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RESEARCH ARTICLE

Few-Shot Lightweight SqueezeNet Architecture for Induction Motor Fault Diagnosis Using Limited Thermal Image Dataset

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ABSTRACT In the realm of renewable energy, wind turbines play a pivotal role in efficiently harnessing wind power, especially in offshore environments, where their significance is amplified. These turbines require vigilant monitoring due to the elevated risk of operational faults. Moreover, vast labeled data is scarce in industrial settings due to the cost associated. Hence, there is a need for fault diagnosis methods that can diagnose precisely with minimal data. This research addresses that problem by proposing an architecture built using prototypical network, few-shot learning, and a modified ultra-lightweight SqueezeNet model specifically made for fault diagnosis. Central to our approach are thermal image datasets captured through infrared (IR) cameras, which enable the detection of subtle temperature variations indicative of faults. The proposed architecture excels in data scarcity. It can swiftly generalize from limited samples, thus reducing the dependence on extensive labeled data and reducing training time. Moreover, the modified model stands out for its highly efficient architecture, featuring 16x lower trainable parameters than SqueezeNet. Despite being ultra-lightweight, our model outperforms the original SqueezeNet by achieving 98% accuracy, 10% higher than the original model, and achieves similar or greater accuracy than other models with significantly more trainable parameters. The proposed architecture achieves optimal computational efficiency while maintaining precise diagnostics. The potential of this technology lies in its ability to be used in real-time fault diagnosis applications on lightweight devices.

INDEX TERMS Few-shot learning, fault diagnosis, deep learning, limited data, prototypical network, induction generator, offshore wind turbine, inter-turn faults, condition monitoring, infrared thermal imaging.

I. INTRODUCTION

Fault diagnosis has received much attention recently, especially in the context of data-driven methodologies used with condition monitoring data [1]. One of the most common electric motors today, induction motors, is crucial in operating various industrial and commercial applications. However, numerous issues can affect induction motors and cause costly repairs and downtime. By monitoring the temperature distribution of the motor, thermal imaging is a non-destructive diagnostic method that may be used to identify and diagnose problems with induction motors. Recent years have seen an increase in the importance of wind energy, which is now the foundation of both large-scale and small-scale energy systems, alongside considerable projected expansion in the coming years. According to the GWEC Global Wind Report 2023, approximately 380 GW of new offshore wind capacity will be installed over the next ten years, opening up a

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new market for the technology [2]. Onshore wind turbines are built on land and use the air's natural movement to produce energy. Offshore wind turbines are situated at sea and use the stronger winds that travel over the ocean in a more predictable direction than they do on land to produce power.

In contrast to offshore wind farms situated at sea, onshore wind farms are often found in rural regions with few structures to impede the wind. Because the winds at sea are more robust and reliable, offshore wind farms can produce more power than onshore wind farms. Offshore wind farms are desirable for this effort because of these advantages. When acceptance costs are considered, onshore wind development does not offer a definite cost advantage over offshore wind development, according to research in [3]. In addition, they cost more to operate and maintain, accounting for between 10 and 35 percent of their overall life costs, and are more likely to fail or malfunction [4]. To save maintenance costs and operational hazards and prevent catastrophic consequences, it is essential to detect generator degradation and electrical faults in offshore wind systems early. Therefore, deep learning (DL) approaches have evolved over the past several years to aid in defect identification and cost reduction [5], [6]. Researchers have been employing various techniques to identify defects in advance and maintain the motors appropriately to last a long time and save money on motor repair.

Data scarcity poses a significant challenge in fault diagnosis, particularly in industries reliant on machinery, compared to other classification or detection problems [7]. Obtaining data from these systems is often rare and costly, hindering the development of accurate diagnostic models. Due to the high expense and logistical constraints associated with collecting sufficient data, fault diagnosis processes are frequently impeded, leading to increased downtime, maintenance costs, and operational inefficiencies. Traditional deep-learning models require a large amount of data to achieve exceptional performance, which may not be a feasible option in this scenario [8]. As a result, strategies for effectively leveraging limited data resources become paramount in the pursuit of robust fault detection and prevention methodologies. The limited and expensive nature of machinery data amplifies the complexity of fault diagnosis tasks, necessitating innovative approaches to overcome these obstacles and ensure accurate and timely detection of potential issues.

Few-shot learning strategies attempt to enhance the capabilities of conventional machine learning (ML) and DL approaches by training models using a few labeled samples [9]. A model is trained to produce accurate predictions using a few instances from each class in the ML paradigm known as few-shot learning. Despite having little training data, the model can generalize effectively to new, unknown data thanks to this method [10].

This research paper introduces a new few-shot learning architecture for diagnosing induction motor faults using thermal imaging. Despite having a relatively light design and minimal training parameters, it achieves extremely high accuracy. The thermographic picture dataset used in the study had relatively small data. Thus, few-shot learning was the ideal method to find errors without the requirement of data augmentation. The dataset was first introduced in [11] and was applied in [12] and [13] for fault diagnosis. The previous work used complex methods to identify the part of the image that is most important for diagnosis. The proposed system takes a different approach, making the process faster and more efficient. This significant improvement makes the system more practical for use in the real world. For example, it could be a viable option in portable devices that have low computational capability to diagnose motor failures on the go.

This study makes several significant contributions to wind turbine fault diagnosis. These contributions collectively enhance the state-of-the-art in renewable energy infrastructure monitoring and are as follows:

- We introduce a modified SqueezeNet model that is designed to be flexible with input size to tackle the challenging task of fault diagnosis while being extremely lightweight. Our novel approach offers a resource-efficient solution that does not compromise accuracy, making it an ideal candidate for real-world applications
- We propose a prototypical network driven few-shot learning strategy to increase the flexibility of our model in settings with minimal data, as data is extremely limited and expensive in industrial fault diagnosis. This model can successfully generalize from small samples, decreasing the need for large amounts of labeled data and speeding up training.
- Thermal image datasets obtained from IR cameras play a crucial role in our strategy. This creative application of IR imaging enables us to gain unique insights into the temperature changes within wind turbine components. By identifying minor temperature anomalies early on, we can proactively spot flaws and prevent potential issues beforehand.
- In this research, we employed several models, such as ResNet-18, ResNet-50, ShuffleNet, DenseNet, MobileNetv3 Large, and the original SqueezeNet, to test and compare the effectiveness of our proposed model. This has allowed us to assess the reliability of our model. Through this evaluation process, we gained valuable insights into the performance of our model.

The remainder of the paper is organized as follows. Section II is the literature review. Moreover, the proposed methodology in this study is described in section III. In section IV, we have discussed our findings. Finally, in section V, we discussed our result and compared it with other related studies. In section VI, we concluded our research study.

II. LITERATURE REVIEW

Wind turbines play a pivotal role in the global shift towards sustainable energy sources [14], [15]. However, their reliable and uninterrupted operation is contingent upon effective fault diagnosis and maintenance [4]. Strong winds, temperature variations, and mechanical wear are just a few of the environmental stressors that wind turbines are subjected to [16], [17], which can lead to an array of potential defects and failures. Not only is it essential to identify and address these issues as soon as possible, but doing so will also prolong the life of wind turbines while increasing energy output and reducing maintenance costs [18]. The requirement for fault diagnosis in wind turbines becomes even more apparent when considering the growth in scale of wind farms and the connection of the turbines to the broader energy grid. According to a study conducted in [19], a single defective turbine in a wind farm can have a domino impact on electricity output and grid stability. Therefore, there is a pressing need for advanced and accurate fault diagnosis methods that can identify issues swiftly, allowing for targeted maintenance and minimizing disruptions in energy production.

In this context, researchers and engineers have been exploring innovative techniques to improve fault diagnosis capabilities in wind turbines. Among these approaches, DL methods have gained substantial attention for their ability to analyze and interpret complex data automatically [20], including thermal data, as shown in [21], which can be instrumental in detecting thermal anomalies associated with faults. Another study conducted in [22] has a different point of view and incorporates a hybrid approach in fault diagnosis on an enormous scale. This paradigm shift in fault diagnosis is also evident in recent studies. Authors in [23] and [24] have taken hybrid approaches where the former study divides the methodology into three different segments, and the latter has achieved an F1-score of 0.998 with an input size of only 32×32 in a Hilbert transformed dataset and a long short-term memory (LSTM) based model, demonstrating the recent advances in the field of fault diagnosis from traditional DL to hybrid methods.

In addition to hybrid methods that fuse DL techniques with other procedures, Transfer Learning techniques have also been applied to enhance the performance of DL models in wind turbine fault diagnosis. Researchers leverage pre-trained models, often trained on vast image datasets, and fine-tune them on wind turbines [25], [26], [27]. This approach capitalizes on the knowledge and feature extraction capabilities embedded in pre-trained models, significantly reducing the need for extensive labeled training data and accelerating model development, as shown in research conducted in [28] and [29].

In recent years, few-shot learning, a specialized area of ML, has gained prominence in wind turbine fault detection due to the scarcity of labeled data for rare faults. The study [30] sheds some light on the potential of few-shot learning and its prospects. Authors in [31] propose a novel few-shot learning based technique to diagnose faults in bearing data while also comprehensively comparing one-shot and few-shot approaches. This study achieves notable accuracy with a minimal amount of data. Another study conducted in [32] introduces another model adept at extracting vector features with the help of auto-encoders, achieving satisfactory results even under noisy environments. Already established models can also be incorporated into few-shot learning with a few tweaks to make it suitable to detect intricate textures resembling faults in machines, especially wind turbine gearboxes, as [33] show.

Alongside these, several feature extraction techniques and methodologies have been introduced that excel at detecting faults, especially in induction motors. A study [34] discusses the importance of transformer health monitoring and accurate fault diagnosis in minimizing equipment damage and improving the reliability of electric power systems. It proposes a novel transformer fault diagnosis method using ensemble machine learning and the Internet of Things (IoT). It includes two separate subsystems: one for data measurement and another for data reception, aiming toward benefits, such as low power consumption and long-term monitoring and addressing certain stress factors (electrical, mechanical, thermal, and environmental) that transformers experience; as these stresses can result in winding and core faults with significant impacts on the power grid. The system's potential impact on power grid reliability lies in its ability to provide real-time observation of the health status as well as accurate fault diagnosis for transformers, thereby reducing financial loss and improving the overall soundness of electrical power systems. Additionally, in a study [35], the authors proposed a Gabor filter and singular value decomposition based extractor that excels in noisy environments. Furthermore, a notable study [36] proposed a method utilizing 2D texture features and multiclass support vector machines, consistently achieving 100% classification accuracy, surpassing three existing fault diagnosis algorithms, even in noisy environments. Moreover, another study [37] discusses the challenges and methods for analog circuit fault diagnosis, emphasizing the importance of efficient feature extraction and the application of deep belief networks (DBN) for unsupervised feature extraction. The paper introduces the use of a quantum-behaved particle swarm optimization (QPSO) algorithm for generating optimal values for the DBN's learning rates and the support vector machine's (SVM) regularization parameter and width factor. Furthermore, the paper presents an analog circuit incipient fault diagnosis method using DBN-based feature extraction, SVM, and QPSO, with a discussion of the organization of the material. The paper demonstrates the effectiveness of the proposed method through a comparison with other typical analog circuit fault diagnosis methods, showing higher diagnosis accuracy. The proposed method addresses the challenges of analog circuit fault diagnosis and provides a promising approach for efficient and accurate fault diagnosis in analog circuits.

While significant progress has been made in the field of wind turbine fault detection, research is often focused on high-accuracy models that are resource-intensive and suitable for offline analysis, as summarized in Table 1. Therefore, a notable gap persists—namely, the absence of lightweight architectures designed for deployment on low-powered devices such as cell phones or IoT devices to detect faults reliably in real-time. In practical operational scenarios, particularly within wind farm environments, the demand for real-time or on-the-go fault diagnosis is undeniable. Extremely light and compact models would enable immediate fault assessments during routine checks or maintenance, minimizing downtime and optimizing energy production. As the wind energy sector grows, prioritizing lightweight architectures becomes paramount for reliable fault diagnosis and efficient renewable energy generation.

III. PROPOSED METHODOLOGY

Few-shot learning proves to be the optimal approach when confronted with insufficient training data, a common scenario in nascent or emerging industries and occupations demanding arduous or costly data collection, such as industrial defect detection. Employing few-shot learning techniques and extrapolating insights from a limited dataset facilitates the acquisition of these tasks. The proposed methodology advocates the utilization of a prototypical network featuring a lightweight convolutional neural network (CNN) comprising only seven layers, tailor-made for few-shot learning applications. This network incorporates Fire Modules, each consisting of a squeeze layer and two expand layers, effectively manipulating channel numbers in the input feature map to derive meaningful representations. In Fig. 1, the dataset under examination is revealed to originate from a 3-phase induction motor. Subsequently, an IR camera, as elaborated upon in later sections, is used to take different motor failure pictures, which makes it easier to compile a thermal dataset. To ensure robust model training and evaluation, the dataset is partitioned into testing and training sets in a balanced 50-50 ratio. The goal of keeping the distribution equal is to improve the model's ability to identify and extrapolate patterns between the two groups. The goal of this tactical strategy is to improve the model's overall performance when it comes to new, untested data. The balanced split gives the model an equal number of cases from each class throughout the training and evaluation stages, which promotes generalization and makes robustness testing easier. This methodical technique helps to provide a more accurate assessment of the model's performance in various circumstances. Under some conditions, a balanced dataset split becomes essential, especially where impartiality and justice are critical. By doing this, it is ensured that the assessment measures accurately represent the performance of the model and prevent distortion from class imbalances. The dataset's emphasis on balance is a fundamental component that fosters accuracy and fairness in performance evaluations.

Leveraging the principles of few-shot learning, a novel approach is adopted wherein two images from each class are randomly selected as support images, and four images from each class are designated as query images. This deliberate sampling strategy aims to enhance the model's ability to generalize and classify faults effectively with limited examples. Finally, the research culminates in the application of few-shot learning techniques in conjunction with a customized architecture tailored for fault classification in the thermal dataset.

Without a doubt, few-shot learning's distinctive approach to model training accounts for its efficacy in cutting training time and promoting quick generalization. There are a few important elements that contribute to these attributes. Few-shot learning often relies on meta-learning approaches, where the model learns "how to learn" from various "mini-problems" involving few-shot classification. When compared to typical large-scale training, this meta-learning feature shortens the total training time by enabling the model to adapt to new tasks with minimum further training [38]. Rather than remembering individual data points, few-shot learning models focus on learning correlations and similarities across classes, which allows them to perform well with fewer parameters. Faster training times result from this, particularly when working with constrained computational resources [39].

Fire modules are a type of neural network module that was designed to be computationally efficient while maintaining good accuracy [40]. It employs a combination of 1×1 and 3×3 convolutions to enhance efficiency without compromising accuracy, followed by a Rectified Linear Unit (ReLU) activation function upon concatenating the output feature maps. Fig. 2 illustrates the composition of fire modules, which consist of a squeeze layer and an expansion layer. The proposed architecture deviates from the original SqueezeNet design by changing the dimension of the first conv layer to 3×3, 64 and also excluding the final two Fire Modules. Instead of the AvgPool2d module, the AdaptiveAvgPool2d module is used, enabling the model to adapt to varying input sizes. In Figs. 2 and 3, it is demonstrated more clearly. This design is particularly suited for lightweight CNN requirements, such as mobile devices or embedded systems. SqueezeNet, a revolutionary convolutional neural network architecture, uses 50x fewer training parameters (4.3 million vs. 60 million) to attain AlexNet-level accuracy on the ImageNet classification test. With a mere 0.5 MB of compact model footprint, this significant size reduction allows for effective deployment and storage on devices with limited resources [40]. Additionally, fewer parameters mean much less memory and processing power needed for inference and training, which speeds up execution times for embedded and mobile devices. These benefits open the door for DL on edge devices and make SqueezeNet a very appealing choice for applications with constrained computing resources [40]. It proves advantageous in scenarios with limited training data, thanks to the mitigating effects of the Fire Module on overfitting risks. Despite having substantially fewer training parameters (approximately 73k), our architecture demonstrates comparable or superior accuracy to other CNNs in this research.

TABLE 1. Summary of several models and their limitations.

Ref.	Model	Accuracy	Limitations
[21]	Pre-trained VGG net	80% - 86.67%	Heavy network. 138M trainable parameters
[24]	Hybrid DCNN-LSTM	100%	Although light and highly accurate, this model still has around 1M parameters and may not be suitable for real-time fault diagnosis
[27]	Hybrid deep transfer learning	Above 90%	Complex and resource-hungry while demonstrating lower accuracy
[28]	Deep boosted transfer learning	92% - 99%	Complex model with 28 layers. Although noble and reliable, it may require more computational resources
[31]	Deep neural network based few-shot learning	77% - 97%	While good for limited data, the accuracy is still lower compared to other research
[33]	ALWM-ResNet	30% higher than original ResNet under noisy environment	ResNet has 11.7M - 64.9M parameters. Although the model achieves good accuracy in noisy labels, the complexity and the high parameter count of the ResNet render the approach as resource-intensive
[35]	Gabor filter and singular value decomposition	99.86%	The complexity of this approach may make it computational resource-hungry
[36]	Multiclass support vector machines	100%	The intensive feature extraction procedure may need computational resources and may not be suitable for real-time diagnosis

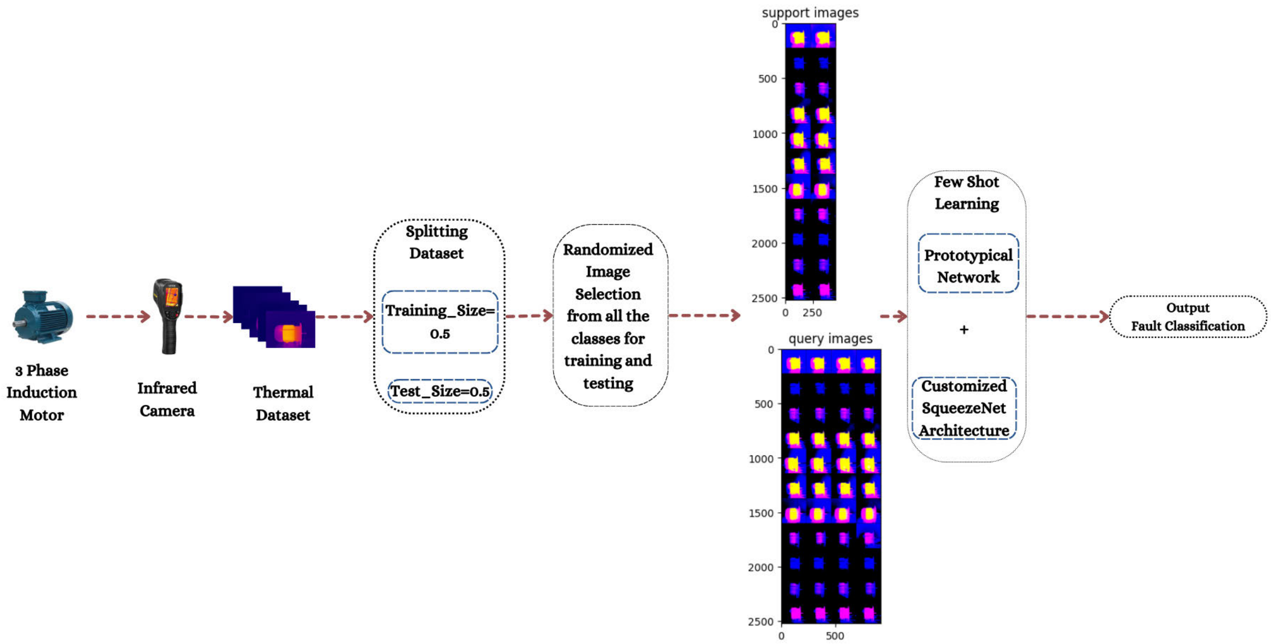

FIGURE 1. The methodology used in this study.

A. DATASET

In this study, stator defects were identified using the dataset of thermographic IR pictures introduced in [41]. The thermal images were captured using the Dali-tech T4/T8 IR thermal imaging camera, the specifications of which can be found in Table 2.

The proportion of shorted turns during the stator phase is indicated by the severity of the fault. On a 3-phase induction motor with a voltage of 380V, 50Hz frequency, 1.1kV, and with no load, the researchers conducted their tests, more briefly described in Table 3. They gathered thermal pictures of the motor under a variety of conditions, such as ''healthy'', ''blocked rotor,'' ''cooling fan failure,'' and ''8 inter-turn faults with varying severity and location''. To train a model to recognize problems with the stator in electric motors, this process produced a dataset of 11 fault classifications.

TABLE 2. Dali-Tech T8 thermal camera properties.

Property	Value
Resolution Capability	384 × 288
Exactness	±2°C or ±2% (of reading, which is greater)
Thermal Sensitivity	<0.04°C@30°C
Temperature Range Capability	-20°C-+650°C
Image Refresh Rate	50/60Hz

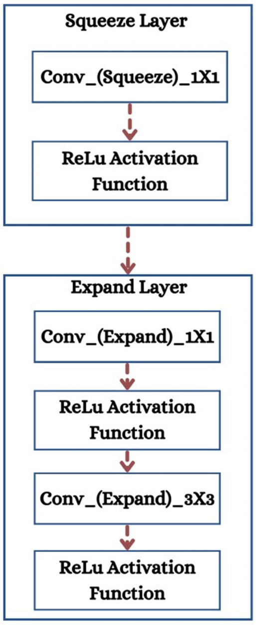

FIGURE 2. Workflow of the proposed methodology: Fire module.

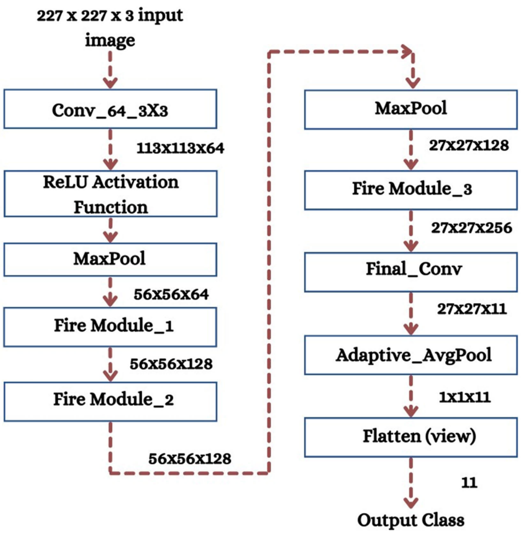

FIGURE 3. Design Framework of the proposed methodology: Custom architecture.

TABLE 3. Equipment specifications.

Property	Value
Type	Induction Motor
Phase	3
Power	1.1 kW
Voltage	220/380 V
Input Current	5 A
Speed	2800 RPM
Frequency	50 Hz

In Fig. 4, we have demonstrated the images of the dataset. An image from each faulty class is used to explain the dataset classes.

Table 4 shows the various categories of faults and corresponding numbers of images that require identification, categorized based on fault type and severity.

TABLE 4. Number of images in each field.

Type of Fault	Severity	Number of Images
Healthy	-	25
Cooling fan	-	28
Blocked rotor	-	30
Two-phase Internal(IT) fault	50%	38
Single-phase IT fault	50%	35
Three-phase IT fault	30%	42
Two-phase IT fault	30%	38
Single-phase IT fault	30%	37
Three-phase IT fault	10%	31
Two-phase IT fault	10%	31
Single-phase IT fault	10%	34

B. DATA PREPROCESSING

In order to adjust the input size of each of the six CNNs employed in the study, the fault pictures are resized. SqueezeNet has an input size of 227 × 227 pixels, whereas MobileNet, ResNet-50, ResNet-18, DenseNet-201, and ShuffleNet all have input sizes of 224 × 224. The input size for the proposed architecture is also 227 × 227. The images are then transformed into PyTorch tensors. A tensor in PyTorch is a multi-dimensional matrix that may represent the pixel values of an image. The tensor was finally normalized by deducting the mean and dividing by the standard deviation. It is known as normalization. Normalization is a common preprocessing step in DL to bring the pixel values to a standard scale, which helps the neural network converge faster during training. This process also makes the model more resilient and less sensitive to the effects of various illumination situations.

C. FEW-SHOT LEARNING

Few-shot learning was first studied in the 1980s [42] to deal with the issue of limited data availability, and has become increasingly popular. It allows us to categorize data with a small number of occurrences efficiently. Fig. 5 illustrates the generic few-shot learning method based on prototypical network. Think about training a model to discriminate between different things, like dogs and cats. Few-shot learning takes a more clever technique than traditional learning, which would require many examples of each. Here's how it functions: To train our model, we first need pairs of data, which might originate from disparate classes (for example, a dog image and an image of a cat) or from the equivalent class (like two different images of cats). A function named f(x, y) must be used to teach the model whether these pairs of numbers (mathematically denoted as x and y) belong

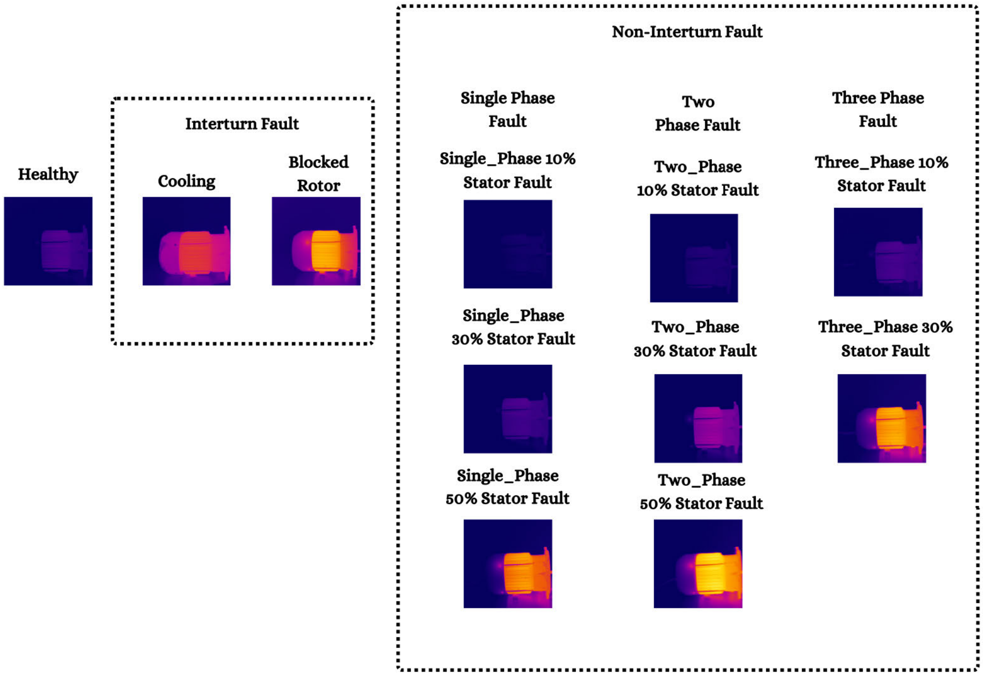

FIGURE 4. Classes of the used dataset.

to the equivalent class (y = 1) or disparate classes (y = 0). Later, we divide our data into the query set and the support set. The query set evaluates the model's performance across many categories, whereas the support set provides examples from numerous categories to learn from. The two main testing strategies are one-shot k-way and N-shot k-way where 'k' denotes the number of distinct categories being evaluated. The one-shot k-way technique assesses the model's ability to classify new categories by providing only a single sample for each category. The objective is to classify the k categories in the query set using the support set's knowledge. On the contrary, the N-shot k-way technique evaluates the model using N examples from k categories from the query set. Based on these scant data, the model must produce precise classifications. In conclusion, few-shot learning was shown to be an effective approach for categorizing data with a few examples. A query set and a support set are created from the data., the model is trained using pairs of samples, and a small sample size is used to evaluate the model.

Different networks are supported in model training through few-shot learning. To improve the effectiveness of few-shot learning models, researchers always sought novel approaches to problems that arise in circumstances with little data. Authors in [43] provided a detailed summary of algorithms in the field of few-shot learning. A noteworthy method that jumps out is prototypical networks, which build category prototypes from examples in the support set. The samples in the query set are then quickly and precisely classified using distance calculations between prototypes and queries. Additionally, Relation networks have also been shown to be effective tools for capturing complicated inter-instance correlations by modeling interactions between input pairs. Another promising solution is Siamese Networks, which consist of twin networks that share weights. In cases requiring distant learning, they are especially helpful since they use common regions to identify and measure distances or similarities, improving earlier techniques.

In our study, we used prototypical network, a few-shot learning method that is simple yet effective [42]. Prototypical networks use a metric-based technique to generalize to new classes [44]. In the context of few-shot learning, prototypical networks have exhibited better performance than other techniques [1]. These networks compute prototypes for defined classes and produce feature vectors using an embedding function. Accurate classification is achieved by measuring the resemblance between classes, and the difference between the distance of the query feature vectors from the prototype of the classes is taken into account to establish this. For training, a support set comprising N-labeled samples is provided, denoted as

$S = \{(x_1, y_1), \ldots, (x_n, y_n)\}$ where each $x_i \varepsilon R^D$ is the dimensional feature vector D and the label of x_i is $y_i\{1 \ldots k\}\varepsilon R^D$. The set S_k refers to the classes within the support set. It is defined as: $S_k = \{(x_i, y_i) \in S \mid y_i = k\}$. An embedding function, $f_\Psi R^D \rightarrow R^M$, is used to calculate the prototype p_k. Therefore, $p_k = \frac{1}{|S_k|}\sum_{(x_i,y_i)\in S_k} f_{\phi(x_i)}$. In order to determine the classification distance, a distance function $d(.)$ is used. The probability that query point x is a member of the class k can be expressed as follows:

$$P_\phi(y = k \mid x) = \log\left(\frac{\exp\left(-d\left(f_\phi(x), p_k\right)\right)}{\sum_{k'} \exp\left(-d\left(f_\phi(x), p_{k'}\right)\right)}\right) \quad (1)$$

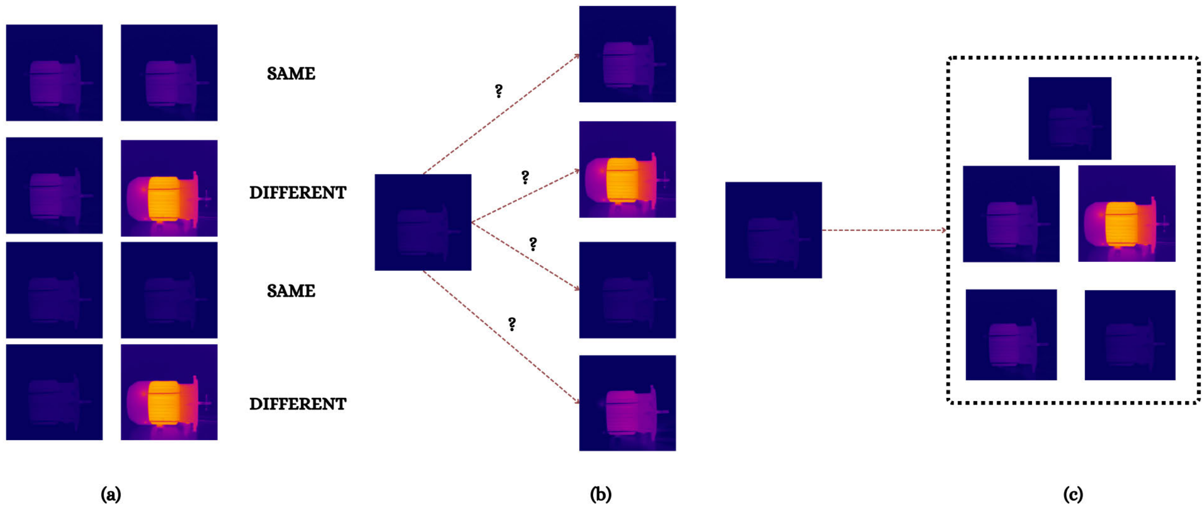

FIGURE 5. Strategies of few-shot learning paradigm: (a) Training, (b) One-shot testing, (c) N-shot testing.

IV. RESULTS

To determine which model was most effective in locating faults in thermal pictures, we examined six distinct CNN models (ResNet-18, ResNet-50, DenseNet201, Large MobileNetV3, Shufflenet, and Squeezenet1.1). We also proposed a new model and compared its performance with the other six models. Leveraging NVIDIA T4 GPUs, we were able to achieve significant speedups in code execution due to GPU acceleration, in contrast to CPU-only systems. To train the models, we used a small number of images from each fault class.

For training, we utilized 2 images from each of the 11 fault classes (including 1 healthy class), and for testing, we used 4 images from each class. All images were randomly selected. When the loss stopped improving, we terminated training the model using the Keras early stopping API because we did not need to train the model for longer epochs than necessary, and we were able to save a significant amount of time and computing resources this way.

A. EVALUATION METRICS

The diagnostic effectiveness of the proposed architecture is evaluated using various assessment criteria. Equations (2-7) include accuracy, sensitivity, specificity, precision, F1-score, and Matthew's correlation coefficient (MCC) respectively. Additionally, the performance of the suggested architecture undergoes evaluation through a confusion matrix. In these equations, TP (true positive), TN (true negative), FP (false positive), and FN (false negative) correspond to accurately classified positive and negative images, as well as incorrectly classified positive and negative images, respectively.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{2}$$

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{3}$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \tag{4}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{5}$$

$$\text{F1-score} = \frac{2 \times \text{TP}}{2 \times \text{TP} + \text{FP} + \text{FN}} \tag{6}$$

$$\text{MCC} = \frac{\text{TP} \times \text{TN} - \text{FP} \times \text{FN}}{\sqrt{(\text{TP} + \text{FN})(\text{TP} + \text{FP})(\text{TN} + \text{FP})(\text{TN} + \text{FN})}} \tag{7}$$

B. EXPERIMENTAL RESULTS

Table 5 compares the accuracy and the training time of the proposed method with six other DL models. The proposed method achieved one of the best accuracy of 98.94%, while the other models achieved accuracy between 88.10% and 99.95%. However, the proposed method also had the fewest training parameters. If we neglect the 1-2% accuracy difference, the proposed method is the best because it has significantly fewer training parameters and requires substantially less time to train; therefore, it is more efficient.

TABLE 5. Performance comparison of several CNN architectures (TT=Training time (mins:secs), Acc.=Accuracy, Sen.=Sensitivity, Spe.=Specificity, Pre.=Precision, F1s=F1-score).

Model	TT	Acc.(%)	Sen.	Spe.	Pre.	MCC	F1s.
ResNet-18	4:03	99.95	1.00	1.00	1.00	1.00	1.00
ResNet-50	10:03	99.58	1.00	1.00	1.00	1.00	1.00
Shuffle-Net	2:16	97.65	1.00	1.00	1.00	0.98	0.98
DenseNet-201	4:32	99.16	1.00	1.00	1.00	1.00	1.00
Mobile-Net-V3-Large	2:52	99.40	1.00	1.00	1.00	1.00	1.00
Squeeze-Net	2:43	88.10	1.00	1.00	1.00	0.83	0.83
Proposed Architecture	2:12	98.94	1.00	1.00	1.00	0.98	0.98

Fig. 6 provides a visual illustration of the accuracy of CNN models used for experiments. It shows that ResNet-

18 outperforms all CNN-based architectures with a 99.95% accuracy, followed by the ResNet-50 with a classification accuracy of 99.58% while the proposed model obtains a 98.94% accuracy.

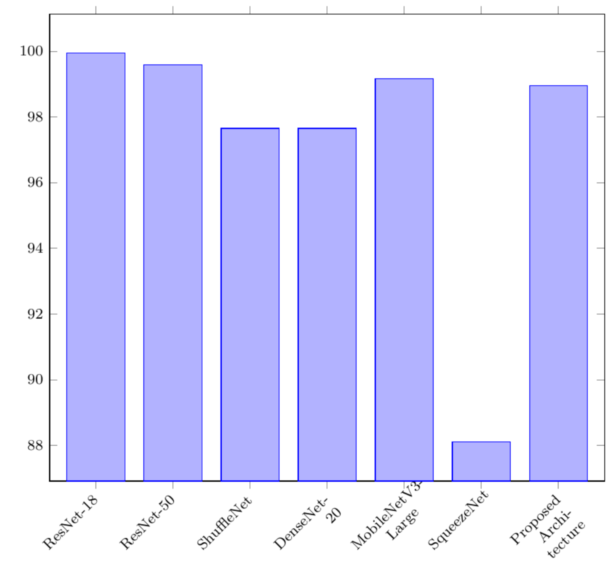

FIGURE 6. Accuracy of the models used for experiments.

Fig. 7 visually represents the F1-scores of CNN models employed in the experiments. It demonstrates that almost every architecture achieved an F1-score of 0.98 to 1.

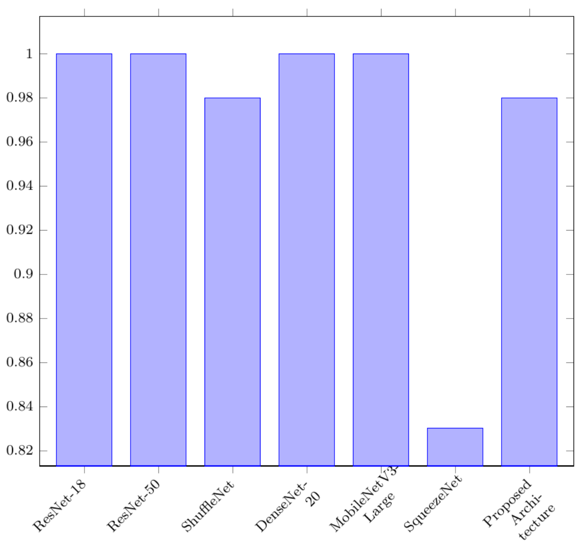

FIGURE 7. F1-scores of the architectures.

The training accuracy curve of the suggested architecture is shown in Fig. 8, providing a visual depiction of the learning dynamics of the model during training cycles. This curve illustrates how accuracy scores changed over the training process, providing information on the model's ability to gradually pick up and adjust to the underlying patterns in the dataset.

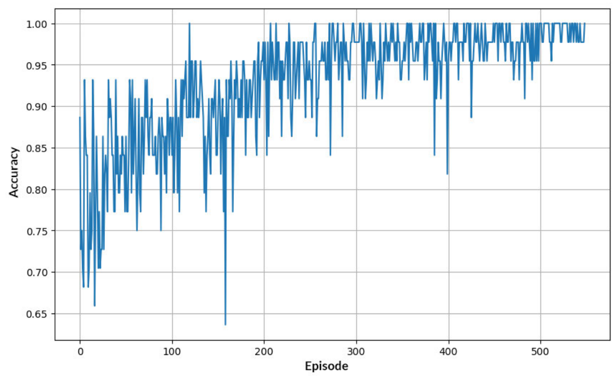

FIGURE 8. Training accuracy curve of the proposed architecture.

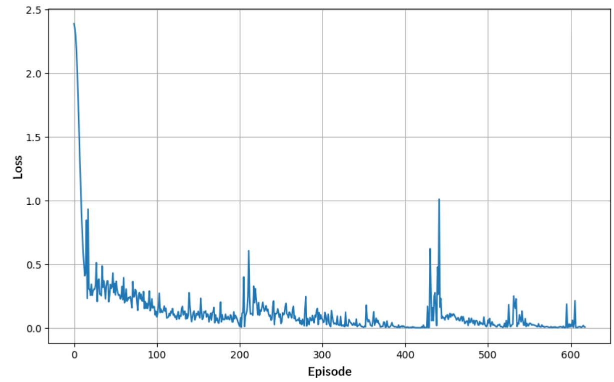

FIGURE 9. Training loss curve of the proposed architecture.

The training loss curve of the suggested architecture is shown in Fig. 9, which provides a dynamic representation of the model's loss optimization throughout the training epochs. The curve shows the path of the loss function for the model and indicates how much the architecture modifies its parameters to reduce mistakes and improve prediction accuracy.

The suggested architecture's confusion matrix, which provides a thorough evaluation of the model's classification performance, is shown in Fig. 10.

Important details about the number of layers and training parameters for each model used in the study are summarized in Table 6. The proposed architecture uses only 73k training parameters to achieve demonstrated accuracy, while the other CNN classification models require millions of parameters [45], [46]. Additionally, the layer structure of each CNN model is more complex than the proposed model, with more layers and more complex operations per layer, resulting in a higher computational burden.

C. COMPARISON WITH RELATED STUDIES

We compared our new architecture with other methods for diagnosing induction machine faults that use the same thermal image dataset. As summarized in Table 7, our system is better than the others in several ways. First,

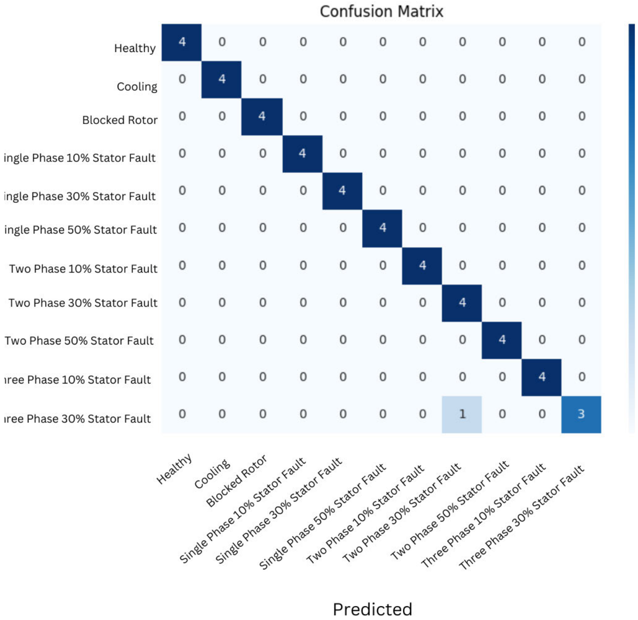

FIGURE 10. Confusion matrix of the proposed architecture.

TABLE 6. Comparison of model complexity.

Model	Number of Trainable Parameters	Number of Layers	Input Size
ResNet-18	11M	18	224x224x3
ResNet-50	23M	50	224x224x3
ShuffleNet	5.3M	11	224x224x3
DenseNet-201	20M	12	224x224x3
MobileNetV3-Large	5.4M	17	224x224x3
SqueezeNet	1.2M	13	227x227x3
Proposed Architecture	73k	7	227x227x3

our model achieved similar accuracy to the other studies but required neither segmentation nor data augmentation. Moreover, it used 3x fewer images to do so. Secondly, it was faster because it had fewer layers and did not need to do as many steps of calculation. In general, our new architecture is a better way to diagnose induction machine faults using thermal images.

V. DISCUSSION

We evaluated the effectiveness of six distinct CNN models, along with our own, in identifying faults within thermal images using a prototypical network powered few-shot learning technique. In our tests, our proposed model outperformed the others in terms of training time and resource intensiveness with a remarkable accuracy of 98.94% while only requiring 73,803 training parameters. On the contrary, the other CNN models achieved accuracy ranging from 88.10% to 99.95% but had millions of training parameters.

The outstanding accuracy of our proposed model can be attributed to its efficient architecture and the usage of few-shot learning. Unlike the other models, our proposed model has a simple structure with fewer layers and less complex operations per layer. This reduces the computational burden while retaining feature extraction capabilities, thus making the model more efficient. Additionally, the utilization of few-shot learning has enabled our model to learn from a small number of training images, which is particularly important for fault diagnosis, where labeled data are often limited. Moreover, our model stands out for its quick training time compared to other CNN models. Because of its lightweight architecture and minimal parameter count, coupled with a simpler structure, our proposed model saves considerable time and computing resources while training.

In conclusion, our approach appears to be a promising means of identifying flaws in the industrial environment. It is practical, precise, and requires fewer resources and time than alternative CNN models.

TABLE 7. Comparison of research on induction machine fault diagnosis using thermogram images (Seg.=Segmentation, DA=Data Augmented, Cla.=Classes, NoI=Number of Images, AU=Architecture Used, and Acc.=Accuracy).

Ref.	Seg.	DA	Cla.	NoI	AU	Acc. (%)
[12]	yes	yes	11	369	AlexNet	100
[13]	yes	no	9	311	Extremely randomized trees	100
[47]	yes	yes	11	369	Random Forest	93.8
[48]	no	yes	11	369	Linear discriminant analysis(LDA)	100
Proposed	no	no	11	132	Modified SqueezeNet	98.94

VI. CONCLUSION

Our research aims to offer concrete advantages to the renewable energy sector, demonstrating the connection between cutting-edge technology and environmental sustainability; particularly in the diagnosis of wind turbine failures. Our proposed model has enabled us to achieve a remarkable balance between computational efficiency and diagnostic accuracy, thereby opening new avenues for resource-efficient fault detection.

In addition, based on the experiment results, it is proved that our model outperforms other alternatives in terms of training time and resource intensiveness while either surpassing or maintaining competitive accuracy and reducing dependency on vast labeled datasets. Its applicability for real-time fault detection on lightweight devices further emphasizes its immediate relevance and potential.

As the renewable energy sector continues to grow, there is a pressing need for efficient and accurate fault diagnosis tools for wind turbines. Our contributions in this field aim to enhance the reliability and sustainability of wind energy production. We believe that this research will inspire further innovations and advancements in the monitoring of renewable energy infrastructure, which will ultimately contribute to a more sustainable and greener future.

DATA AVAILABILITY

The dataset used in this manuscript was collected from ''Thermal image of equipment (Induction Motor)'', Mendeley Data, V2, doi: http://doi.org/10.17632/m4sbt8hbvk.2 (accessed on 08 November 2023).

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