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BROKEN MAGNETS FAULT DETECTION IN PMSM USING A CONVOLUTIONAL NEURAL NETWORK AND SVM

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ABSTRACT

The Permanent Magnet Synchronous Motor (PMSM) stands as a pivotal component in various applications, yet it remains susceptible to an array of faults within both its rotor and stator, there arises an imperative to swiftly and intelligently address these issues. In this study, a novel approach was undertaken wherein a PMSM design was conceptualized within the Ansys Maxwell program, followed by the deliberate introduction of a fault at the rotor's magnetic level. Specifically, three distinct fault scenarios were delineated based on the number of broken magnets (BM), namely 2, 3, and 4, localized within specific rotor areas. Notably, the magnetic flux density was selected as the focal parameter for this investigation. To effectively detect and diagnose faults stemming from BM, an innovative Convolutional Neural Network (CNN) architecture was devised. Leveraging images of the PMSM design captured during operational phases at various time intervals, the CNN exhibited remarkable efficacy in discerning and categorizing fault instances. Upon analysis of the derived outcomes, it becomes evident that the CNN exhibited unparalleled accuracy in fault detection, achieving a remarkable 100% success rate when juxtaposed with alternative methodologies such as Support Vector Machines (SVM) and K-Nearest Neighbors (KNN), which yielded accuracy rates of 97%.

I. INTRODUCTION

The industrial sector's reliance on electric motors stems from their versatility and widespread applications across various domains, serving as the linchpin of development in critical areas such as aircraft, electric cars, and ships [1-3]. Despite their proven efficiency, electric motors are subject to degradation over time, succumbing to various faults across different components. Hence, there exists a pressing need to explore methodologies facilitating the rapid detection, diagnosis, and mitigation of these faults.

The PMSM stands as a cornerstone of the industrial sector, yet it is susceptible to a myriad of faults, particularly at the rotor and stator levels, which can significantly impact operational quality [4],[5]. In response to this challenge, artificial intelligence emerges as a potent and expedient tool for fault detection.

The design and analysis of electric motors, alongside the study of operational phenomena, are typically conducted using specialized software platforms such as Ansys Maxwell [6],[7].

These programs offer standardized templates tailored for diverse machinery, facilitating the study of magnetic phenomena distribution and enabling fault simulations to evaluate their impact on machine performance.

Recent research endeavors have focused on employing advanced techniques such as the finite element method to design induction motors and investigate fault scenarios, including broken bars [8], [9], Bearing Fault, where Line Currents were relied upon to detect the fault in the induction motor [10]. Additionally, machine learning methodologies have proven instrumental in fault detection and diagnosis across various motor types [11]. Interest in diagnosing the Broken Rotor Bar using Adaptive Neuro-Fuzzy Inference in the induction motor [12], Convolutional Neural Network was used in diagnosing the Broken Rotor Bar [13].

In the realm of PMSM, common mechanical and electrical faults include Bearing Fault, Demagnetization, and Eccentricity [14],[15], The demagnetization fault was detected in PMSM [16], while the Neural Network was used to detect the Rolling Bearing Fault in PMSM [17], Efforts have been directed towards the detection and mitigation of these faults using machine learning approaches.

Techniques such as Convolutional Neural Networks (CNN) and Support Vector Machines (SVM) have been employed to discern faults, including broken magnets, with a focus on monitoring magnetic flux density and analyzing images captured during specific operational intervals [18],[19] In summary, this study proposes the integration of CNN and SVM algorithms for the detection of broken magnets in PMSM [20]. Leveraging the design capabilities of Ansys Maxwell, simulations encompassing various fault scenarios were conducted. Magnetic flux density serves as a crucial parameter for monitoring machine performance, with images extracted at specific intervals to facilitate a comparative analysis between healthy and fault states, thereby contributing to the advancement of fault detection methodologies in electric motors.

II. DESIGN PMSM AND BROKEN MAGNETS

Designing a PMSM and simulating a broken magnet scenario involves several steps and considerations. Here is a general description of this process consisting of the following steps:

- Motor Design: Firstly, the specifications of the PMSM are defined. These specifications include parameters such as rated power, voltage, current, speed, torque, and physical dimensions. The motor model is created using design software such as Ansys Maxwell. Details like the number of poles, slot geometry, winding configuration, and magnet material are specified.
- Magnet Arrangement: The arrangement of magnets within the motor structure is determined. Permanent magnets are typically mounted on the rotor surface and interact with stator windings to produce torque.
- Finite Element Method (FEM): FEM techniques are used to analyze the electromagnetic performance of the motor design. This involves solving Maxwell's equations to calculate magnetic flux distribution, induced currents, and electromagnetic forces within the motor.
- Fault Definition: Adjustments are made within the PMSM model to simulate the broken magnet scenario. Changes are made to the shape, size, or magnetic properties of one or more magnets to simulate them being partially or fully damaged.
- Stress Analysis: Stress analysis is conducted to evaluate the mechanical effects of the broken magnet within the motor structure. Mechanical stress, deformation, and vibration are considered to assess the structural integrity of the motor under fault conditions.
- Performance Evaluation: The performance of the PMSM under normal and fault conditions is assessed. Parameters such as torque-speed characteristics, efficiency, power factor, and electromagnetic noise are measured to evaluate the impact of the broken magnet on motor operation.
- Fault Detection Algorithm: A fault detection algorithm is developed and implemented using machine learning techniques. By training the algorithm with data based on motor performance indicators, such as Convolutional Neural Networks (CNN) or Support Vector Machines (SVM), the presence of a broken magnet is accurately detected.
- Testing and Validation: The motor design and fault detection algorithm are validated through experimental testing.

By comparing simulation results with experimental data, the accuracy and effectiveness of the proposed design and detection method are verified.

Ansys Maxwell plays a pivotal role in both designing and analyzing PMSM, offering a comprehensive platform where machine characteristics can be meticulously defined and parameters seamlessly incorporated. This software not only furnishes a detailed depiction of the studied machine's specifications, as delineated in Table 1, but also facilitates the visual representation of the PMSM design, as illustrated in Figure 1. Moreover, Ansys Maxwell empowers engineers to specify the materials used in magnet formation and simulate faults within the rotor assembly.

The extent of rotor damage, quantified by the number of broken magnets, is meticulously determined for each case, as elucidated in Figure 2. Through these capabilities, Ansys Maxwell serves as an indispensable tool in the meticulous design and fault analysis of PMSMs, providing engineers with the insights needed to optimize motor performance and reliability.

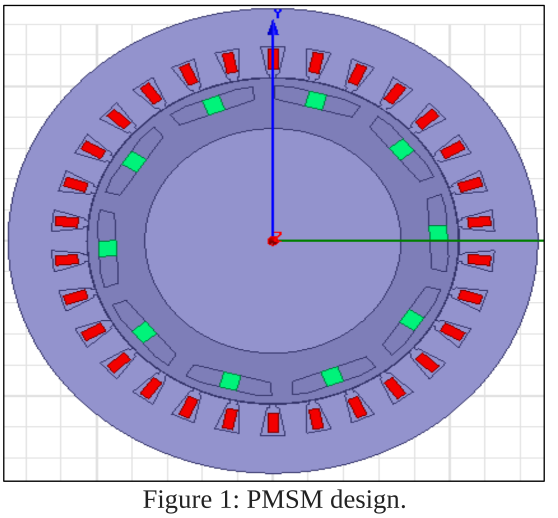


Figure 1: PMSM design.
Source: Authors, (2024).

Table 1: Design parameters.

Component	Value
Diameter stator outer / inner	300 mm / 211mm
Diameter rotor outer / inner	210 mm / 145mm
Rotor and stator material	steel M27_29G
Magnet material	Br=0.39T, Mu=1.1
Stator slots	30
Number of poles	10

Source: Authors, (2024).

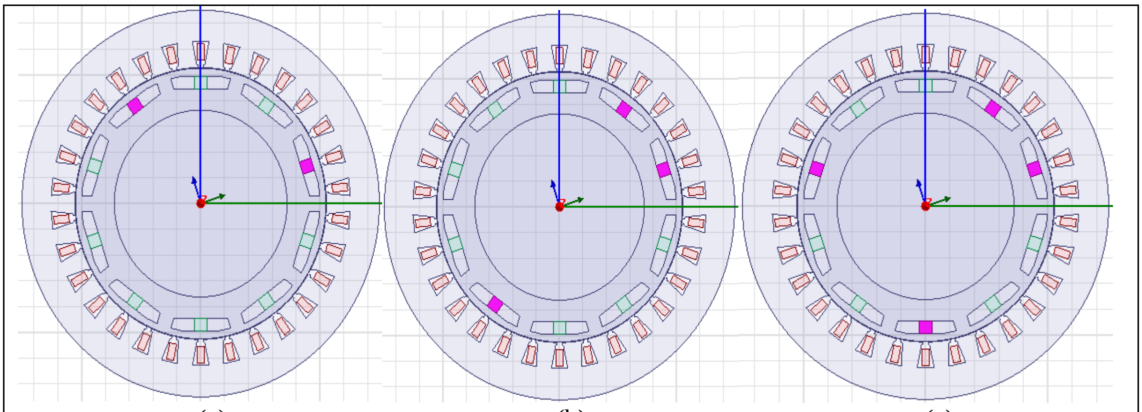


Figure 2: Broken magnets fault: (a) 2 BM, (b) 3BM, (c) 4BM.
Source: Authors, (2024).

III. SUGGESTED ALGORITHMS

III.1 SUPPORT VECTOR MACHINE

Support Vector Machine (SVM) is a powerful supervised learning algorithm used for classification and regression tasks. It is particularly effective in scenarios where the data is complex and not linearly separable. SVM works by finding the optimal hyperplane that best separates the data points into different classes while maximizing the margin, which is the distance between the hyperplane and the nearest data points of each class.

The key idea behind SVM is to transform the input data into a higher-dimensional space using a kernel function. In this higher-dimensional space, the data points become more separable, allowing for the construction of a hyperplane that effectively separates different classes. One of the main advantages of SVM is its ability to handle high-dimensional data and effectively deal with overfitting. Additionally, SVM has been shown to perform well even with relatively small training datasets.

SVM can be used for both classification and regression tasks. In classification, the goal is to predict the class label of new data points, while in regression, the goal is to predict a continuous value. Overall, SVM is a versatile and powerful machine learning algorithm that has been successfully applied in various domains, including image recognition, text classification, and bioinformatics.

SVM is a model for classifying data that relies on separating classes with equal limits through a dividing line between the support vectors of the data and the hyperplane [21], [22], which is the resolution, as Figure 3 shows.

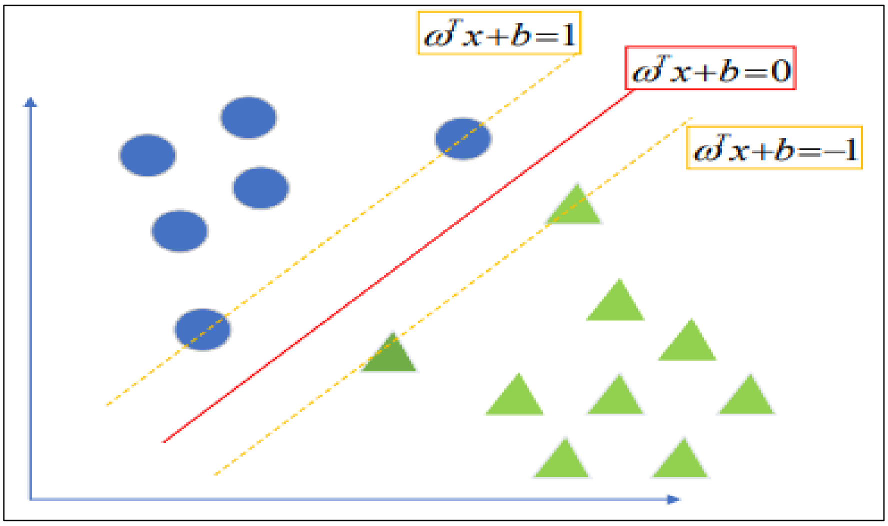


Figure 3: Support Vector Machine principles.
Source: [21].

III.2 K-NEAREST NEIGHBORS

The k-Nearest Neighbors (k-NN) algorithm is a simple yet effective supervised learning method used for classification and regression tasks. It is a non-parametric algorithm, meaning it does not make any assumptions about the underlying data distribution.

In k-NN classification, the algorithm works by finding the k nearest data points (neighbors) to a given query point based on a distance metric, typically Euclidean distance. The class label of the query point is then determined by a majority vote among its k nearest neighbors. For example, if k=3 and two neighbors belong to class A and one neighbor belongs to class B, the query point will be classified as class A.

In k-NN regression, the algorithm predicts the output value for a given query point by averaging the output values of its k nearest neighbors. This can be useful for predicting continuous variables. One of the main advantages of the k-NN algorithm is its simplicity and ease of implementation. It does not require training a model in the traditional sense, making it suitable for online learning scenarios where new data points are continuously added to the dataset.

However, k-NN has some limitations, such as being computationally expensive for large datasets since it requires calculating distances between the query point and all other data points. Additionally, the choice of the parameter k can significantly impact the performance of the algorithm, and it may not perform well in high-dimensional spaces. Overall, k-NN is a versatile algorithm that can be used for both classification and regression tasks, especially in scenarios where the dataset is small or the underlying data distribution is unknown.

KNN is a machine learning algorithm used to classify data and extract features based on the number K of neighbors. The distance between the unclassified sample and the rest of the samples is calculated, and the classification class is determined by determining the smallest distance to the largest number of neighbors [23],[24].

III.3 CONVOLUTIONAL NEURAL NETWORK

A Convolutional Neural Network (CNN) is a type of deep learning algorithm commonly used for analyzing visual imagery. It is particularly well-suited for tasks such as image classification, object detection, and image segmentation. CNNs are inspired by the organization of the visual cortex in animals, where neurons in the brain respond to specific stimuli located in a small region of the visual field, known as the receptive field. Similarly, CNNs consist of layers of interconnected neurons organized in a hierarchical manner, each layer processing increasingly complex features of the input image. The key components of a CNN include [25],[26]:

- Convolutional Layers: These layers apply a set of learnable filters (also known as kernels) to the input image to extract various features, such as edges, textures, and shapes. Each filter slides across the input image, performing element-wise multiplication and summing the results to produce a feature map.
- Pooling Layers: Pooling layers downsample the feature maps produced by the convolutional layers, reducing the spatial dimensions of the input. This helps to make the network more robust to variations in input images and reduces the computational cost.
- Activation Functions: Non-linear activation functions, such as ReLU (Rectified Linear Unit), are applied to the feature maps to introduce non-linearity into the network and enable it to learn complex patterns and relationships in the data.
- Fully Connected Layers: These layers connect every neuron in one layer to every neuron in the next layer, allowing the network to learn high-level representations of the input features and make predictions.
- Loss Function: The loss function measures the difference between the predicted output of the network and the true labels. It serves as a feedback signal to update the network's parameters during the training process.

CNNs are trained using large datasets of labeled images through a process called backpropagation, where the network learns to adjust its parameters to minimize the loss function. Once trained, CNNs can accurately classify and analyze images, making them widely used in various applications, including computer vision, medical imaging, and autonomous driving [27],[28]. The working principle of CNN is shown in Figure 4.

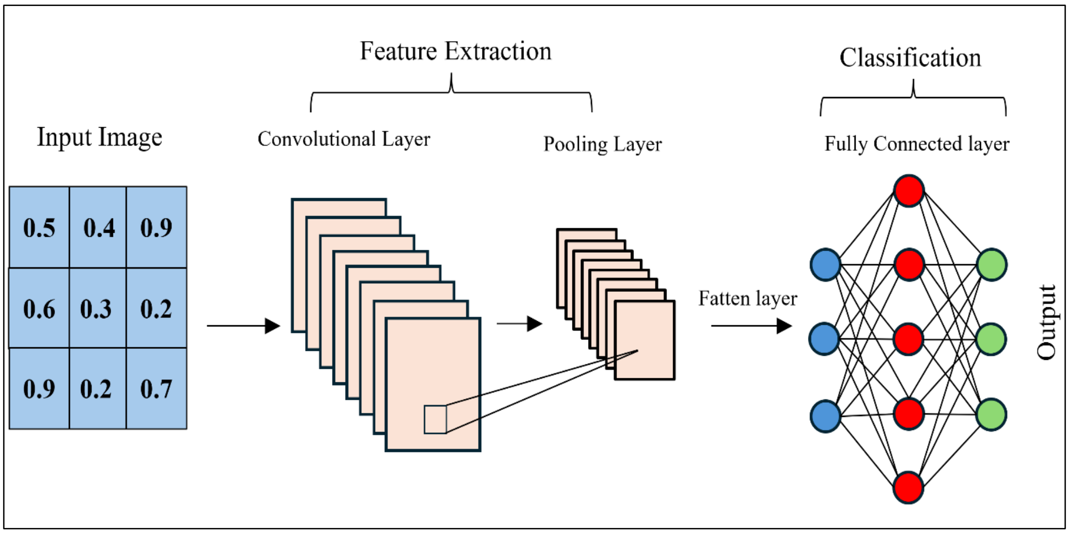


Figure 4: Architecture of a CNN.
Source: Authors, (2024).

IV. RESULTS AND DISCUSSIONS

During the operation of the machine, spanning from 0 seconds to 0.2 seconds, a meticulous examination of the magnetic flux density across different regions of the apparatus was conducted. Notably, as time progressed, discernible variations in the distribution of magnetic flux density emerged, delineated in detail in Figure 5.

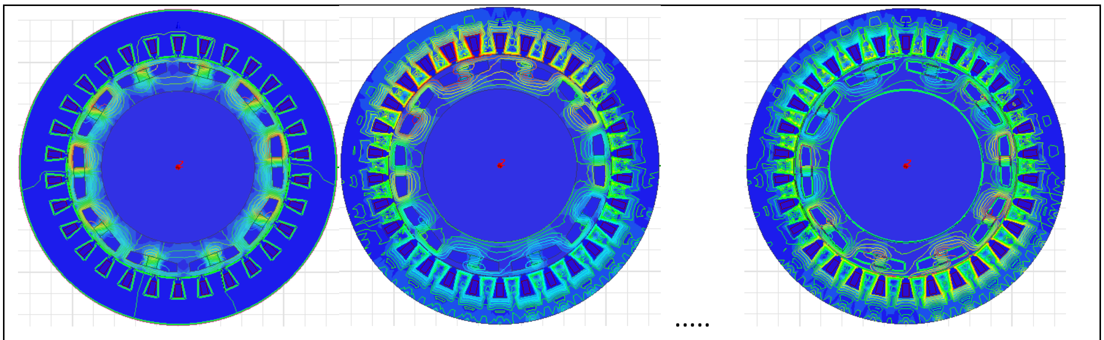
To further scrutinize the performance of the machine, a deliberate fault was induced at the magnet level, warranting an in-depth analysis of the magnetic flux density in each distinct scenario. This meticulous study enabled the collection of pertinent images crucial for the subsequent detection and diagnosis of magnet breakage, employing the robust capabilities of Convolutional Neural Networks (CNN).

Figures 6, 7 and 8 offer comprehensive visualizations of magnet breakage instances, showcasing the distinct magnetic flux density distributions observed in each case. Leveraging the power of CNN, these images serve as invaluable inputs for the classification process.

The convolutional process, pivotal in CNN's functionality, is adeptly employed utilizing a filter mechanism to extract fundamental features inherent in the collected images. Subsequently, based on the extracted features, classification into either a healthy state or a fault state is determined, as succinctly illustrated in Figure 9.

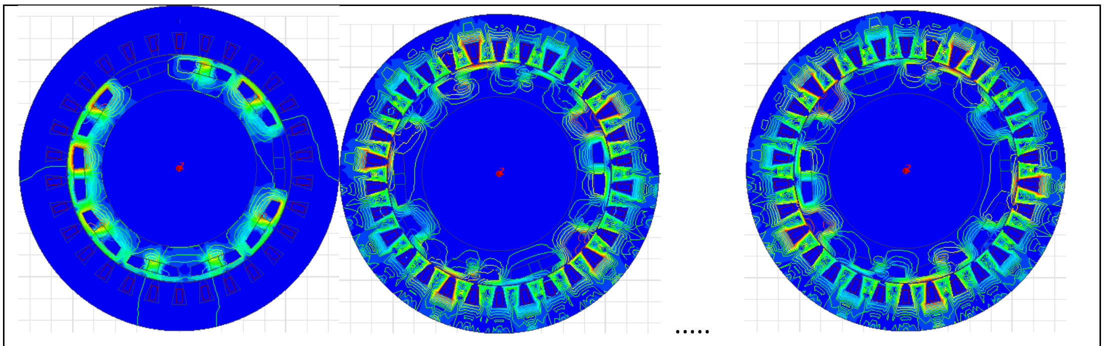
Through this meticulous process, CNN effectively discerns and categorizes the state of the machine, facilitating prompt diagnosis and remediation of potential faults.

Table 2 shows the structure and parameters used in the CNN algorithm



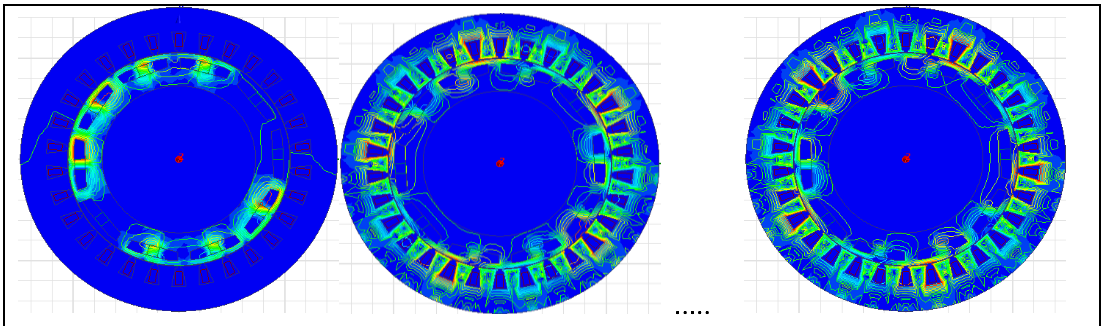
(a) (b) (c)

Figure 5: healthy case: (a) t=0s, (b) t=0.13s, (c) t=0.2s.
Source: Authors, (2024).



(b) (b) (c)

Figure 6: 2MB fault case: (a) t=0s, (b) t=0.13s, (c) t=0.2s.
Source: Authors, (2024).



(c) (b) (c)

Figure 7: 3MB fault case: (a) t=0s, (b) t=0.13s, (c) t=0.2s.
Source: Authors, (2024).

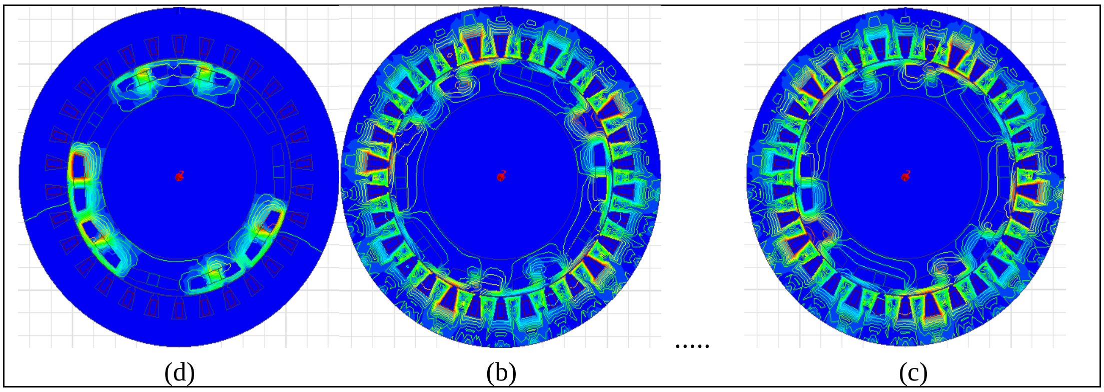


Figure 8: 4MB fault case: (a) t=0s, (b) t=0.13s, (c) t=0.2s.
Source: Authors, (2024).

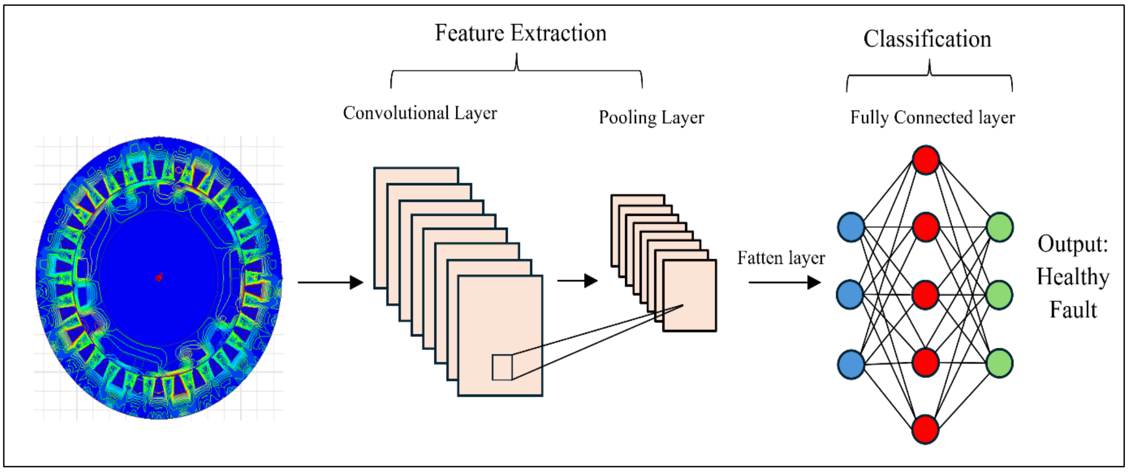


Figure 9: Health or fault status from images using CNN.
Source: Authors, (2024).

Table 2: CNN parameters.

Layer	Output Shape	Parameter
Conv2d (Conv2D) max_pooling2d (MaxPooling2D)	(None,438,438,16) (None,219,219,16)	4480
Conv2d (Conv2D) max_pooling2d (MaxPooling2D)	(None,217,217,32) (None,108,108,32)	46400
Conv2d (Conv2D) max_pooling2d (MaxPooling2D)	(None,106,106,64) (None,53,53,64)	184960
flatten (Flatten)	(None,179776)	0
dense (Dense) dense_1 (Dense)	(None,64) (None,1)	1150572865

Source: Authors, (2024).

Three distinct cases were meticulously delineated to evaluate the performance metrics of accuracy and loss across varying epochs. Through rigorous experimentation, it was discerned that the third case yielded superior results, showcasing enhanced accuracy and minimized loss, as visually depicted in Figures 10 and 11. By systematically varying the epochs, the CNN model was rigorously trained and fine-tuned to optimize its performance across different scenarios. The evolution of accuracy and loss metrics over successive epochs provides invaluable insights into the model's learning dynamics and convergence behavior.

These figures serve as comprehensive visual aids, succinctly summarizing the observed trends in accuracy and loss across the three identified cases. Notably, the superior performance exhibited by the third case underscores the efficacy of the training strategy employed, signifying a successful convergence towards an optimal solution. These findings underscore the importance of meticulous experimentation and parameter tuning in achieving robust performance outcomes in machine learning tasks. Through iterative refinement and evaluation, researchers can ascertain the most effective strategies for training CNN models to achieve desired performance objectives.

In Table 3, the accuracy of CNN is 100% compared to the rest of the techniques.

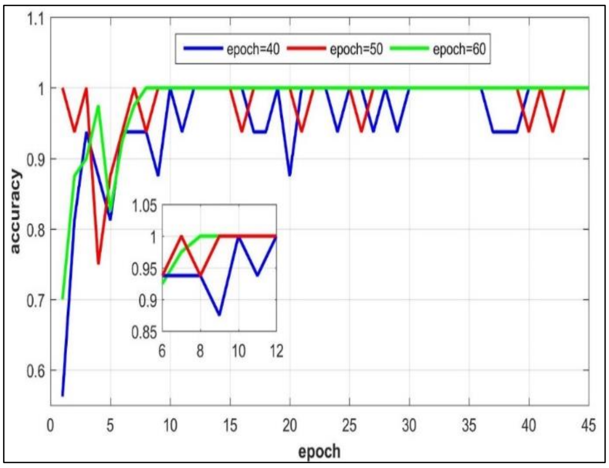


Figure 10: accuracy with epoch number.
Source: Authors, (2024).

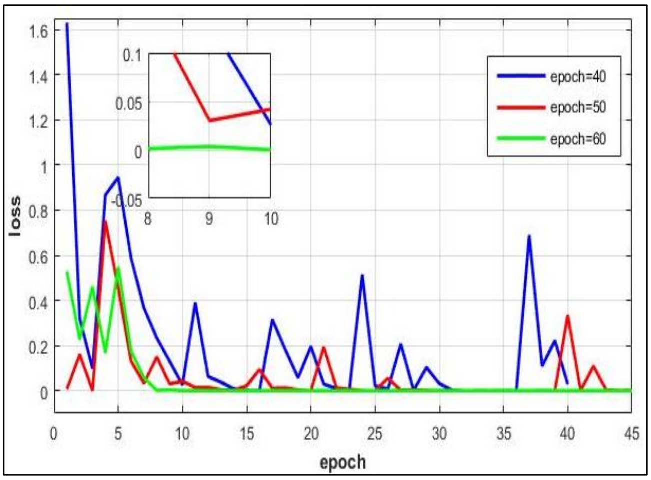


Figure 11: Loss by epoch number.
Source: Authors, (2024).

Table 3: accuracy.

Methods	Accuracy(%)
SVM	97
KNN	97
CNN	100

Source: Authors, (2024).

V. CONCLUSION

In the scope of this research endeavor, a novel approach utilizing both Convolutional Neural Network (CNN) and Support Vector Machine (SVM) algorithms was introduced to detect faults stemming from magnet breakage within the rotor assembly. The study encompassed three distinct cases categorized by the number of broken magnets: 2, 3, and 4, each representing varying degrees of fault severity. Leveraging sophisticated image processing techniques, these algorithms were adeptly deployed for fault classification based on meticulously selected features. Notably, magnetic flux density emerged as the focal parameter for this investigation, chosen for its efficacy in capturing subtle variations indicative of magnet breakage. The resultant findings, extracted through rigorous experimentation and analysis, underscore the remarkable capability of CNN in discerning and diagnosing faults within the rotor assembly. Through comprehensive evaluation, CNN demonstrated notable proficiency in accurately detecting and classifying fault instances, thereby showcasing its potential as a reliable tool for fault diagnosis in complex machinery such as PMSMs.

VI. AUTHOR’S CONTRIBUTION

Conceptualization: Said BENKAIHOUL, Lakhdar MAZOUZ, Toufik Tayeb NAAS, Özüpak YILDIRIM and Ridha Djamel MOHAMMEDI.
Methodology: Said BENKAIHOUL, Lakhdar MAZOUZ and Toufik Tayeb NAAS.
Investigation: Said BENKAIHOUL, Lakhdar MAZOUZ, Özüpak YILDIRIM
Discussion of results: Said BENKAIHOUL, Lakhdar MAZOUZ, Toufik Tayeb NAAS, Özüpak YILDIRIM and Ridha Djamel MOHAMMEDI.
Writing – Original Draft: Said BENKAIHOUL,Toufik Tayeb NAAS and Özüpak YILDIRIM.
Writing – Review and Editing: Said BENKAIHOUL, Lakhdar MAZOUZ, Toufik Tayeb NAAS, Özüpak YILDIRIM and Ridha Djamel MOHAMMEDI.
Resources: Said BENKAIHOUL and Özüpak YILDIRIM.
Supervision: Said BENKAIHOUL, Lakhdar MAZOUZ, Toufik Tayeb NAAS, Özüpak YILDIRIM and Ridha Djamel MOHAMMEDI.
Approval of the final text: Said BENKAIHOUL, Lakhdar MAZOUZ, Toufik Tayeb NAAS, Özüpak YILDIRIM and Ridha Djamel MOHAMMEDI.

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