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Optimizing Induction Motor Fault Detection with Transfer Learning: A Comparative Analysis of Deep Learning Models

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Abstract:- With the advancements of Industry 4.0, condition monitoring maintenance has become essential for preventing equipment failures and operational disruptions. Motor Current Signature Analysis (MCSA) is commonly utilized for condition monitoring to detect and diagnose various faults in Induction Motors (IMs). Despite its popularity, there is limited research comparing deep learning models for Induction Motor fault detection and classification with traditional approaches. This study explores the detection and classification of Induction Motor faults using three Transfer Learning (TL) models: InceptionV3, ResNet152, and VGG19.

The research began by modeling a Squirrel Cage induction motor in MATLAB to simulate healthy, single-phasing, and double-phasing conditions, capturing time-domain stator current signatures (current spectrum) to identify fault characteristics. The data were then used to assess the effectiveness of the TL models in detecting and classifying motor faults. Around 500 datasets were created from these simulated conditions, labeled accordingly, and used to train and validate the TL models, each incorporating additional convolutional layers to enhance performance. Model evaluation utilized metrics such as the multiclass confusion matrix, precision, recall, and F1-score across various fault scenarios.

Results indicate that stator current signatures can effectively reveal individual faults, with ResNet152 outperforming the other models in classification accuracy. These findings highlight that applying transfer learning techniques with a limited amount of current signature data can support predictive maintenance in industrial settings, potentially reducing costly equipment shutdowns and disruptions in production.

Keywords:- *Convolutional Neural Network, Transfer Learning, Simulink.*

I. INTRODUCTION

The most well-known method of converting electrical to mechanical energy is the use of an induction motor, also called an asynchronous motor. This is because it runs at a speed lower than the synchronous speed. The operation of the induction motor is based on the principle of induction of EMFs and currents in the rotor that is not directly connected to any power supply.

Induction motors are the most widely used type of electric motor in residential, commercial, and industrial applications. They are favored for their affordability, durability, and dependable performance, even under challenging environmental conditions, including potentially explosive atmospheres. These qualities make induction motors a preferred choice over other motor types in a variety of settings. This motor plays an important role in modern industrial plants. They are widely used due to a large number of favourable features such as low price, reliability, rugged construction, and low maintenance costs [1]. With the increasing evolution in industrial processes, induction motors have replaced 90 percent of the actuators altogether exercised in the production line and were surveyed to be more fault tolerant [2].

While induction motors are known for their reliability, they can be affected by environmental conditions, operational demands, and installation issues, leading to various failures that shorten their expected lifespan. Faults in induction motors progress through three stages [3]. The first stage, known as the incipient fault, marks the initial degradation of internal components. At this stage, despite some damage, the motor typically continues to function without noticeable issues. The second stage, or developed fault, involves more extensive damage that significantly impacts motor performance, though it remains operational. In the final stage, called a catastrophic fault, the damage has spread, affecting multiple components and causing the motor to cease functioning altogether.

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➢ *Faults:*

Induction motor (IM) faults generally fall into two primary categories: mechanical and electrical, as illustrated in Fig. 1. According to data from the Institute of Electrical and Electronics Engineers (IEEE) and the Electric Power Research Institute (EPRI), stator electrical faults represent 30–40 percent of issues, while rotor faults contribute about 5–10 percent. Mechanical faults, including issues like bearing and eccentricity faults, account for roughly 40–50 percent of motor breakdowns. Given the significant impact of faults in core components such as stators, rotors, and bearings, this study focuses on the most prevalent motor faults.

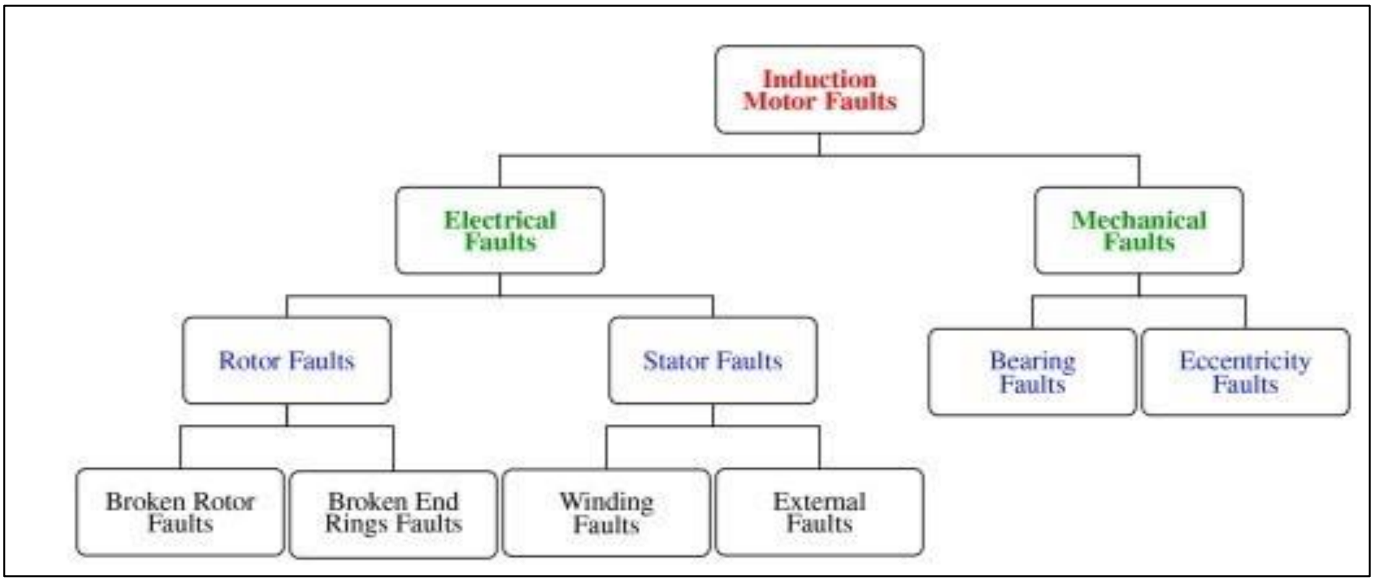

Fig 1: Classes of Faults in Induction Motors

Failures of motor core components such as stators, rotors and bearings account for a large percentage of motor breakdowns. Hence in this setting, the most common motor faults would be examined.

In terms of stator faults, the stator includes a laminated core, external frame, and insulated windings, all of which experience electrical and environmental stresses that can lead to failures. Stator faults are typically classified based on their location: they may occur in the stator frame, the winding, or the laminations of the stator core. Among these, winding failures are particularly serious, often resulting from insulation breakdown. This leads to localized overheating, which, if not detected, can cause further insulation damage, potentially resulting in a catastrophic short circuit inter-turn fault [4].

Understanding the behavior of induction motors (IMs) under fault conditions and diagnosing these issues has posed a longstanding challenge for researchers in electrical machinery. Common motor faults are often associated with key components like stators, rotors, and bearings. If these faults are not identified in their initial stages, motor performance can deteriorate, potentially leading to complete failure. Detecting faults early in IMs brings significant benefits to industrial operations by enabling cost-effective failure prediction and proactive maintenance planning. This approach allows for timely preventive measures, reducing the need for costly part replacements and preventing unplanned production halts and downtime [1]. Additionally, early fault detection contributes to motor efficiency by addressing operational inefficiencies, resulting in considerable energy savings and lowered running costs. In sum, early detection of motor faults is essential for maintaining consistent production and remaining competitive in the industry.

II. LITERATURE REVIEW

Research into fault detection in induction motors employs various methodologies, each providing insights into challenges in scalability, accuracy, and adaptability. [5] utilizes cyclostationarity to capture the periodic characteristics of electrical signals, enhancing early fault detection by identifying subtle statistical changes. However, its adaptability is limited when applied to motors under varying loads. [6] implements Convolutional Neural Networks (CNNs) for three-phase induction motor diagnostics, excelling in fault pattern recognition. Yet, CNNs encounter computational constraints, making real-time applications challenging. Similarly, [7] employs Two-dimensional Time-Domain Gray Coded Image (TDGCI) coupled with CNNs to diagnose rotor faults. While effective in identifying visual fault patterns, the reliance on Fast Fourier Transform (FFT) preprocessing limits TDGCI's effectiveness in low-severity conditions where FFT is noise-sensitive.

[8] explores random multi-frequency resonant sparse noise power spectrum (rMFRSNPS) in conjunction with probability vector resonance analysis (PVRA), effectively identifying faults in isolated conditions. However, the method struggles to generalize to complex fault scenarios, limiting its applicability in environments with multiple

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simultaneous faults. In [9], Discrete Wavelet Transform (DWT) is used to decompose current signals, aiding stator fault diagnosis. While advantageous for detailed signal analysis, DWT faces scalability issues, particularly when adapting to real-world, multi-variable conditions. [10] further utilizes CNNs, focusing on rotating machinery fault detection through image feature extraction. Though CNNs improve recognition of intricate fault patterns, their high computational demand continues to present a barrier to real-time, large-scale diagnostics.

[11] investigates current signature monitoring, a straightforward approach for identifying bearing damage. Despite its simplicity and diagnostic utility, this method lacks robustness across varied operational conditions. [12] applies Wavelet Packet Transform (WPT) for enhanced signal decomposition, offering insights into complex fault signals. However, WPT's high computational requirements hinder its scalability, particularly in larger motor systems with overlapping fault conditions. Transfer learning, also explored in [12], shows promise in broadening the applicability of diagnostic models but requires further investigation to support diverse motor types and conditions. [13] presents the Park's Vector Approach (PVA) for fault detection in low-severity cases. While PVA can identify subtle abnormalities, its reliability decreases in noisy environments, limiting its utility in real-world scenarios.

[14] introduces Adaptive Neuro-Fuzzy Inference Systems (ANFIS), which combine neural network learning with fuzzy logic for motor fault diagnosis. Although ANFIS models offer adaptability and precision, their computational complexity may hinder scalability. [15] uses Support Vector Machines (SVMs) to classify fault patterns, demonstrating solid performance in well-defined data sets but facing limitations with more nuanced or overlapping faults. Lastly, [16] implements Principal Component Analysis (PCA) combined with K-means clustering to identify fault patterns. While PCA aids in dimensionality reduction, the model's effectiveness decreases when confronted with high-dimensional, noisy data common in motor diagnostics.

In summary, these studies reveal significant advancements in fault detection methodologies, yet challenges remain in scalability, adaptability, and real-time application. Many methods, such as CNNs, WPT, and ANFIS, excel in controlled environments but struggle under varied operational loads or noisy conditions, as seen in [6], [10], and [12]. Traditional techniques like FFT and PVA demonstrate limited sensitivity to low-severity faults ([7] and [13]). To enhance these methods, future research must focus on reducing computational demands, increasing model robustness across diverse motor conditions, and improving noise resilience to make these systems viable for broader, practical applications.

III. THEORY

A. Problem Overview

Detecting faults early is essential to prevent electrical failures, insulation damage, and complete production stoppages as faults progress to advanced stages. Early fault detection methods based on signal analysis involve capturing one or more physical properties of the induction motor, processing these signals with appropriate techniques to identify fault patterns, and analyzing these patterns to classify the fault type. Recent advancements in computational technology have enhanced condition monitoring methods, integrating signal processing techniques in both time and frequency domains with heuristic approaches like machine learning, genetic algorithms, artificial intelligence, and deep learning. This combination offers improved accuracy and effectiveness in early fault detection.

B. Approach

In our approach, we adopt a quantitative methodology, focusing on data collection and analysis to derive insights and make predictions while minimizing bias and ensuring no key factors are overlooked. Traditional machine learning (ML) techniques classify healthy and faulty motor conditions by using extracted features from signals in various representations (time, frequency, and time-frequency domains) as inputs to knowledge-based systems. To overcome some limitations of these ML methods, we propose using a deep learning model, specifically Convolutional Neural Networks (CNNs), to address the following issues:

- Traditional methods rely heavily on hand-crafted feature engineering and feature selection from raw data.
- Feature significance can vary with changing conditions.
- Advanced signal processing is needed to reduce noise in the signal, adding complexity to feature extraction

C. Design

➢ *Induction Motor Model:*

Modelling is done in MATLAB Simulink, which involves creating a simplified representation of a real-world induction motor using mathematical equations, specific parameters, and assumptions. The model is designed to replicate the behavior and characteristics of the actual 3-phase induced motor being simulated, allowing analysis and understanding of the system's performance and obtaining the necessary signatures under different conditions (healthy, single-phasing, phase-phase). MATLAB Simulink would be used, where many of the components to be used for modeling are found, like the AC Electrical Elements, Induction motor block, three-phase source, and others. The blocks needed are easily dragged and dropped unto the Simulink window, and their parameters like rated power, rated voltage, torque and rated frequency, are specified. In our experiment, healthy and stator faults (single-phasing, phase-to-phase) would be simulated alongside healthy conditions. To simulate a stator fault, we disconnect one or more phases of the stator winding.

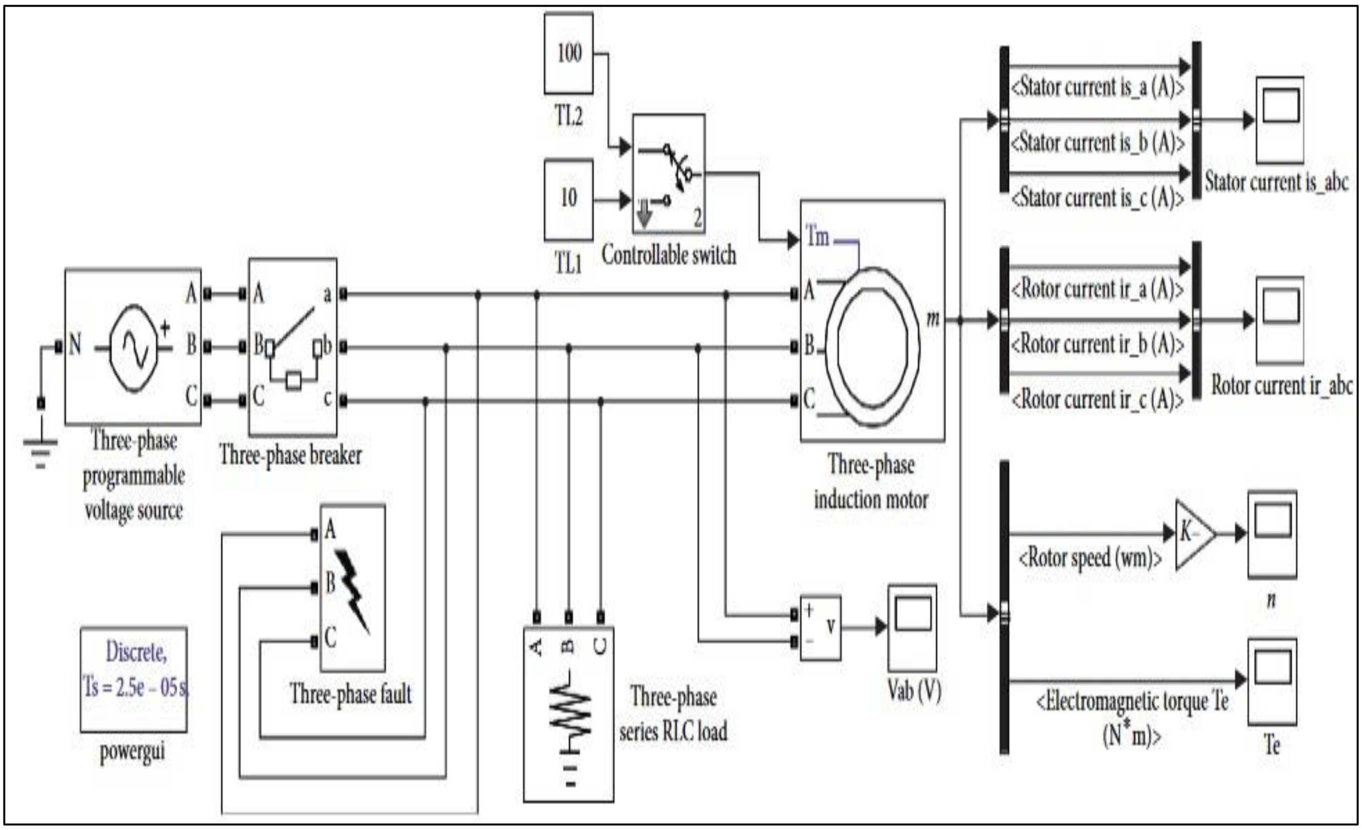

Fig 2: Model of Three-Phase Asynchronous Motor

➢ *Data Processing:*

Before inputting data into the Transfer Learning model, which would be RGB images, distinguishing healthy and stator fault conditions, it is essential to clean and pre-process the data to ensure accurate and effective training of the model. This action is executed with libraries that include TensorFlow, Scikit-Learn, and NumPy in Google Colab. Some common steps we take in cleaning data for a CNN model include:

- Data Exploration: This involves understanding the dataset, visualizing and analyzing the data, identifying missing values, and removing irrelevant or redundant data.
- Data Pre-processing: This step includes converting data into a machine-readable format, scaling the data, and removing noise or outliers.
- Data Augmentation: Used to improve the diversity of the training dataset by using transformations such as flipping, rotating, and shifting the images.
- Data Labelling: In the dataset, each image is assigned a label that corresponds to its class, such as a cat or dog.

Convolutional Neural Networks (CNNs) are trained using the backpropagation algorithm, which adjusts network weights based on error rates calculated during training. This optimization process aims to reduce the discrepancy between predicted and actual outputs by updating the network's weights. After data cleaning, the dataset is divided into a training set (83%) and a validation set (17%). The training set is used to fit the model, while the validation set is used for tuning hyperparameters.

During training, input data (images) are fed into the CNN, where essential features are identified and extracted, ensuring consistent feature selection across samples, and class predictions are generated. The model's predictions are then compared to actual labels, with errors measured through a loss function. The model's parameters are updated accordingly to minimize this loss. Validation is performed after each training cycle to monitor the model's performance and prevent overfitting. In this phase, hyperparameters, such as learning rate, batch size, filter count, epochs, and padding, are fine-tuned to optimize accuracy on the validation set, enhancing the model's generalization to new, unseen data.

➢ *The CNN Base Layer:*

A specific type of CNN deep learning algorithm can process an input image, apply weights and biases to recognize significant elements, and distinguish between different objects in the image. Unlike traditional methods that require manual engineering of filters, ConvNets can learn these distinguishing characteristics with sufficient training, greatly reducing pre-processing needs compared to other classification algorithms.

One key benefit of CNNs over other neural networks is their ability to identify critical features autonomously, without human intervention. CNNs are also highly computationally efficient due to their use of convolution and pooling operations, along with parameter sharing. This efficiency makes CNNs adaptable to various devices, enhancing their universal appeal. Furthermore, CNNs reduce the need for pre-processing while learning distinctive filters and features on their own. CNNs also offer computational advantages over traditional neural networks, with weight sharing being a major asset.

CNN architecture is inspired by the human brain's connectivity patterns, specifically the organization of the visual cortex. Each neuron in a CNN responds to a small region in the visual field, known as its receptive field, and these fields collectively span the entire visual area. In our model, several CNN layers are used, reflecting these concepts in their structure.

The Flatten Layer in CNNs serves to reshape the multidimensional tensors generated by preceding convolutional and pooling layers in the TL model into a one-dimensional vector, preparing them for input into fully connected layers. This layer acts as a bridge between the spatial feature maps extracted by TL layers and the linear structure required by fully connected layers for classification or regression. Mathematically, if the input tensor has dimensions (batch size, height, width, channels), the flatten layer converts it into a vector of shape (batch size, height * width * channels), effectively rearranging the data for seamless integration with subsequent dense layers. This transformation facilitates the learning of higher-level relationships in the data.

In a Convolutional Neural Network (CNN), the fully connected (or dense) layer serves to translate the high-level features identified by the convolutional layers into the final model output, whether for classification or regression tasks. This dense layer is composed of neurons, each connected to every neuron in the preceding layer. It computes a weighted sum of inputs from the prior layer and typically applies an activation function, such as softmax, to generate the final predictions. For multi-class classification, the softmax function (S) transforms the last layer's outputs into a probability distribution across mutually exclusive classes. In contrast, for binary classification, a sigmoid function is applied, categorizing the outcome as 0 or 1.

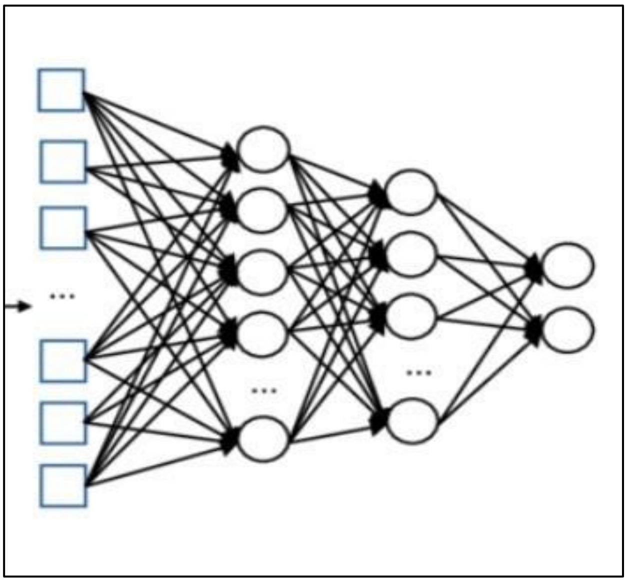

Fig 3: Architecture of the Flatten (in blue) and the Fully Connected Layer (in Black)

➢ *Transfer Learning Model:*

To enhance the training process for a new model on a related task, we introduce a pre-trained model as the foundational layer. Transfer learning leverages the pre-existing knowledge of this model, which has been trained on the extensive ImageNet dataset, to capture general features and patterns. This approach enables efficient training on a smaller dataset by reusing learned representations, minimizing the computational demands and data requirements. The pre-trained CNN model is fine-tuned and adapted with our new dataset, functioning as the initial layer of the transfer model for feature extraction. Integrating transfer learning into our experimental model offers several advantages:

- The use of pre-trained knowledge significantly reduces the need for extensive data and computational power for training from the ground up.
- It enhances the accuracy of the new model.
- The resulting model is better equipped to handle data variability, noise, and outliers.

Transfer models like InceptionV3, VGG 19 and ResNet152 are imported from the libraries of the Keras library. All would be trained with the base layer's small dataset, and the model that gives the best performance would be chosen for our experimental model. Not forgetting, the layers and dimensions of the base layer and transfer model are same, preventing overfitting.

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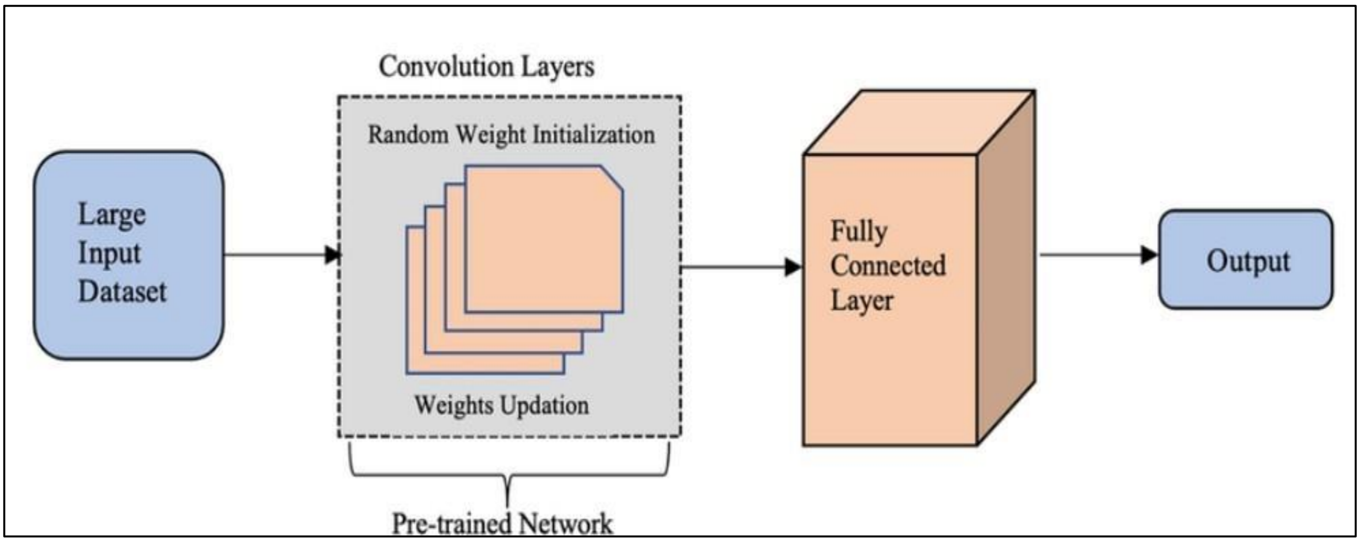

Fig 4: Transfer Learning Model Architecture

RESULTS

A. Simulation

After the Simulink simulation, 276 current time signatures where obtained at various time range and load. Signatures between the training and validation dataset was 82 and 18 percent respectively.

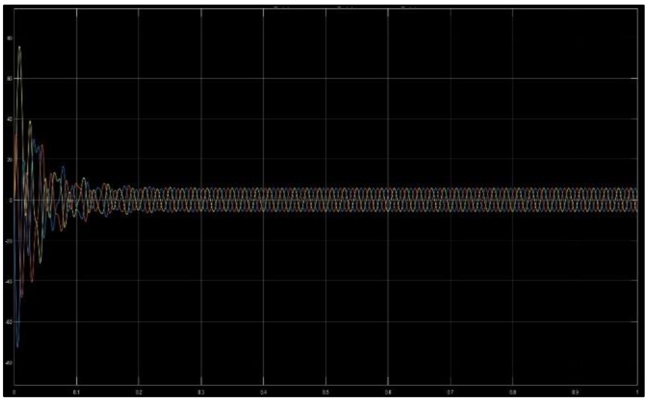
Fig 5: Healthy Waveform at no Load

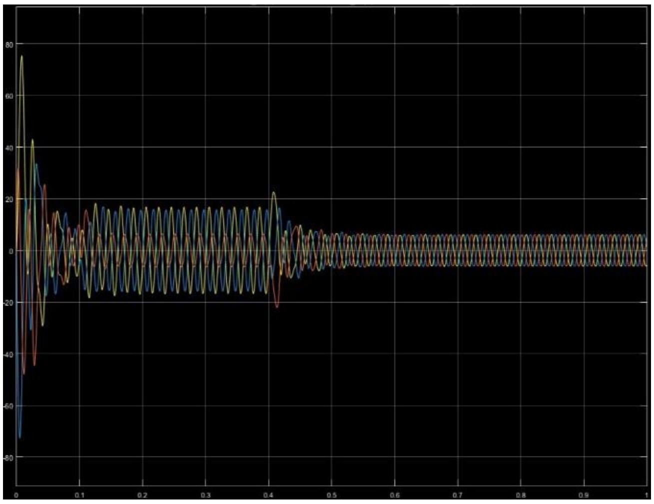
Fig 6: Single Phasing Fault Waveform at 25% Load

Table 1: Split Dataset

Load (%)	Training Healthy	Training Phase-Ground	Training Phase-Phase	Validation Healthy	Validation Phase-Ground	Validation Phase-Phase	Total
0	16	16	16	4	4	4	60
25	15	15	15	3	3	3	54
50	15	15	15	3	3	3	54
75	15	15	15	3	3	3	54
100	15	15	15	3	3	3	276

B. Performance of Transfer Learning Models

In existing research, deep learning (DL) models have been shown to effectively classify faults using raw current signature data and frequency-based features extracted from it. These models can identify motor health states (e.g., Healthy, Single phasing, Phase to Phase) and determine which specific phase is affected. To evaluate the classification capabilities of DL models, we created a dataset by recording current signature data in the time domain from a simulated motor model in various operating states within MATLAB/Simulink. The collected data was then saved in CSV format. After appropriate labeling, the dataset was used for training and validating the DL models. Detailed information about the dataset is outlined in Table 4, which includes approximately 300 samples for each condition of the motor, both healthy and faulty.

Table 2: Classes and their Labels

Condition	Class	Label
Healthy	Healthy	0
Single-Phasing	Single-Phasing	1
Phase-Phase	Phase-Phase	2

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For this research, transfer learning models such as InceptionV3, ResNet50, and VGG19 were utilized due to their strong capabilities in analyzing time-series and sequential data. These models are known for their advanced learning abilities, even when working with raw input data, and can accurately predict outcomes as multiclass labels due to their varied layer structures. The choice of model architecture, including the number of layers and units, is influenced by the dataset's nature and complexity. In cases where the input data is complex and nonlinear, deeper models may be necessary to achieve optimal performance.

Table 3: Architecture of Modified Transfer Learning Model

Layers		**Units**	
	InceptionV3	**ResNet152**	**VGG19**
Pre-trained Model	21,802,784	58,370,944	20,024,384
Flatten	1	1	1
1 x Dense	128	128	128
1 x Dense	64	0	64
Output	3	3	3

Table 4: Hyper Parameters of TL Models

Hyper Parameters	**InceptionV3**	**ResNet152**	**VGG19**
Learning Rate	0.0001	0.001	0.0001
Batch Size	16	28	32
Loss function	Categorical cross entropy	Categorical cross entropy	Categorical cross entropy
Epochs	20	15	20

We have trained and tested the 3 TL models for fault detection and classification in Google Colab using the dataset elaborated in Table 1. The Confusion matrix evaluates the performance of classification models. It provides a comprehensive overview of how well a model predicts different classes in a multi-class classification problem. The confusion matrix is constructed based on the comparison of predicted class labels and the actual ground truth labels of the dataset. The matrices of the three TL models are illustrated in Figure 7, 8, and 9.

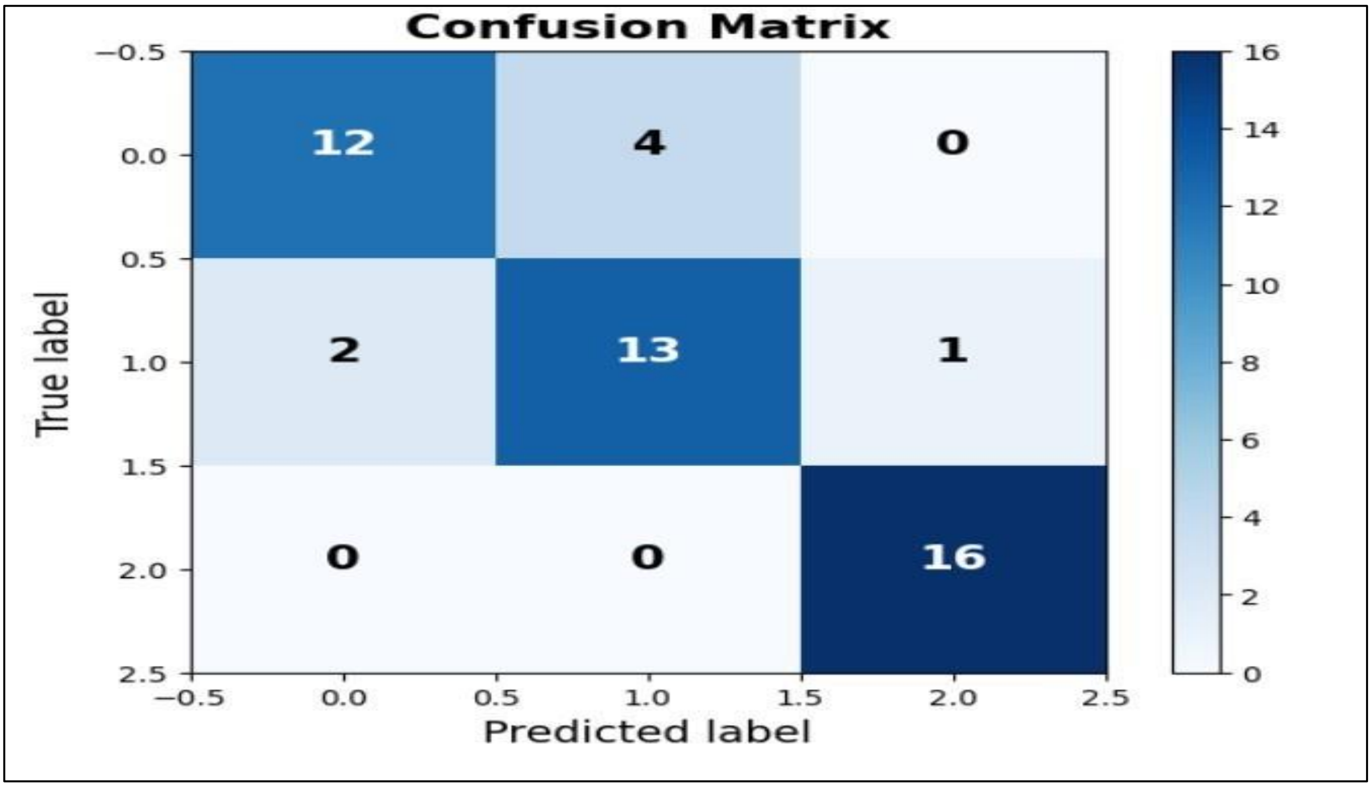

Fig 7: Confusion Matrix of InceptionV3

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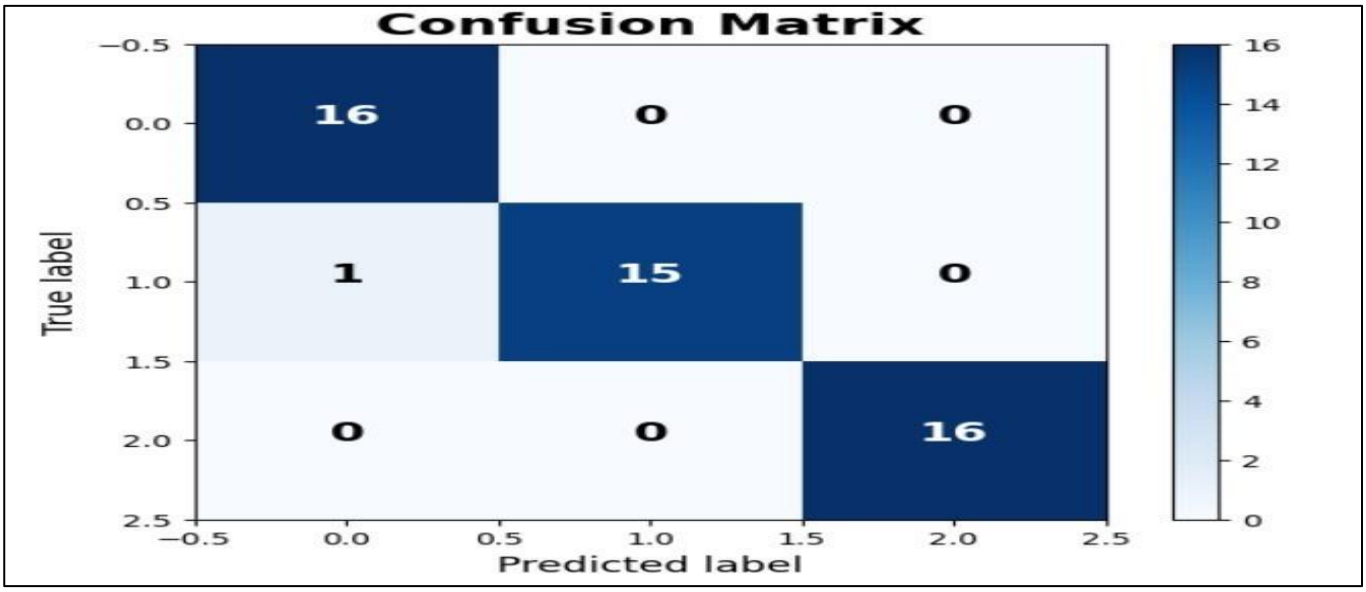

Fig 8: Confusion Matrix of ResNet153

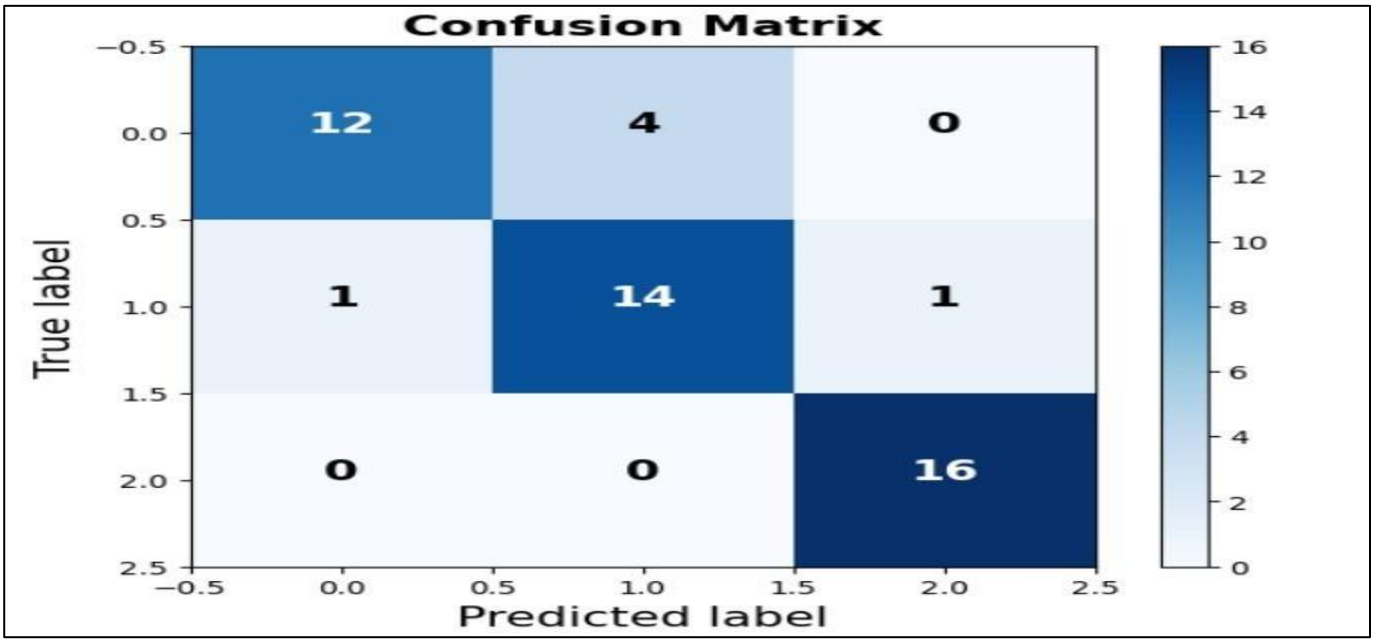

Fig 9: Confusion Matrix of VGG19

From the matrices, various performance metrics are derived for insight. One is the accuracy of the individual conditions, shown in Table 3. It shows that ResNet152 exhibits a better model or algorithms for each condition. Other metrics include: Precision: It represents the proportion of correctly predicted positive instances among all instances predicted as positive. Formula: P = TP / (TP + FP)

Recall: It represents the proportion of correctly predicted positive instances among all actual positive instances. Formula: R = TP / (TP + FN)

F1-Score: The harmonic mean of precision and recall. It balances precision and recall and is useful when dealing with imbalanced classes. Formula: 2 * (Precision * Recall) / (Precision + Recall)

From 10, the performance metrics of ResNet152 stands out with precision, recall and f-1 score of 97%, 96% and 97% respectively, due to its complexity and better feature representation. Also in 11, this model leads in the accuracy domain with a training accuracy and validation accuracy of 96.49% and 97.92% respectively. The least losses displayed are by the ResNet152 model in 12, with values main loss being 12.59% and validation losses, 14.1%. It can be said the ResNet152 model has the best suitable architecture that captures the underlying patterns in the data effectively. Also the hyperparameters were tuned optimally. It also has the best weight initialization to help the optimization process find a more optimal set of parameters during training.

Table 5: Condition Accuracy Comparison of TL Models

Class	**InceptionV3(%)**	**ResNet152(%)**	**VGG19(%)**
Healthy	75	100	75
Single Phase	81	94	88
Phase to Phase	100	100	100

Fig 10: Performance Scores of TL Models

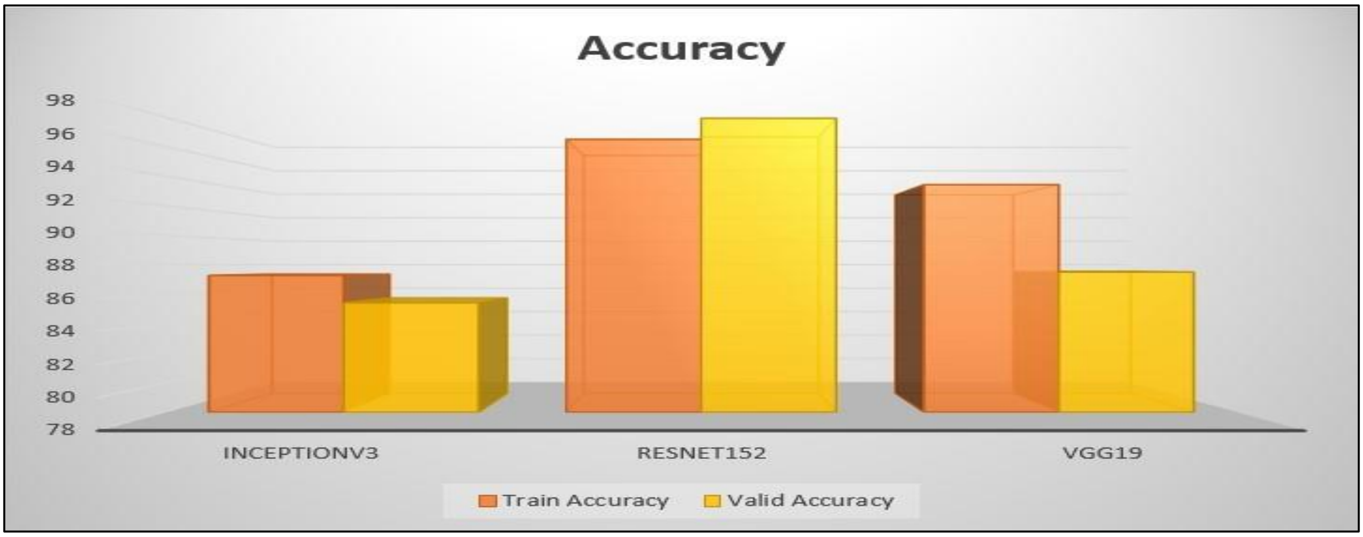

Fig 11: Accuracy Comparison of TL Models

Fig 12: Losses Comparison of TL Models

IV. CONCLUSION

This paper explores the detection and classification of faults in three-phase induction motors by analyzing current signatures in the time domain using deep learning techniques. Simulations were conducted in MATLAB to introduce faults such as single phasing and phase-to-phase disruptions into healthy waveforms. Due to the challenge of distinguishing between different fault types, accurately classifying the affected phase(s) is essential for condition monitoring systems. To address this, transfer learning models—InceptionV3, ResNet152, and VGG19—were fine-tuned, trained, and evaluated using a locally generated dataset representing both healthy and faulty motor states. Each model was tested for its ability to classify different fault conditions based on raw stator current data. The findings indicated that these models achieved effective fault detection and classification, with performance evaluated through metrics including the confusion matrix, precision, recall, F1-score, and average score. Of the three models, ResNet152 outperformed the others and was therefore selected as the best option for meeting the project's objectives.

RECOMMENDATION

A larger dataset, probably in the millions, used for learning, would significantly improve the performance of the TL models. This project can also be extended to include rotor faults and eccentricity faults. Such robust models should be tested using real-time industry current signatures.

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APPENDIX A

CODE AND ORIGINAL DATASETS USED FOR PROJECT

- VGG MODEL: VGGGitHub
- INCEPTIONV3: GitHub
- RESNET152: GitHub
- DATASET: Google Drive
- INDUCTION MOTOR MODEL: Google Drive