FFT of the raw signals provide a time-frequency representation of the input signals, allowing the CNNs to capture temporal and frequency domain features simultaneously thus allowing for an efficient classification of the data. The evaluation scores of fault detection for CNN is given in Figure 12.

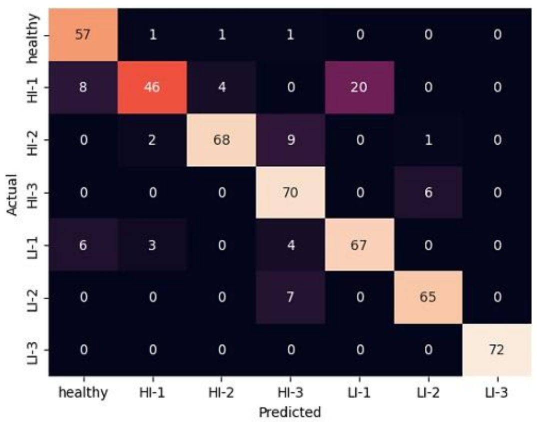


Figure 11. Confusion matrix of CNN for current signature

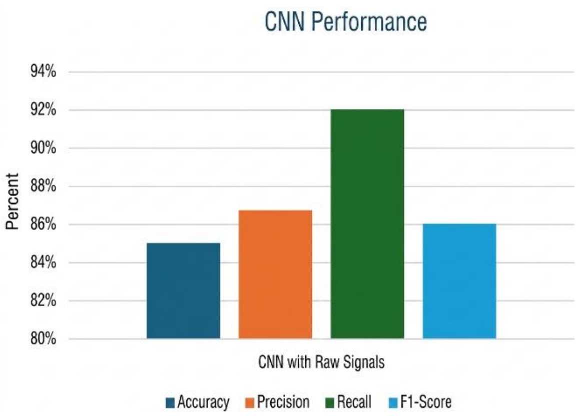


Figure 12. Evaluation scores for CCN

4. INFERENCES AND DISCUSSION

The performance of machine learning algorithms for fault classification of induction motors are evaluated in this work. The experimental setup involved collecting current and flux signatures from both healthy and faulty motors. Initially, the dataset consisted of 100,000 time-domain samples recorded over a 10-second interval. To facilitate analysis, these signals were converted to the frequency domain using FFT, reducing the data to 50,000 samples after a strategic down-sampling process that eliminated redundant information.

The first approach employed was a decision tree classifier. However, the results were underwhelming. The decision tree model identified only a few high-frequency bins as significant, resulting in shallow decision boundaries and an accuracy rate of approximately 71%. This performance was insufficient for reliable fault detection, indicating that the decision tree struggled to capture the complex relationships within the data.

To improve upon these results, a random forest classifier was implemented. This ensemble learning technique aimed to enhance robustness and flexibility by combining multiple decision trees. Despite these enhancements, the random forest classifier did not achieve significant improvements, maintaining an accuracy similar to the decision tree, around 71%. While it offered better handling of data complexity, the gains were marginal.

Seeking further improvement, an ANN with eight layers was introduced. The ANN incorporated ReLU activation functions and dropout layers for regularization, which resulted in a noticeable performance boost. The ANN achieved an accuracy of 82%, outperforming the previous models. This improvement was primarily due to the ANN's ability to capture complex nonlinear relationships and higher-order interactions within the data, making it more suitable for fault classification.

The final model tested was a 1D CNN developed using PyTorch. The CNN employed convolutional layers with GELU activation functions, designed to process spectrogram inputs as well as raw signals. The CNN outperformed all other models, achieving an accuracy of 96% when using spectrogram inputs. This superior performance can be attributed to the CNN's capability to simultaneously capture temporal and frequency domain features, which are crucial for accurate classification. The analysis also highlighted the distinction between using flux and current data for fault detection. While flux data generally yielded better classification results, the practical considerations of cost and sensor availability make current data a more economical choice, despite the slight compromise in accuracy.

5. CONCLUSION

This paper aimed to address the complexities of fault classification of induction motor faults. A real time data capturing is done with the help of an experimental setup for interturn faults. The data include the current and the flux signals. A reasonably good accuracy and recall was provided by the classical machine learning models. ANN and CNN provided improved accuracy. The 1D CNN outperformed ANN with 96% accuracy making it highly effective for fault classification.

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This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
V. Rajini	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	
Karunya Harikrishnan		✓				✓		✓	✓	✓	✓	✓		
Krismadinata	✓		✓	✓			✓			✓	✓		✓	✓

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [VR], upon reasonable request.

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BIOGRAPHIES OF AUTHORS

Dr. V. Rajini is a professor and head in the Department of Electrical and Electronics Engineering, Sri Sivasubramaniya Nadar College of Engineering, and is a resourceful academic advisor, graduate mentor, and accomplished researcher. She has numerous publications in IEEE, IET, Elsevier, Wiley, and Taylor & Francis. She has also authored three books on 'electrical machine design', 'electric motor drives', and 'special electric machines' with Pearson International Publishers. She can be contacted at email: rajiniv@ssn.edu.in.

Karunya Harikrishnan is an undergraduate student in the Department of Computer Science and Engineering, Shiv Nadar University, Chennai. Her academic interests include machine learning, data analytics, and intelligent systems. She can be contacted at email: karunyaharikrishnan01@gmail.com.

Krismadinata is the director of Center for Energy and Power Electronics Research, Universitas Negeri Padang, Indonesia, where he is also the rector of Universitas Negeri Padang. He was one of the awardees India-ASEAN Research Fellowship Training. His research interests are power electronics, control systems, and renewable energy. He can be contacted at email: krisma@ft.unp.ac.id.