Development of a Deep Learning Technique to detect and classify faults in induction motors

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***Abstract*—Owing to the 4.0 industrial revolution condition monitoring maintenance is widely accepted as a useful approach to avoiding plant disturbances and shutdown. Recently, Motor Current Signature Analysis (MCSA) has been widely reported as a condition monitoring technique in the detection and identification of individual and multiple Induction Motor (IM) faults. However, checking the fault detection and classification with deep learning models and its comparison among themselves or conventional approaches is less reported in the literature compared to others. Therefore, in this paper, we present the detection and identification of induction motor faults with three Transfer Learning (TL)models namely InceptionV3, ResNet152, and VGG19. Initially, we developed the model of the Squirrel Cage induction motor in MATLAB and simulated it for healthy, single-phasing and double-phasing faults to detect and identify healthy and unhealthy conditions. The faults' impact on stator current is presented in the time domain (i.e. current spectrum). The simulation results show that the signatures have shown good results in time analysis for fault.**

This is further investigated with the three transfer learning models for checking the fault detection and identification (i.e., classification) improvement in a three-phase induction motor. By simulating the three-phase induction motor in various healthy and unhealthy conditions in MATLAB, we have collected current signature data in the time domain, labelled them accordingly, and created about 500 datasets for TL models. All the TL models are trained and validated with their respective pre-trained models in addition to a suitable number of Convolutional Neural Network architecture layers. By simulation, the multiclass confusion matrix, precision, recall, and F1-score are obtained in several conditions. The result shows that the stator current signature of the motor can be used to detect individual faults. Moreover, transfer learning models can efficiently classify the induction motor faults based on time-domain data of the stator current signature. Among the transfer learning (DL) models, the ResNet152 has shown better accuracy than all other three models. These results show that employing transfer learning with not up to millions of current signatures in fault detection and identification of induction motors can be very useful in predictive maintenance to avoid shutdown and production cycle stoppage in the industry.

***Index Terms*—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.

The induction motor is the most common family of electric motors used in homes, businesses, and industry. IMs are often preferred over other kinds of motors since they are significantly less expensive, more robust, and capable of reliable operation in harsh ambient conditions, even in an explosive atmosphere. 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. 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.

Though induction motors are very reliable, they are exposed to problems relating to environment, duty, and installation which make these motors subjected to various types of failures, shortening the intended life expectancy of motors. Three states characterize a faulty condition in IM[10]. The first is an incipient fault, known as the early stage, where the degradation begins to develop in one or several of the internal components. Although the motor component is damaged, the induction motor can continue operating with no apparent symptoms. In the second, known as the developed fault, the damage to the motor component is advanced. In this condition, the IM still operates; however, the damaged component severely affects the motor performance. Finally, the third faulty condition, known as a catastrophic fault, occurs when the developed failure has propagated to other components, and the IM is no longer operating.

1) FAULTS: There are two main categories of IMs' faults: mechanical and electrical, as shown in Fig. 1. Stator electrical faults are 30–40 percent, while rotor faults are around 5–10 percent. Mechanical faults, like eccentricity and bearing faults, present a percentage of 40–50 percent. These fault percentages were stated by the Institute of Electrical and Electronics Engineering (IEEE) and the Electric Power Research Institute (EPRI)

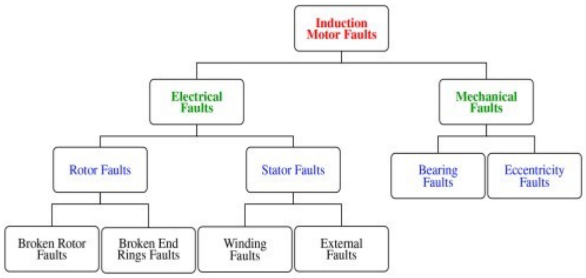

Fig. 1: Classes of faults in induction motors.

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.

For stator faults, the stator consists of a laminated core, an outer frame, and insulated electrical windings. Its components are subjected to electrical and environmental stresses, which severely affect the stator condition leading to faults. Stator faults (SF) can be categorized based on their localization as failure in the stator frame, fault in the stator winding, and failure in the laminations of the stator core. Among these, stator winding failures are the most severe faults and are often caused by failure of insulation of winding, which leads to local heating. If unnoticed, this local heating further damages the insulation of the stator winding until a catastrophic failure may occur. This fault is also known as the short circuit inter-turn fault.

The studies of induction motor (IM) behaviour throughout abnormal conditions due to the presence of faults and the likelihood to diagnose these conditions have been a challenging topic for many electrical machine researchers. Motor faults are typically related to core components such as stators, rotors, and bearings. If the detection of motor faults is not done at the early stage of development, it will lead to the declination of performance and eventual failure of the motor. Early fault detection in induction motors provides numerous advantages for industrial processes. It offers cost savings by estimating potential failures before they occur, allowing for pre-planned preventive machine schedules and better maintenance activities that avoid the need for component replacement. This, in turn, prevents unexpected stoppages in production lines and extended periods of downtime due to extensive machine failure. Additionally, early fault detection can improve the efficiency of induction motors by identifying and rectifying inefficiencies, resulting in significant energy savings and reduced operating costs. Overall, early fault detection is crucial for maintaining production targets and staying competitive in the marketplace.

II. Literature Review

There are numerous approaches researchers have taken in solving this problem, particularly through AI algorithmic paths. For example, [1] introduces two novel methods for fault detection: one utilizing deep learning (DL) with fractional wavelet decomposition (FWT), independent convolutional neural networks (CNN), and long short-term memory (LSTM), and the other employing fuzzy C-means (FCM) algorithms to detect novelty in Partially Unsupervised Learning (PUL). The experiments conducted on two test rigs demonstrated high accuracy in condition monitoring and bearing damage identification. However, the method's reliance on denoising techniques like FWT and tracking long-term behavior with LSTM highlights deficiencies in handling noisy current-based signals and the complexity of capturing pertinent information.

In [9], a novel methodology for automatic detection of incipient broken rotor bars (BRBs) in induction motors is presented, utilizing vibration signals and the orthogonal matching pursuit (OMP) algorithm. The proposed technique achieves over 90% accuracy in detecting faults as small as 1 mm, outperforming traditional methods. While promising, challenges such as separating IM condition information from environmental disturbances and time-consuming computations are acknowledged.

With the employment of Electrical-Time-Synchronous-Averaging (ETSA), Fuzzy Logic Algorithm, and Discrete Wavelet Transform (DWT), [3] seeks to categorize different partial broken bars under varying stresses. While achieving 95% accuracy in remote diagnosis, the method's reliance on stator current signals instead of vibration signals raises concerns about the comprehensiveness of fault detection. Moreover, the approach's time-consuming nature and data requirements pose practical challenges.

Furthermore, [4] modified fuzzy reasoning spiking neural P systems (rMFRSNPSs) are utilized for fault analysis in three-phase induction motors. The proposed approach offers abductive fault diagnosis and fault prediction, contributing to lowering fault rates. However, the method's practical applicability and scalability may be limited by its complexity and reliance on criterion rules.

Finally, [7] introduces a methodology using time-domain grayscale current signal imaging (TDGCI) and convolutional neural networks (CNN) for detecting broken rotor bar faults in induction motors. Achieving high fault classification accuracy of 99.58%, the proposed approach demonstrates effectiveness in fault diagnosis without interrupting motor operation. However, challenges such as frequency overlap and computation time in traditional techniques are addressed, highlighting the method's efficiency and efficacy. Overall, while these papers offer innovative approaches to fault detection in induction motors, challenges such as noise handling, computational complexity, and practical implementation remain to be addressed for real-world deployment. In our work, we carefully handle these issues.

III. Theory

A. Problem Overview

Early detection of faults is relevant, as it prevents machine electrical breakdown, insulation damage, and overall stop in production if the fault is developed to the advanced stage. Early fault detection techniques based on signal analysis rely on acquiring one or various physical magnitudes of the induction motor, processing the measured magnitudes (signals) with suitable tools to extract fault patterns, and analysing the patterns to determine the fault class. Recent condition monitoring approaches have benefited from advances in computational technologies that allow the combination of signal processing methods (time and frequency domain) with heuristic techniques such as machine learning, genetic algorithms, artificial intelligence, surface learning, and deep learning. Taking this route ensures better performance and results in early fault detection.

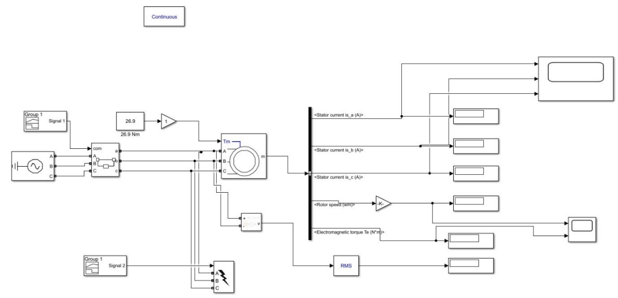

Fig. 2: Model of three-phase asynchronous motor.

B. Approach

We consider taking the quantitative approach, which involves collecting and analyzing data to draw conclusions and make predictions while trying not to be bias or overlook certain factors. Traditional ML techniques after features are extracted from the acquired signal and its various representation (time, frequency, and time-frequency domain), acts as an input to the knowledge-based system to classify healthy and faulty conditions. We seek to involve the use of a deep learning model, specifically the Convolutional Neural Network to address these challenges ML models face:

•These techniques rely on hand-crafted feature engineering to extract relevant features from raw data and feature selection.

•Importance of the feature is condition-dependent.

•Selection of suitable advanced signal processing techniques to eliminate noise from the acquired signal for extracting features imposes a challenge.

C. Design

1) 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 behaviour 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.

2) 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:
1. Data Exploration: This involves understanding the dataset, visualizing and analyzing the data, identifying missing values, and removing irrelevant or redundant data.
2. Data Pre-processing: This step includes converting data into a machine-readable format, scaling the data, and removing noise or outliers.
3. Data Augmentation: Used to increase the diversity of the training dataset by applying transformations such as flipping, rotating, and shifting the images.
4. Data Labelling: Each image in the dataset is assigned a label that corresponds to its class, such as a cat or dog.

CNNs (Convolutional Neural Networks) use a backpropagation algorithm to train datasets. Backpropagation is an optimization algorithm that is used to adjust the weights of the neural network based on the error rate obtained during training. The goal of backpropagation is to minimize the difference between the predicted output and the actual output by adjusting the weights of the network. The cleaned data is split into training and validation sets. The training set (83 percent of the data) is used to train the model and the validation set (17 percent) is used to tune the model's hyperparameters. During the training phase, the CNN model is trained on the training dataset. This involves feeding the input data (images) into the model, where specific features are identified and extracted, consistency of features across multiple samples are assured, only important features are made, and the class is computed, and comparing the model's predictions with the ground-truth labels. The difference between the predictions and the ground truth labels is measured using a loss function, and the model's parameters are updated to minimize this loss. Then after each training cycle, the model is evaluated with the validation dataset. This is done to ensure that the model is not overfitting to the training data and to monitor the model's performance during training. Also, the hyperparameter is found in this phase. Examples like the learning rate, batch size, number of filters, epochs, and padding are fine-tuned to improve model performance and optimize validation accuracy. Its performance on unseen data is determined.

3) The CNN Base Layer: Delving deeper, the is a type of CNN Deep Learning algorithm that can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image, and be able to differentiate one from the other. The pre-processing required in a ConvNet is much lower as compared to other classification algorithms. While in primitive methods filters are hand-engineered, with enough training, ConvNets have the ability to learn these filters/characteristics. The main advantage of CNN compared to other neural networks is that it automatically detects important features without any human supervision. CNN is also computationally efficient. It uses special convolution and pooling operations and performs parameter sharing. This enables CNN models to run on any device, making them universally attractive. They require less pre-processing in comparison to other classification algorithms and are able to learn filters and characteristics. Convolutional neural networks also minimize computation in comparison with a regular neural network. Weight sharing is another major advantage of CNNs. The architecture of the base layer is analogous to that of the connectivity pattern of Neurons in the Human Brain and was inspired by the organization of the Visual Cortex. Individual neurons respond to stimuli only in a restricted region of the visual field known as the Receptive Field. A collection of such fields' overlaps to cover the entire visual area. The layers of a CNN used in out model include:

The Flatten Layer in CNNs serves to reshape the multi-dimensional 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.

The fully connected or dense layer (FC) in a Convolutional Neural Network (CNN) is used to map the high-level features extracted by the convolutional layers to the final output (e.g., classification or regression). The fully connected layer consists of a set of neurons that are connected to all the neurons in the previous layer. Each neuron in the fully connected layer computes a weighted sum of the outputs of the previous layer and applies an activation function(softmax) to produce the final output. The softmax function(S) is used in the output layer of a neural network for multi-class classification problems to convert the output of the last layer into a probability distribution over a set of mutually exclusive classes. Binary classification requires the use of sigmoid, 0 or 1.

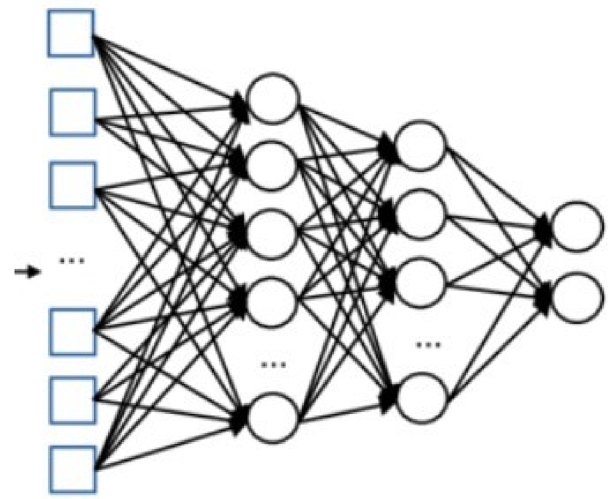

Fig. 3: Architecture of the Flatten(in blue) and the fully-connected layer(in black)

4) Transfer Learning Model: We would also introduce a pre-trained model as a starting point for training the new model (the base layer) on a different but related task. The idea behind transfer learning is that the pre-trained model has already learned general features and patterns from a large dataset, and these features can be reused for the new modelling task, thus reducing the need for large amounts of data and computing resources. This pre-trained model is a CNN one that has been trained on a large dataset, ImageNet. It is later fine-tuned and re-trained with our new dataset, with the base layer placed at the beginning of the Transfer model layer, for feature extraction. Some of the benefits of the addition of the transfer learning model to our experimental model is that:

• The transfer learning relies on the pre-trained model's knowledge, reducing the amount of data and computing resources required for training the base layer from scratch.

• It improves the accuracy of this new model

• The new model is more robust to variations in data, 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.

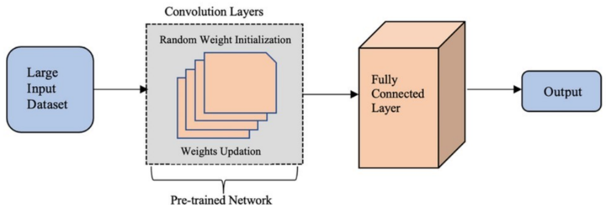

Fig. 4: Transfer Learning Model Architecture

IV. 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.

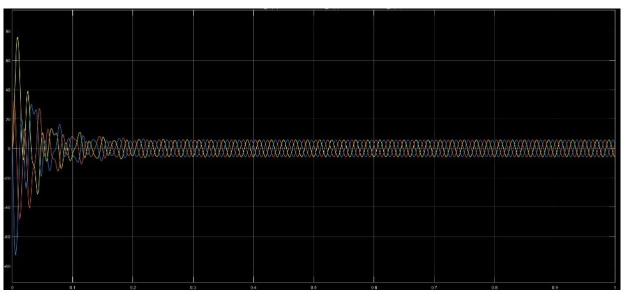

Fig. 5: Healthy waveform at no load

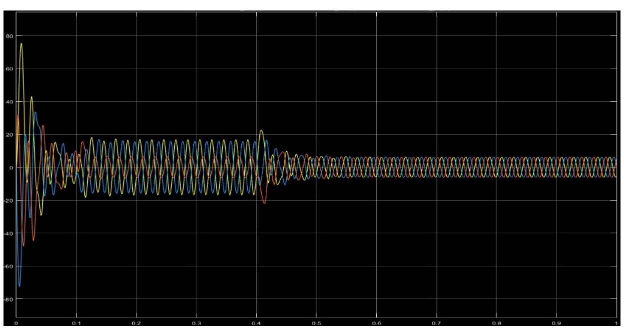

Fig. 6: Single phasing fault waveform at 25% load

	Training			Validation			
Load(%)	Healthy	Phase-Ground	Phase-Phase	Healthy	Phase-Ground	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

TABLE I: Split Dataset

B. Performance of Transfer Learning Models

In literature, DL models are reported to have an input of raw data of current signature and based on frequency features extracted from raw data as an input, fault classification can be done by the DL model. Therefore, DL models are employed, which can effectively classify the motor health conditions (Healthy, Single phasing, Phase to Phase) with the classification about which phase has been exposed to the fault. For checking the classification performance of DL models, a dataset is generated by collecting current signature data in the time domain from the simulated motor model operating under various healthy and unhealthy conditions in MATLAB/Simulink workspace and then stored in CSV format. After proper labeling, it is used as input for training and validation of the DL models. The details of the dataset are provided in Table 4. The obtained dataset comprises about 300 samples of stator current in each simulated healthy and unhealthy condition.

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

TABLE II: Classes and their labels

Transfer Learning Models employed InceptionV3, ResNet50 and VGG19. these models are widely used for time-series or sequential data analysis, such as higher learning capabilities even with raw input data. These models predict outcomes as multiclass labels with high accuracy owing to different layers employed in their structure. The selection of model structure (number of layers and number of units) depends on the type and complexity of the dataset on which model is to be trained. Sometimes model could be deep if the input data is complex and nonlinear.

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 III: Architecture of modified Transfer Learning model

Hyperparameters	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

TABLE IV: Hyperparameters of TL models

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.

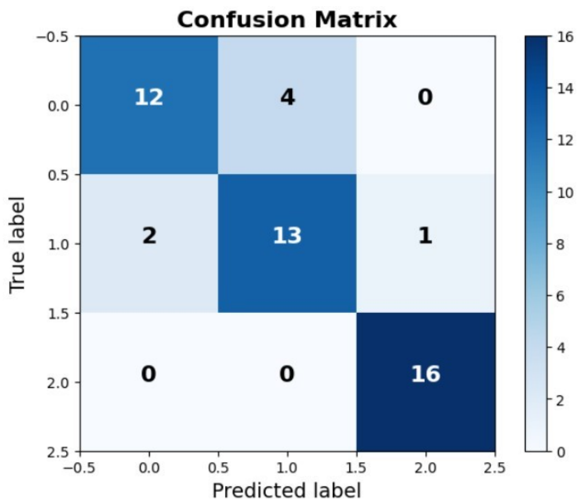

Fig. 7: Confusion Matrix of InceptionV3

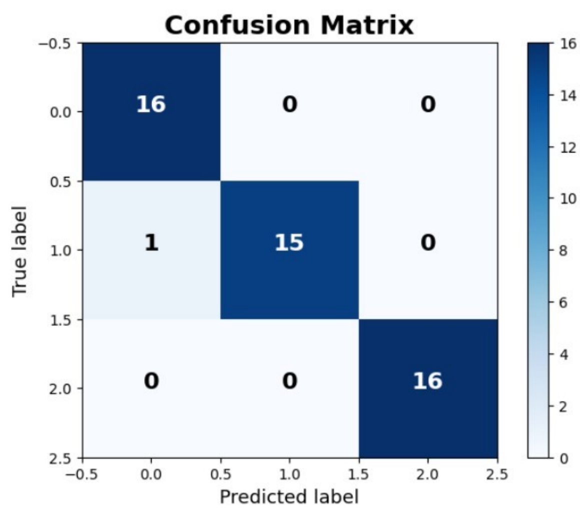

Fig. 8: Confusion Matrix of ResNet153

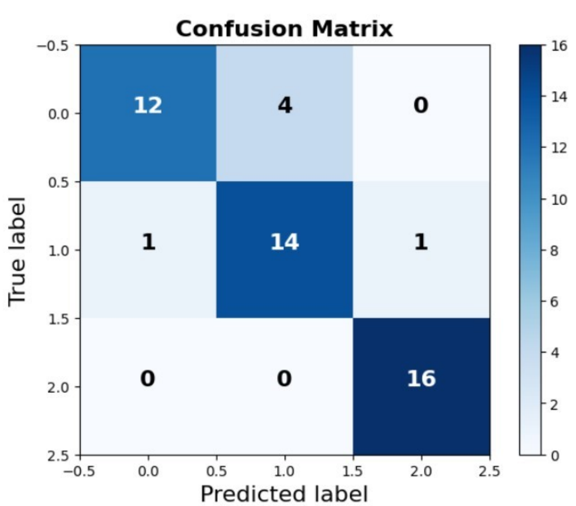

Fig. 9: Confusion Matrix of VGG19

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.

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

TABLE V: Condition Accuracy Comparison of TL models

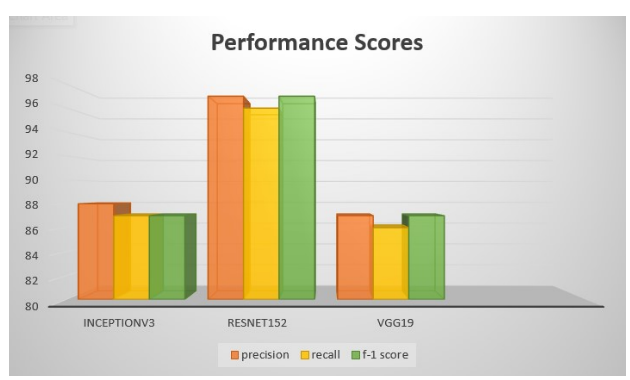

Fig. 10: Performance scores of TL models

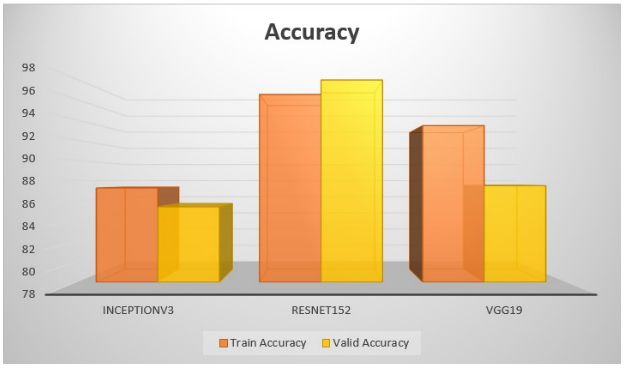

Fig. 11: Accuracy comparison of TL models

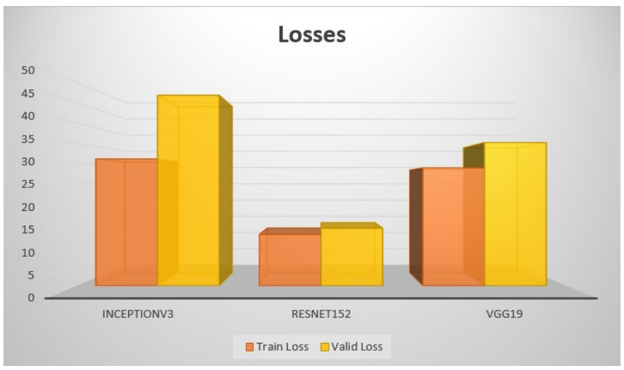

Fig. 12: Losses comparison of TL models

V. Conclusion

In this paper we presented the three-phase induction motor fault detection and classification by obtaining varying current signatures in time domain and deep learning approaches in healthy and unhealthy conditions. The three-phase induction motor faults, which include single phasing and phase-to-phase where induced in healthy waveforms, and simulations where carried out in MATLAB. Since it is difficult to distinguish between the various faults, classification of the faulty phase(s) are necessary in condition monitoring systems. Therefore, three transfer learning models InceptionV3, ResNet152 and VGG19 were fine-tuned, trained and tested with the dataset generated locally for the purpose of healthy and unhealthy conditions of the induction motor. All three were simulated for classifications of different fault conditions with raw data of stator current. The results show these employed techniques provided better fault detection and classification in the various conditions. Their performance is measured by confusion matrix, precision, recall, F1-score and average score. Among the three models, ResNet152 had the best performance and hence was chosen for the project objective.

VI. 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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VII. References

[1] A. A. Qazi, J. Daudpoto, S. A. Shaikh “Comparison of Fault Detection Techniques for Induction Motors”, International Journal of Computer Applications (0975 – 8887), Volume 183, pp. 1

[2] Barcelos, A.S.; Cardoso, A.J.M. Current-based bearing fault diagnosis using deep learning algorithms. Energies 2021, 14, 2509.

[3] Zhu H., Tao W., Wei L., Luis V-C, “A fault analysis method for three-phase induction motors based on Spiking Neural P Systems” Complexity. 2021. 1-19.

[4] Majid K., Mehdi E., “Electrical fault detection in three-phase induction motor using deep network-based features of thermograms”, Measurement, Volume 173, 2021, ISSN 0263-2241

[5] Swapnil G, Prasad K., Atul A., ”Detection of broken rotor bar fault in an induction motor”, Journal of Advanced Mechanical Design, Systems, and Manufacturing, Vol.16, No.2, 2022

[6] Majid H., Dileep K., Imtiaz H, Tayab D, ”Stator Winding Fault Detection and Classification in Three-Phase Induction Motor”, Intelligent Automation and Soft Computing, DOI:10.32604/iasc.2021.017790

[7] Majid H.,Tayab D., Imtiaz H., Zubair A., Dileep K., ”Fault Detection and Identification Using Deep Learning Algorithms in Induction Motors”, Computer Modeling in Engineering and Sciences Tech Science Press, DOI: 10.32604/cmes.2022.020583

[8] Jong L., Jae P., and In-Soo L.,”Fault Diagnosis of Induction Motor Using Convolutional Neural Network” Jong L., Jae P., and In-Soo L., School of Electronics Engineering, Kyungpook National University, Daegu 41566, Korea.

[9] C. Morales-Perez, J. Rangel-Magdaleno, H. Peregrina-Barreto, J. P. Amezquita-Sanchez and M. Valtierra-Rodriguez, ”Incipient Broken Rotor Bar Detection in Induction Motors Using Vibration Signals and the Orthogonal Matching Pursuit Algorithm,” in IEEE Transactions on Instrumentation and Measurement, vol. 67, no. 9, pp. 2058-2068, Sept. 2018

[10] T. G. Calva, D. M. Sotelo, V. F. Calero, R. R. Tronsoco “Early Detection of Faults in Induction Motors—A Review”,

Energies, pp. 2

APPENDIX A
CODE AND ORIGINAL DATASETS USED FOR PROJECT

VGG MODEL: VGGGitHub

INCEPTIONV3: GitHub

RESNET152: GitHub

DATASET: Google Drive

INDUCTION MOTOR MODELK: Google Drive