A New Rotor Broken Bar Fault Diagnosis by Using CNN Based Current Signal of An Induction Motor

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***Abstract*— In industrial contexts, the efficient operation of induction motors is paramount, necessitating robust condition monitoring and fault diagnosis techniques to mitigate costly disruptions. In this study, we introduce an innovative approach for intelligent fault detection of broken rotor bars in induction motors, harnessing the "Signal2Image" method and convolutional neural networks (CNN). Leveraging a comprehensive current signal dataset from Aline Elly Treml Western Parana State University, encompassing various levels of broken rotor bar (BRB) faults and diverse loading conditions, our method automatically extracts essential features from input data. The "Signal2Image" process transforms time-domain current signals into 2D grayscale pixel images, facilitating CNN-based image classification to identify fault-related patterns. Through meticulous CNN parameter tuning, we achieve an impressive fault classification accuracy of 88% across all fault cases while optimizing computational efficiency. A significant contribution of this work is the substantial reduction in computational time for fault classification, surpassing existing approaches. This research enhances fault detection accuracy and streamlines the process, contributing to the field of predictive maintenance for induction motors.**

Keywords—broken bar fault diagnosis, convolutional neural network, deep learning, information fusion, signal-based fault diagnosis.

I. INTRODUCTION

A important step in preventing the hazardous condition in the industrial system is system fault diagnosis. The development of smart manufacturing has given rise to a new trend: intelligent problem diagnostics. The amount of data being generated in businesses today is increasing, and it can be gathered more quickly and widely than ever before [1]. As a result, there is a greater need for data analysis techniques to find hidden relationships in the massive amounts of mechanical data in order to support intelligent fault diagnosis. Model-based online data-driven methods, signal-based methods, and knowledge-based history data-driven methods can all be utilized for fault identification and diagnosis, depending on the data process and the data type [2]. The data-driven strategy, sometimes referred to as the knowledge-based approach, has gained significant attention in recent years [3]. The first well-known artificial intelligence method that was used for fault diagnostics was published in the 1980s [4]. The data-intensive machine learning approach has been applied in the manufacturing sector's decision-making process [5]. However, because most machine learning techniques struggle with raw signals, feature extraction from signals becomes crucial and significantly influences how well a machine learning technique predicts the future. However, this drawback has been overcome since deep learning has become a new possible strategy in the field of artificial intelligence. Deep learning has the capacity to automatically represent features of the raw data [6].

The main benefit of deep learning is that the represented features can reflect more in-depth, typical properties of the raw data and are not biased by the engineers. A traditional deep learning technique is the convolutional neural network (CNN), which has been effectively used in a wide range of scientific, engineering, and commercial fields. A common version of CNN dubbed AlexNet was proposed by Alex Krizhevsky et al in 2012, and it was hailed as a breakthrough on the challenging task of large-scale image classification [7].

The convolution layer and weight-shared architecture of CNN, which can achieve the translation invariance feature of images, make it unique. In this study, a brand-new data-driven CNN-based intelligent defect diagnostic method is suggested. Prior to submitting the data to the learning system, the majority of data-intensive methods require a prescribed complicated data preprocessing.

The studied method's key highlight is the investigation of a time-domain learning system using a new straightforward data preparation technique. This technique converts time-domain signals into image data before suggesting a deep CNN to categorize the image data. The outcome demonstrates that this approach produces positive results. The remainder of this work is structured as follows: In Section II, a CNN-based intelligent fault diagnosis is presented. An experiment has been done, and the findings are explained in Section III. Section IV is the conclusion.

II. PROPOSED INTELLIGENT FAULT DIAGNOSIS BASED ON CNN

A. The Convolutional Neural Network

A unique type of artificial neural network is the CNN (ANN). Each neuron of the feature map in each layer is only loosely connected to a small number of neurons in the previous layer, in contrast to the fully connected ANN. The idea of simple and complicated cells in the visual cortex of the brain [8] and the presence of some cells in the visual cortex that are only responsive to a local receptive field [9] served as inspiration for this.

In CNN, there are three main layers: Convolutional layer, pooling layer, and fully linked layer are the first three. Raw photos make up CNN's input data. It is often a 2-dimension datatype. The feature maps of the input images are obtained by the convolutional layer by applying a predetermined number of filters. To decrease the size, the pooling layer down samples the data images. To classify the output, a fully connected layer is then applied, and a softmax regression is then used. It receives 28×28 photos as input. The model consists of a one-layer fully connected ANN, two convolutional layers, and pooling layers. A modified CNN is created in this study to handle the classification task for fault diagnosis. The concepts in more depth are covered in the part after this one, and CNN is created using tensorflow.

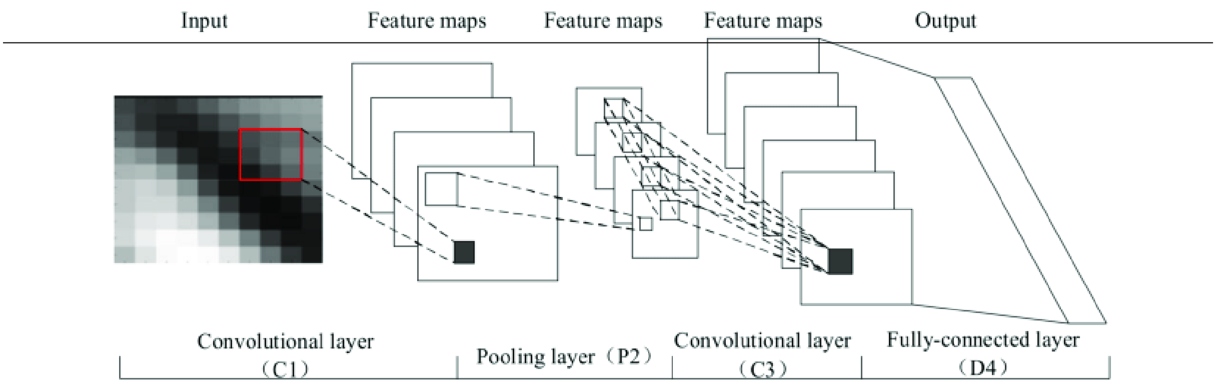

Fig. 1. Structure of a typical convolutional neural network (CNN)[10]

B. *A Signal2image Transformation (Information Fusion)*

Traditional data-driven fault diagnostic methods mine signal patterns from large volumes of historical data using statistical analysis, fuzzy logic expert systems, or neural networks. In this study, a new data preprocessing approach for converting signals to images in order to investigate the 2D feature of the signals is studied [9]. Fig.2 depicts the change. Because the signals are being sampled in time, each time, acquire a 2 × M length signal to obtain a picture of M × M size. Each image has been individually adjusted from 0 to 255. L(i),i=1... M^2 signifies the signal value, and P(j,k) is the picture pixel strength. There are connections:

$$P(j,k) = \frac{L(j\times M+k)-Min(L)}{Max(L)-Min(L)} \times 255 \quad (1)$$

III. CASE STUDY AND RESULT ANALYSIS

In this section, the setup and the data are presented first. Following that, the results of the testing and signal transformation are presented. The discussion of this case study is presented below.

A. *Data Description*

In this study, we utilized the open-source motor current dataset from Aline Elly Treml at Western Parana State University (AETWPSU) to detect and diagnose broken rotor bars in a three-phase induction motor as shown in fig.3. This dataset contains electrical and vibration signals obtained during experiments on the motor [12]. We specifically focused on the electrical signal dataset, which includes stator current signals for all three phases. The experimental setup involved a three-phase induction motor connected to a direct current (DC) machine acting as a generator to simulate load torque. These two motors were linked by a shaft with a rotary torque wrench.

The specifications of the induction motor are as follows: 1hp, 220V/380V, 3.02A/1.75A, 4 poles, 60 Hz, with a nominal torque of 4.1 Nm and a rated speed of 1715 rpm. The rotor in the induction motor is a squirrel cage type with 34 rotor winding bars. Load torque variations were achieved by adjusting the field winding voltage of the DC generator using a full-bridge rectifier. Testing was conducted at 12.5%, 25%, 37.5%, 50%, 62.5%, 75%, 87.5%, and 100% of full load.

The dataset includes recordings of four broken rotor bars and one healthy rotor bar is seen in Table I. Current signals were simultaneously sampled from all phases for 20 seconds, with ten repetitions for each loading condition. The current signals were measured using an alternating current probe (Yokogawa 96033) with a capacity of up to 50 ARMS and an output voltage of 10 mV/A. The data provides ten repetitions for each phase current signal under different loading conditions.

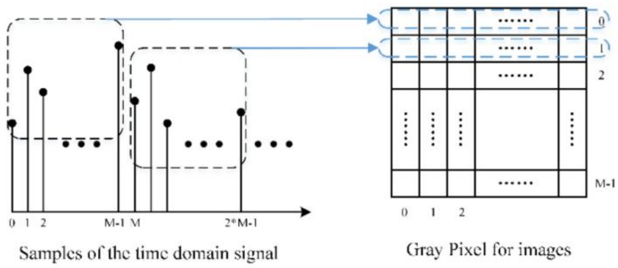

Fig. 2. The Signal-to-image Transformation method [11]

TABLE I. DETAILED DESCRIPTION OF AETWPSU DATASETS

Fault Mode	Description
Health State (N)	the normal rotor
BB_1R	Rotor broken bar fault 01
BB_2R	Rotor broken bar fault 02
BB_3R	Rotor broken bar fault 03
BB_4R	Rotor broken bar fault 04

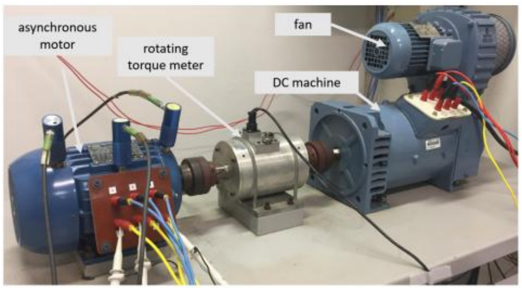

Fig. 3. Experimental setup of Dataset [12]

B. Signals Convert to Images

The image size is set to 28×28. All of the images are grayscale, with 784 pixels per image. Fig.4 depicts the remaining 5 types of image samples. The data collects a large number of M^2 segments to create the dataset. The training dataset has 7006 samples for each fault type, whereas the testing dataset contains 3002 samples for each fault type. The results of the tests are listed below.

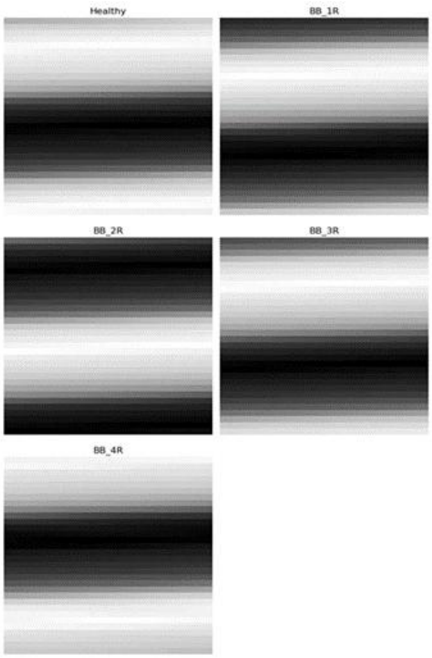

Fig. 4. Converted images on fourteen fault conditions.

C. Result of Proposed CNN

The CNN created specifically for this testing. Table II depicts their structures. CNN has two Conv-Maxpool layers, with a stride of 1 for the Conv and Maxpool operators. This CNN is developed in Tensor flow 2.10.0 and runs on Windows 11. In the training process, the batch size is set at 200. The final prediction result in the test data set is shown in Fig.5. The convergence speed of prediction accuracy is rapid. CNN has achieved satisfactory results, as seen in Fig.5

TABLE II. THE LAYER CONFIGURATION OF CNN

LAYER NO	LAYER CHARACTERISTICS
1	Convolution (32 filters, kernel size = 3)
2	MaxPooling (Pool size = (2,2))
3	Convolution (64 filters, kernel size = 3)
4	MaxPooling (Pool size = (2,2))
5	Flatten layer
6	Dense layer (Units = 128)
7	Dense layer (Units = 14)
9	Output layer (Units = 5)

D. Result Analysis

To validate the efficacy of our proposed CNN-based intelligent defect diagnostic method, we conducted a comprehensive comparative analysis with several standard statistical methods and deep learning techniques on the case study dataset. Our goal was to demonstrate the superior performance of the suggested CNN approach in fault diagnosis for induction motor

Upon comparing the prediction results with existing methods, it is evident that our CNN model outperforms the alternatives. The forecast accuracy achieved by our CNN model is 88%, surpassing the prediction values of other methods. Specifically, the Deep Belief Network (DBN) and DBN Based HDN methods yielded prediction accuracies of 87.45%, while the Support Vector Machine (SVM) method achieved an accuracy of 87.45%. The traditional Artificial Neural Network (ANN) approach, often used in similar contexts, demonstrated a significantly lower accuracy of 67.7%, emphasizing the superior predictive power of our CNN-based model.

Fig.6 illustrates CNN's confusion matrix The rows represent the actual label, while the columns represent the anticipated label for each class. As a result of this, first conditions were predicted with 82% accuracy, followed by two conditions with an accuracy of 87% and 88%.

Additionally, we employed t-SNE [13] projection to visualize the data-driven traits for each fault category on a low-dimensional surface. Fig. 7 showcases the discrete clusters formed by the activation patterns during the testing phase, further confirming the CNN model's ability to separate and classify fault conditions effectively.

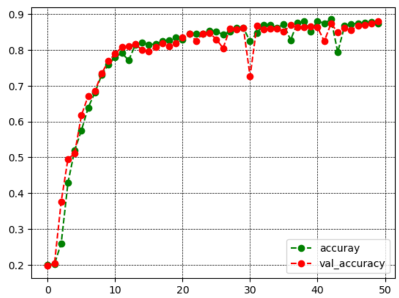

Fig. 5.The prediction on testing dataset of the proposed CNN

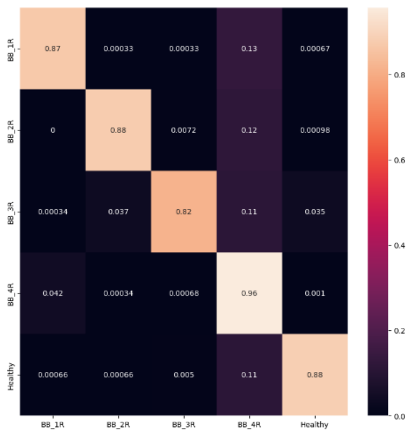

Fig. 6. The confusion matric of the prediction result on CNN

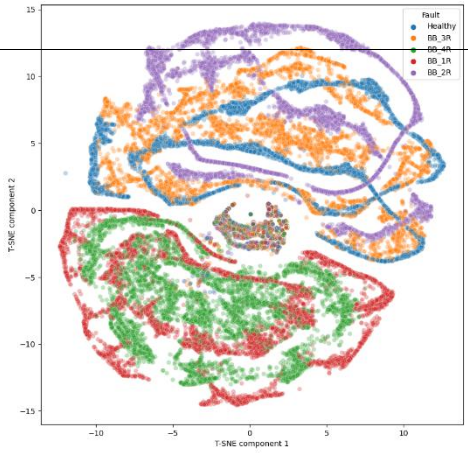

Fig. 7. t-SNE projection of activations of test data

E. Discussion

This case study demonstrates the potential of the suggested CNN. It investigated its two-dimensional features after transforming signals into images using a transformation technique. It surpasses the accuracy of conventional ANN and SVM by a large margin, reaching 88%. The success of this approach was shown by the results, which outperformed those of other deep learning techniques. Additionally, we might reduce expert bias and increase the usefulness of the proposed method by employing the recently advocated data pretreatment technique in this study.

IV. CONCLUSION

In this work, a new intelligent fault diagnosis method is presented. One study the utilization of the signals to pictures transformation and the subsequent creation of a new CNN network. The suggested method yields positive results on the motor current dataset provided by Aline Elly Treml Western Parana State University. The result shows how the newly suggested data preparation method helped CNN get a great result. Thus, this strategy can lessen the expert's bias. With a prediction rate of up to 88%, the suggested strategy shows promise in the area of intelligent diagnostics. To advance the investigations in the future, the following actions can be taken. First, there is no upper limit to building a stronger CNN. Second, more well-known testing needs to be conducted. Third, this approach is expandable to allied fields like online fault diagnostics.

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