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Diagnosis of Permanent Magnet Assisted Synchronous Reluctance Motor Winding Fault by Convolutional Neural Network

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Abstract: In recent years, the use of machine learning models for fault detection has become commonplace. Its goal is to identify and fix problems with permanent magnet synchronous reluctance motors. This research's primary goal is to identify and categorize errors in their early stages. We classified winding faults using machine learning approaches, such as Independent Component Analysis and Deep Learning models. We could distinguish between vibration and current signals from the engine signals by using Independent Component Analysis (ICA). We experimented on multiple architectures using the convolutional neural network (CNN) architecture we designed from scratch and the Transfer Learning technique, testing two distinct datasets we generated using the signals we got. According to experimental findings, the suggested scratch CNN model performed exceptionally well in classification, achieving 98.6% with current signals and 99.4% with vibration signals.

Key words: Circuit faults, fault detection, machine learning, permanent magnet motors.

Kalıcı Mıknatıs Destekli Senkron Relüktans Motor Sargı Arızasının Evrişimli Sinir Ağı ile Teşhisi

Öz: Son yıllarda hata tespiti için makine öğrenmesi modellerinin kullanımı yaygınlaşmıştır. Amacı, kalıcı mıknatıs destekli senkron relüktans motor ilgili sorunları tanımlamak ve düzeltmektir. Bu araştırmanın temel amacı, hataları erken aşamalarında tanımlamak ve sınıflandırmaktır. Bağımsız Bileşen Analizi ve Derin Öğrenme modelleri gibi makine öğrenimi yaklaşımlarını kullanarak motor arızalarını sınıflandırdık. Bağımsız Bileşen Analizi (ICA) kullanarak titreşim ve akım sinyallerini motor sinyallerinden elde ettik. Sıfırdan tasarladığımız evrişimsel sinir ağı (CNN) mimarisini ve Transfer Öğrenme tekniğini kullanarak birden fazla mimari üzerinde denemeler yaptık ve elde ettiğimiz sinyalleri kullanarak oluşturduğumuz iki farklı veri setini test ettik. Deneysel bulgulara göre, önerilen sıfırdan CNN modeli, sınıflandırmada son derece iyi performans göstererek akım sinyallerle %98,7 ve titreşim sinyalleriyle %99,4'e ulaşmıştır.

Anahtar kelimeler: Devre arızaları, arıza tespiti, makine öğrenmesi, kalıcı mıknatıslı motorlar.

1. Giriş

Permanent magnet synchronous reluctance motors have become popular in recent years and are widely used in various industries, including high-speed trains, electric vehicles, household appliances, and production processes [1]. These motors feature non-conductive rotors with a cavity structure and flux barrier, requiring minimal maintenance. Their brushless design, efficient material usage, low cost, and ease of production have contributed to their increased utilization. Ensuring the seamless operation of these motors in diverse industrial applications is crucial. Prompt diagnosis and intervention in case of system malfunctions while the motor is in operation directly impact its efficiency.

With the continuous development of computer technology in recent years, intelligent diagnostic methods have been preferred by researchers and have developed rapidly. Intelligent diagnostic methods for fault detection and diagnosis of complex systems have higher accuracy than traditional analysis methods such as support vector machines (SVM), expert systems, neural networks, fuzzy logic, and machine learning theory-based diagnostic methods. The intelligent diagnosis method uses artificial information technology such as expert systems, fuzzy logic reasoning, and neural networks to imitate the human mind's judgment process using accumulated fault detection and diagnosis knowledge and logical reasoning knowledge. In addition, the intelligent diagnostic method performs complex fault monitoring and diagnosis of motors in engineering applications [2].

When the literature studies were examined, it was observed that malfunctions were detected using various methods. The most common methods used in recent years are signal-based approaches. In all diagnostic methods, acquiring signal data is essential to determine the type of fault in the motor. These signals include current, voltage,

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vibration, torque, etc., which are indicative of motor faults. Signals such as noise and heating that may occur in the motor are processed using machine learning methods to analyze and address fault situations for detection and classification. The primary objective of these studies is to identify and categorize faults at an early stage [3].

Torres et al., in their study titled "Detection of Eccentricity Faults in Five-Phase Ferrite-PM Assisted Synchronous Reluctance Machines" published in 2017, stated that faults in the air gap disrupt the magnetic flux. They mentioned that various strategies are employed for detecting this fault, including spectral vibration analysis, acoustic analysis [4-5], thermal analysis [6], air gap flux analysis, and MCSA (motor current signature analysis). They also highlighted the lack of information on this topic in the literature and suggested that their study could be beneficial for developing fault diagnosis strategies after thorough analysis and interpretation [7]. In [8], eccentricity failures of 3-phase and 5-phase motor faults were analyzed using finite element analysis, irrespective of their phase numbers. The fault characteristics of the motor, such as torque fluctuations, average torque, and back-EMF harmonics, were extracted because of these analyses. Arafat and Choi [9] explored fault tolerance control and optimal phase progression for various fault conditions in 5-phase in their study. They analyzed an optimally designed five-phase permanent magnet synchronous reluctance motor under different open-phase fault conditions. Furthermore, fault endurance tests were conducted commonly used in air applications [10]. In the study, a 3-phase motor was separately isolated and divided in a manner that prevented phase overlap, and the motor's behavior was analyzed using the finite element method under various fault conditions.

In his 2017 study, Wided Zine [11] examined the machine learning method for sensor control of IPMSMs, which is structurally the closest motor type. Since fault diagnosis is crucial at an early stage for this motor type, widely used in electric vehicles, the signal injection method is chosen to cover zero and low speeds while the engine is running, while the machine learning method is utilized at high and medium speeds. In a publication from 2018 [12], motor fault diagnosis was conducted using a deep learning method. Based on Long Short-Term Memory (LSTM), one of the deep learning algorithms, the 3-phase current values from previous sampling moments are stored in memory, making the next sampling instantly predictable by the system. In another study [13], Kao et al. detected faults at various intensities across a wide speed range using a deep learning algorithm. They employed two methods for feature extraction in their research. The first method involved wavelet packet transform for classification, while the second method utilized a deep 1-D convolutional neural network with a softmax layer in a 2019 study titled "Faults and Diagnosis Methods of Permanent Magnet Synchronous Motors: A Review" [14]. This study explains fault and diagnostic methods for PMSM motors, commonly used in the industrial field. The electrical, mechanical, and magnetic faults in the motor are summarized, followed by an explanation of the diagnostic methods found in the literature. Among these methods, it is noted that the most used fault diagnosis method is artificial intelligence-based.

As a result of the literature studies, it is seen that various methods are used for fault detection in permanent magnet synchronous reluctance motors. However, it has been understood that studies based on machine learning are not used frequently. In this study, vibration and current data of a 3-phase 1 kW motor in different stator fault states are used. Vibration and current data in healthy and stator inter-coil short circuit fault operating conditions were obtained for the motor used. The motor was operated under the same torque and rotational speed. By applying the confusion matrix method, one of the machine learning methods, to the obtained data, the existing situation in the data set and the number of correct and incorrect predictions of the classified model are given in a table.

2. Fault Detectıon of Permanent Magnet Synchronous Reluctance Motors

Faults occurring can be classified as electrical, magnetic, and mechanical faults. Magnetic faults generally include magnet demagnetization and fracture. Electrical faults include short circuits between windings, connection errors in windings, stator open-circuit, phase-to-ground short circuits, and phase-to-phase short circuits. Mechanical failures consist of unstable conditions such as bent shafts or dynamic misalignment, static and dynamic air gap irregularity, and damaged bearing failures [15].

In Figure 1, the basic block diagram of the signal-based approach for fault diagnosis in a motor is provided.

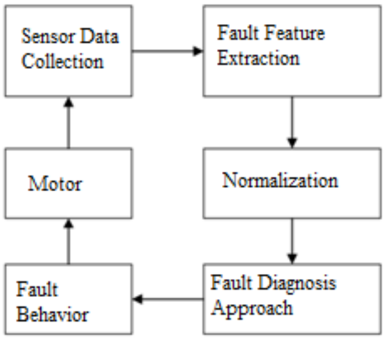


Figure 1. Signal-based diagnostic approach used in motors [16].

This study, it is aimed to diagnose faults on the motor with deep learning and ICA. A defect situation was created by making various changes to the motor. The parameter values of the motor used in the study are provided in Table 1.

Table 1. Parameters of the proposed approach.

Parameter	**Value**
Rated power	1 kW (kilowatt)
Input Voltage	380 V
Frequency	60 Hz (hertz)
Number of phases	3
Rated speed	3000 RPM
Rated torque	3.18 Nm (Newton meter)
Inter-coil resistance value (Rcc)	0.0409 Ohm

The data used in the study were obtained by short-circuiting the motor stator. One method to induce a fault in the motor stator is by increasing the stator resistance (open circuit fault), while another method is by reducing the stator resistance (short circuit fault). Short-circuiting the stator leads to more pronounced and severe faults in the motor, creating a direct path for the driving current. Consequently, the normal current flowing through the stator coil decreases in accordance with Kirchhoff's law, resulting in a short circuit in the stator and a torque induced in the motor's electromagnetic field [17].

Stators short-circuit faults of two different intensities were created by reducing the motor resistance value with the short-circuit fault on the motor used in this study. The healthy and stator short-circuit malfunctioning operating states of the motor were analyzed in the MATLAB Simulink environment. The simulation results of the motor used in normal operating conditions are shown in Figures 2, 3, and 4.

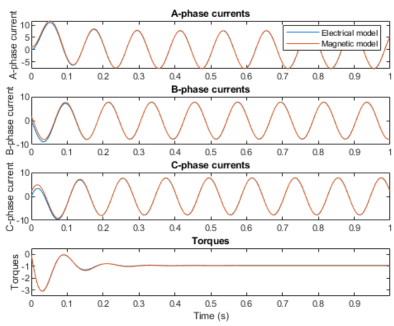


Figure 2. Current and torques waveform in healthy condition.

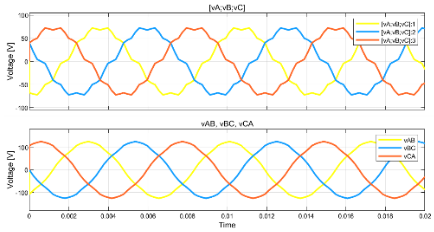


Figure 3. Phase voltages waveform in healthy condition.

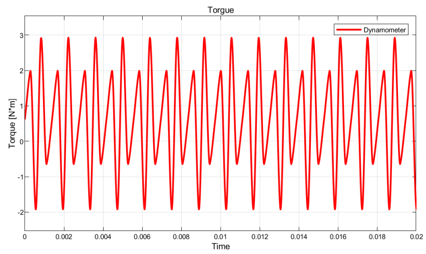


Figure 4. Torgue waveform in healthy condition.

In Figure 5, simulation results show stator inter-coil short circuit faults with intensities of 0.68% and 0.81%, healthy and defective respectively.

(a) (b)

Figure 5. (a) Healthy and (b) defective current and torques waveform inter-coil short circuit fault.

3. Material and Method

Classification of motor faults involves a two-stage approach: ICA and CNN. We transformed the current and vibration signal data acquired from a 3-phase 1 kW motor in various stator fault conditions into images using ICA. Due to the large volume of data in the signal images, approximately 1 million, we conducted signal sampling based on the sampling period for the current and vibration signals. Each set of current and vibration signal data falls into three categories (normal, fault-1, and fault-2). These data were segmented using a 10-second sampling period and converted into image format. Consequently, our image dataset is prepared for use in the proposed model. Examples of sample current and vibration signal images are depicted in Figure 6 and Figure 7. Each signal is categorized into three types: normal, fault type 1, and fault type 2. Figures 6 and 7 display two sample images of the current and voltage signals in our dataset.

The proposed CNN network model includes 5 convolution layers, 5 maxPooling layers, 2 dense layers, and SoftMax classifier layers. The hyperparameters of the model are as follows: input size 150x150, epoch 100, batch size 32, optimizer Adam, learning rate 0.001, pooling size 2x2, convolution filter size 3x3, numbers of convolution filters 32, 64, 64, 128, and 256, stride value 1, no padding, ReLU activation function, L2 regularization, pooling type MaxPooling. We presented this model in Figure 9. We also used the Transfer Learning (TL) technique to compare the network model we developed. We tested both our current and vibration datasets on DenseNet121, DenseNet169, DenseNet201, InceptionResNetV2, MobileNet, MobileNetV2, and VGG16 architectures. TL involves freezing all parameters, layers, and weights in a pre-trained network architecture and applying it to a new dataset. In our study, we only updated the number of classes by adjusting the value on the Softmax layer, which is the classifier layer.

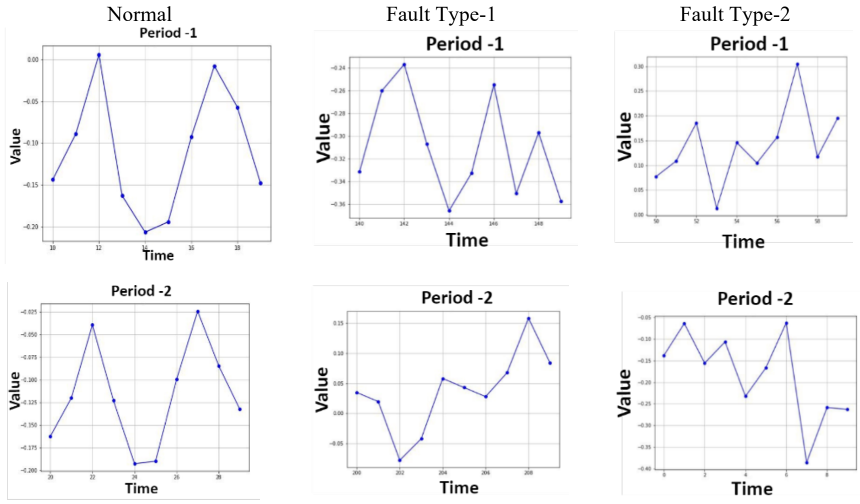


Figure 6. Samples of the current signals.

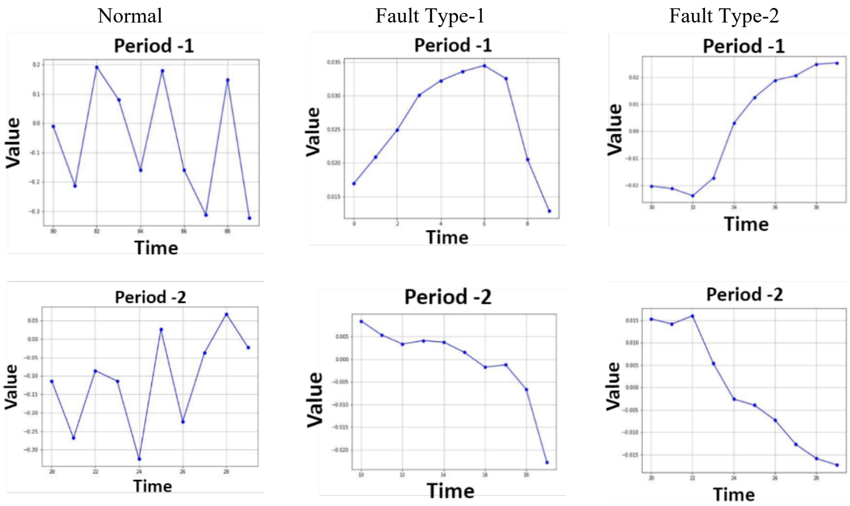


Figure 7. Samples of the vibration signals.

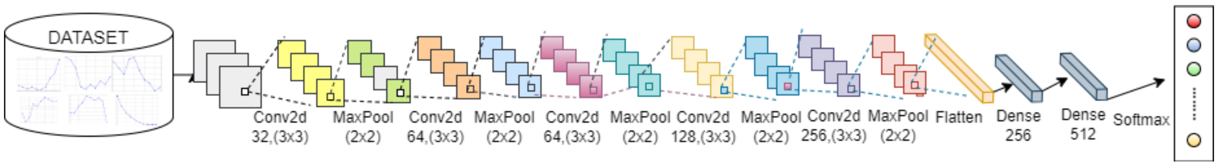


Figure 8. Proposed scratch CNN model.

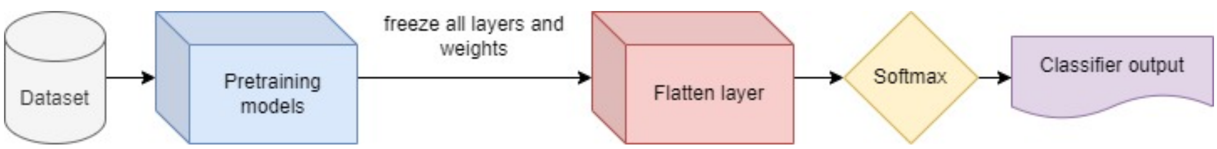


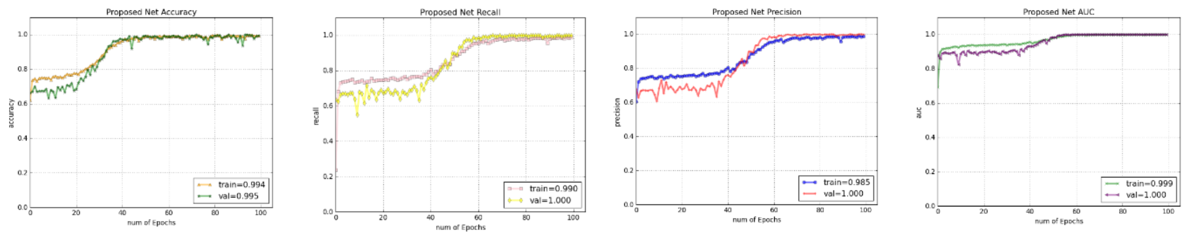
Figure 9. General scheme of TL method functioning.

4. Experimental Results

Fault diagnosis is conducted by analyzing the signal information received from the motor in an actual setup. The technical specifications of the motor used in the experiments are as follows: The motor has a nominal power of 1 kW and operates with a 380 V input voltage. It is designed to function in a three-phase system with a frequency of 60 Hz. The motor's nominal speed is 3000 RPM, and its nominal torque value is 3.18 Nm. The intermediate winding resistance (Rcc) of the motor was measured as 0.0409 Ohm.

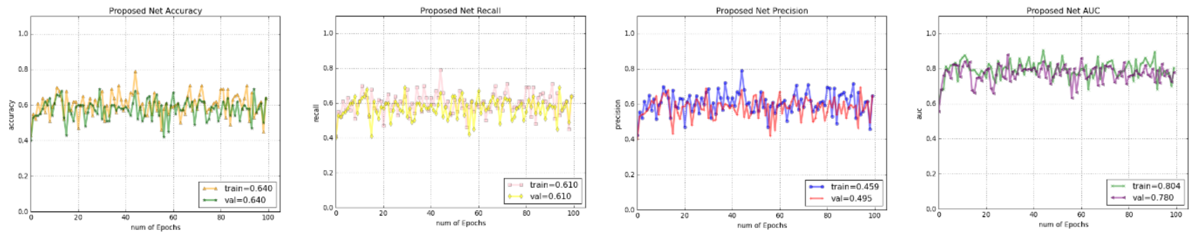
For direct current signals, current values are determined by measuring the voltage drop across shunt resistors placed in the motor circuit. Hall effect sensors detect the magnetic field generated by the motor and calculate the current. In the case of alternating currents, high currents are safely measured using current transformers. Vibration signals are typically captured using accelerometers or piezoelectric sensors, which transform mechanical vibrations into electrical signals for transmission to data acquisition systems. The acquired data is digitally recorded at a specified sampling rate. Subsequently, the numerical data is analyzed in both time and frequency domains and converted into image data. These images are further transformed into current and voltage representations with a sampling interval of 10 seconds. This process allows for the evaluation of the motor's performance and the identification of potential malfunctions.

The results for the motor with vibration – intercoil – 1kW data are provided in this section. A total of 1,048,575 data points were entered into the system. The vibration data class obtained from normal operation was labeled as the vibration data class from the short circuit fault condition, operating with intensities of 0.68 and 0.81, was labeled as Type-1 and Type-2, respectively. This research was conducted using a desktop computer equipped with an Intel(R) Core(TM) i7 processor with Turbo Boost up to 5.0 GHz, running at 5.20GHz, 32GB of DDR5 RAM, and an NVIDIA RTX 4070 GPU.



(a) **(b)** **(c)** **(d)**

Figure 10. a) Accuracy b)Recall c)Precision and d)AUC rates of proposed CNN model on vibration signal.

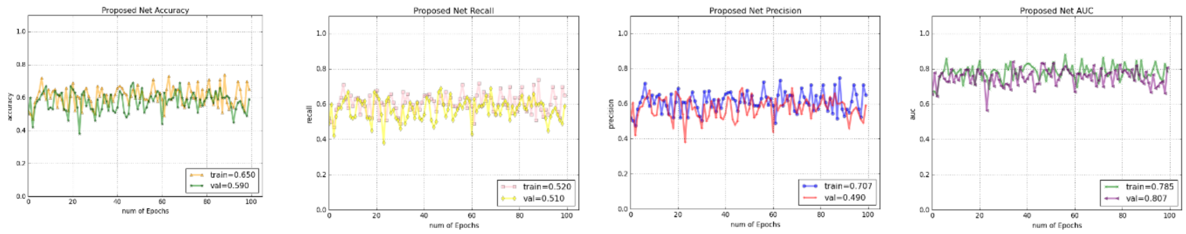


(a) **(b)** **(c)** **(d)**

Figure 11. a) Accuracy b)Recall c)Precision and d)AUC rates of DenseNet121 on vibration signal.

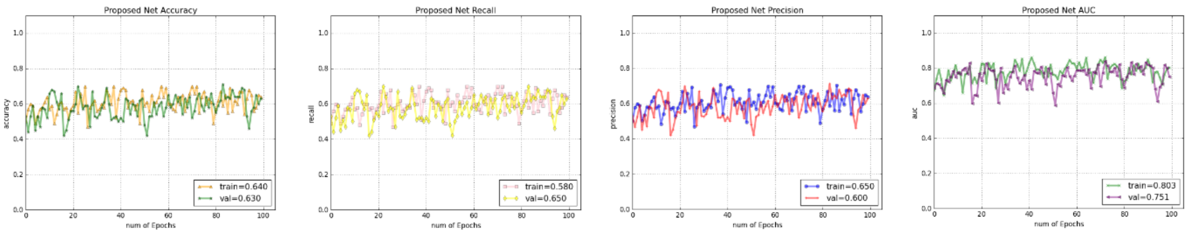
Table 2. Performance of Vibration –intercoil – 1kW result.

Method	Accuracy	Recall	Precision	AUC
Proposed CNN	**0.994**	**0.990**	**0.985**	**0.999**
DenseNet121	0.640	0.610	0.459	0.804
DenseNet169	0.650	0.520	0.707	0.785
DenseNet201	0.640	0.580	0.650	0.803
InceptionResNetV2	0.520	0.550	0.694	0.718
MobileNet	0.630	0.630	0.580	0.795
MobileNetV2	0.610	0.630	0.640	0.738
VGG16	0.660	0.610	0.713	0.850



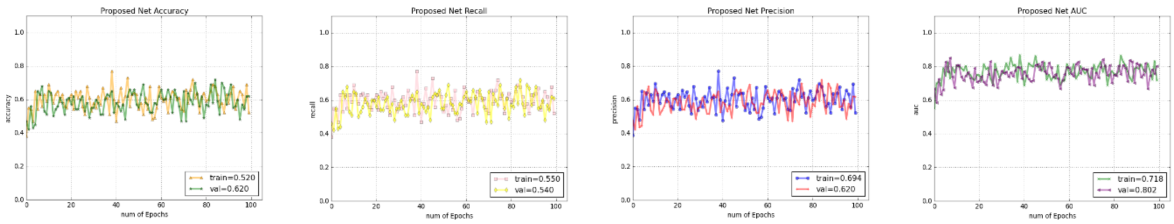
(a) **(b)** **(c)** **(d)**

Figure 12. a) Accuracy b)Recall c)Precision and d)AUC rates of DenseNet169 on vibration signal.



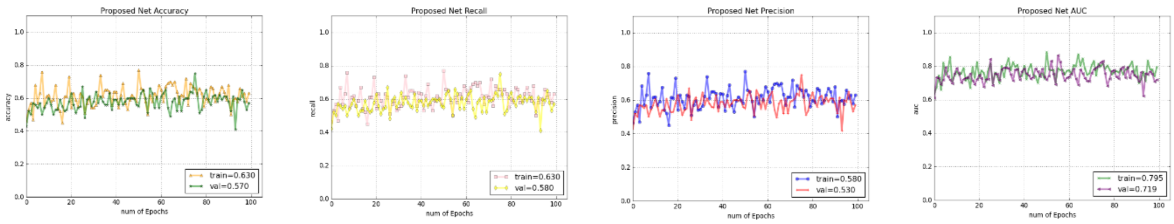
(a) **(b)** **(c)** **(d)**

Figure 13. a) Accuracy b)Recall c)Precision and d)AUC rates of DenseNet201 on vibration signal.



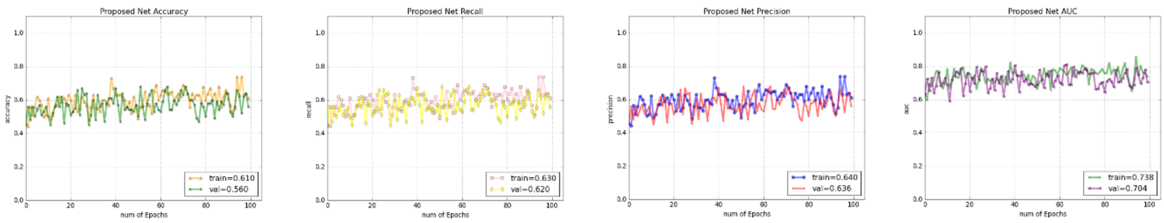
(a) **(b)** **(c)** **(d)**

Figure 14. a) Accuracy b)Recall c)Precision and d)AUC rates of InceptionResNetV2on vibration signal.



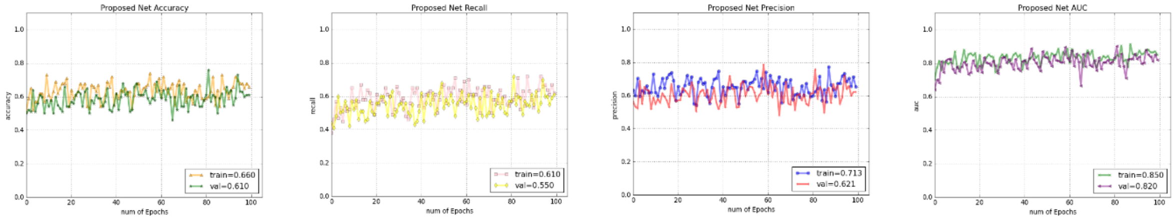
(a) **(b)** **(c)** **(d)**

Figure 15. a) Accuracy b)Recall c)Precision and d)AUC rates of MobileNet vibration signal.



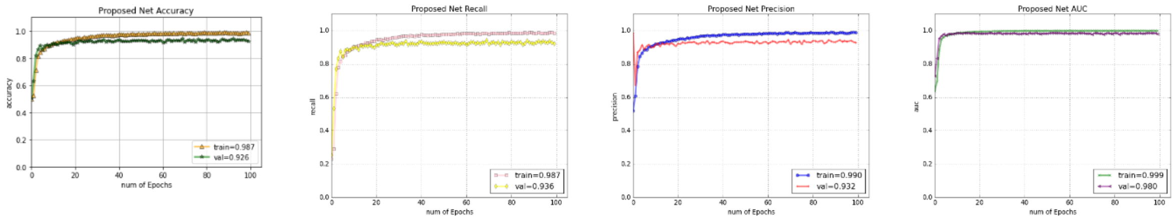
(a) **(b)** **(c)** **(d)**

Figure 16. a) Accuracy b)Recall c)Precision and d)AUC rates of MobileNetV2 vibration signal.



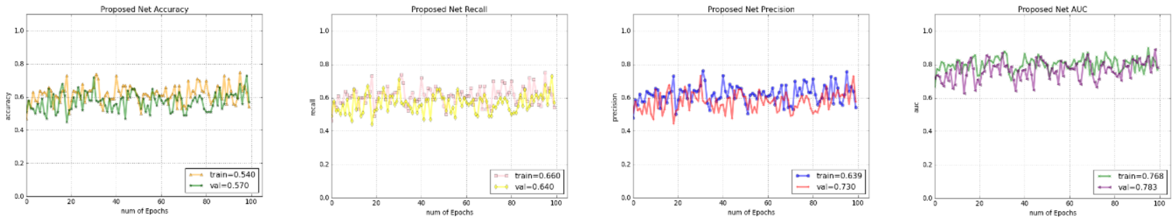
(a) **(b)** **(c)** **(d)**

Figure 17. a) Accuracy b)Recall c)Precision and d)AUC rates of VGG16 vibration signal.



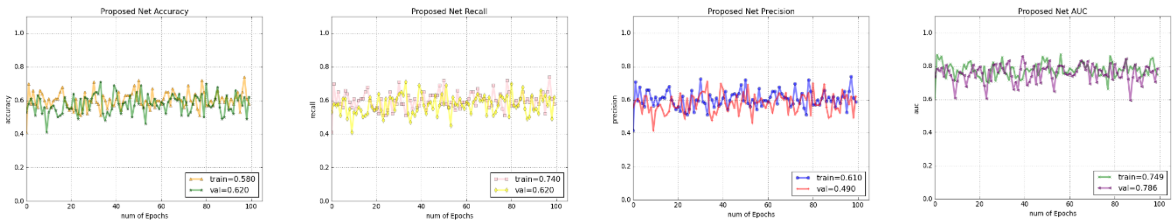
(a) **(b)** **(c)** **(d)**

Figure 18. a) Accuracy b)Recall c)Precision and d)AUC rates of proposed CNN model on current signal.



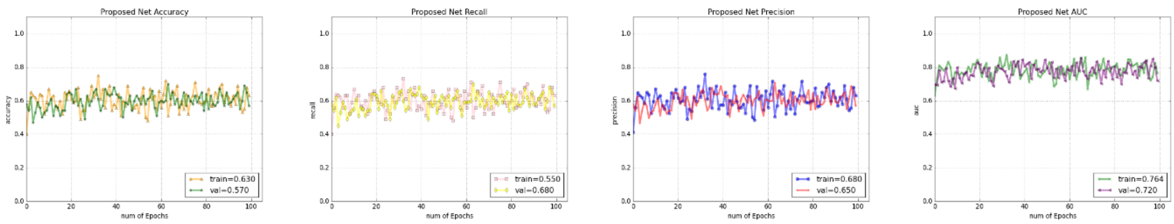
(a) **(b)** **(c)** **(d)**

Figure 19. a) Accuracy b)Recall c)Precision and d)AUC rates of DenseNet121 on current signal.



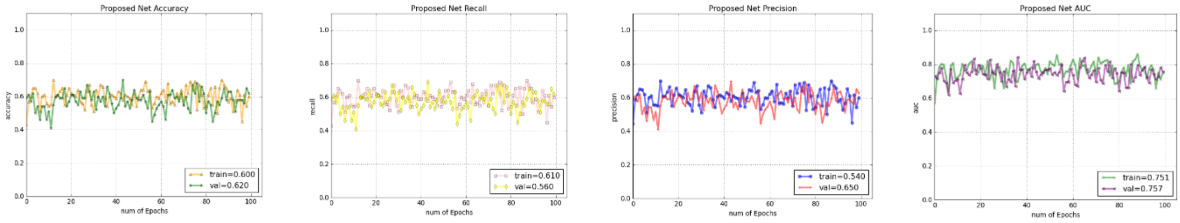
(a) **(b)** **(c)** **(d)**

Figure 20. a) Accuracy b)Recall c)Precision and d)AUC rates of DenseNet169 on current signal.



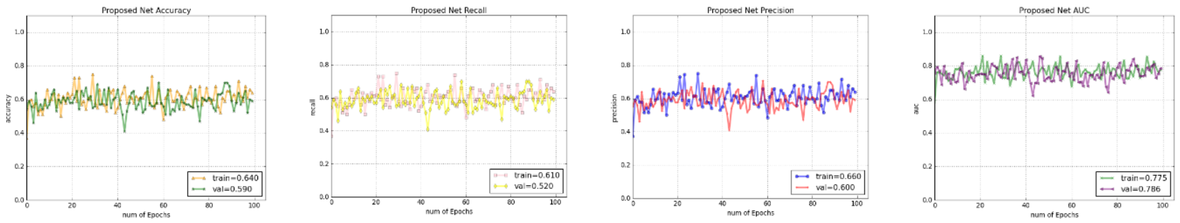
(a) **(b)** **(c)** **(d)**

Figure 21. a) Accuracy b)Recall c)Precision and d)AUC rates of DenseNet201 on current signal.



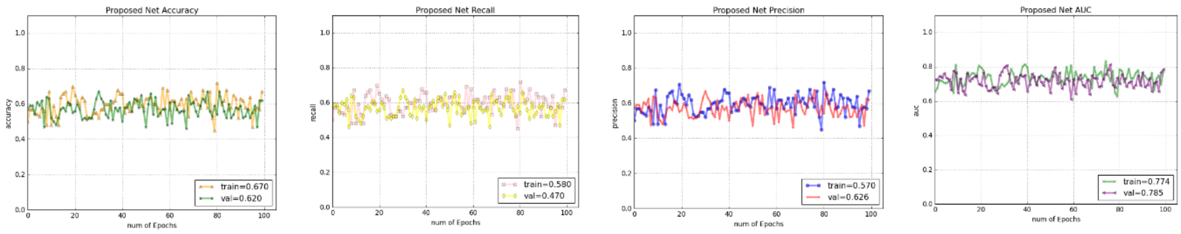
(a) **(b)** **(c)** **(d)**

Figure 22. a) Accuracy b)Recall c)Precision and d)AUC rates of InceptionResNetV2 on current signal.



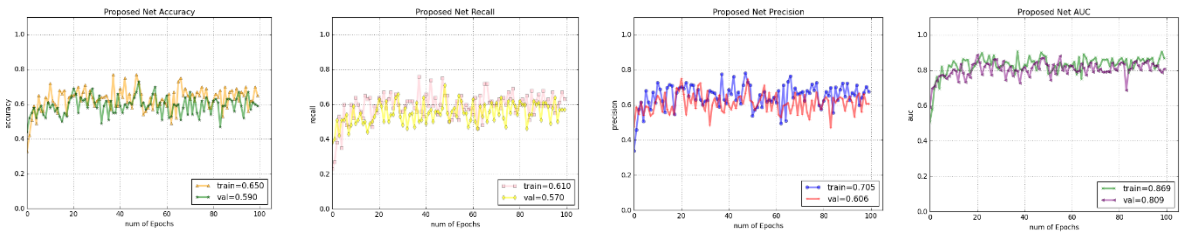
(a) **(b)** **(c)** **(d)**

Figure 23. a) Accuracy b)Recall c)Precision and d)AUC rates of MobileNet on current signal.



(a) **(b)** **(c)** **(d)**

Figure 24. a) Accuracy b)Recall c)Precision and d)AUC rates of MobileNetV2 on current signal.



(a) **(b)** **(c)** **(d)**

Figure 25. a) Accuracy b)Recall c)Precision and d)AUC rates of VGG16 on current signal.

Table 3. Performance of Current –intercoil – 1kW result.

Method	Accuracy	Recall	Precision	AUC
Proposed CNN	**0.987**	**0.987**	**0.990**	**0.999**
DenseNet121	0.540	0.660	0.639	0.768
DenseNet169	0.580	0.740	0.610	0.749
DenseNet201	0.630	0.550	0.680	0.764
InceptionResNetV2	0.600	0.610	0.540	0.751
MobileNet	0.640	0.610	0.660	0.775
MobileNetV2	0.670	0.580	0.570	0.774
VGG16	0.650	0.610	0.705	0.869

Table 2 and Table 3 illustrate the classification performance in fault diagnosis of voltage and current signals. Upon examining the results generated by these data using various methods in the tables, it is evident that the method proposed in this study yields significantly higher results in terms of accuracy, recall, precision, and AUC factors compared to other transfer learning methods. The graphical representations in Figure 10 and Figure 25 depict the results of accuracy, recall, precision, and AUC metrics on the transfer learning of current and vibration data, as well as the proposed methods. The experimental results obtained indicate that the proposed scratch CNN architecture is highly successful in both current and vibration chemical data, achieving 98.70% and 99.40% accuracy, respectively. Furthermore, TL, a machine learning method used for comparison, has been evaluated across various architectures. Following the proposed CNN architecture, the highest success rates were achieved with VGG16 at 66.00% on vibration data and MobileNetV2 at 67.00% on current data. The results demonstrate that the proposed method outperforms transfer learning methods. This success can be attributed to the fact that transfer learning models train the network on different datasets and update the weight values accordingly. This discrepancy arises because the images in our dataset are unrelated to the datasets.

5. Conclusions

In this study, fault detection and classification of a permanent magnet synchronous reluctance motor using a confusion matrix, one of the machine learning methods, has been conducted. The synchronous reluctance motor, widely utilized in various industries, has seen increased popularity in electric vehicles and hybrid electric vehicles, particularly in recent years. Early-stage diagnostics for motor are crucial. By inducing a short circuit fault in the study, the motor’s resistance value was decreased, resulting in two different stator short circuit faults with magnitudes of 0.68% and 0.81%. Initially, normal operation and faulty states’ vibration and current motor data occurring in the stator were trained on the model. The motor signal data was transformed into vibration and current signals using the ICA technique. Subsequently, the datasets containing the current and vibration signals were tested on the proposed CNN model and TL. Each dataset comprised three classes: Normal, Defective Type-1 (0.68%), and Defective Type-2 (0.81%). A success rate of 99.40% was achieved on the vibration dataset, and 98.7% on the current dataset.

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