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RESEARCH ARTICLE

Diagnosis of Chaotic Ferroresonance Phenomena Using Deep Learning

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ABSTRACT Ferroresonance is a non-linear and dangerous resonance phenomenon that can affect power networks and damage electrical equipment. The ferroresonance phenomenon is examined by dividing it into classes, with chaotic ferroresonance being the most dangerous type that causes overvoltage's. Detecting chaotic ferroresonance in a short period of time is of great importance in terms of taking measures and reducing equipment damage. In this study, we explored the application of deep convolutional neural networks (DCNNs) for the identification and classification of chaotic ferroresonance phenomena. Two pre-trained AlexNet models were adapted using transfer learning to perform these tasks. The first model was utilized to identify chaotic ferroresonance, while the second was employed to distinguish between different subtypes of chaotic ferroresonance by dividing voltage curve graphs into different periods and shapes. The training and testing of both DCNN models were conducted using snapshot images extracted from the voltage curves of all phase voltages. The results of the experiments showed high accuracy in both the identification and classification of chaotic ferroresonance phenomena.

INDEX TERMS Alexnet, chaotic ferroresonance, classification, deep convolutional neural networks, identification, transfer learning.

I. INTRODUCTION

Ferroresonance is an abnormal phenomenon in three-phase electrical systems that can cause equipment failure due to unstable high voltage. It involves interactions between capacitors and iron-core inductors, resulting in unusual voltages and/or currents. Ferroresonance occurs when a nonlinear inductor is connected to a series capacitor in power systems. This phenomenon can occur when an unloaded three-phase system, primarily consisting of inductive and capacitive components, is disrupted by a single-phase disturbance. It is commonly observed in medium voltage distribution networks, where transformers act as the inductive component and power cables serve as the capacitive component [1], [2], [3].

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Temporary events such as the presence of inductance and capacitance in electrical networks, interruptions that may occur or break of the line, lightning, energizing of transformers and loads may cause fluctuations in the network voltage. These oscillations can evolve into unpredictable over-voltages or different periodic structures and complex harmonic voltages, a complex event referred to as ferroresonance. Detecting ferroresonance in advance is challenging due to its dependence on various factors in power systems. Ferroresonance causes high overvoltage, overcurrent, and high-level harmonic distortion and cannot be eliminated by conventional suppression methods, resulting in serious equipment damage and long-term power supply failure. Thus, it must be avoided. [1], [2], [3].

In the scientific literature, ferroresonance is categorized into four main types: basic, subharmonic, quasiperiodic, and chaotic. The quasiperiodic and chaotic modes of

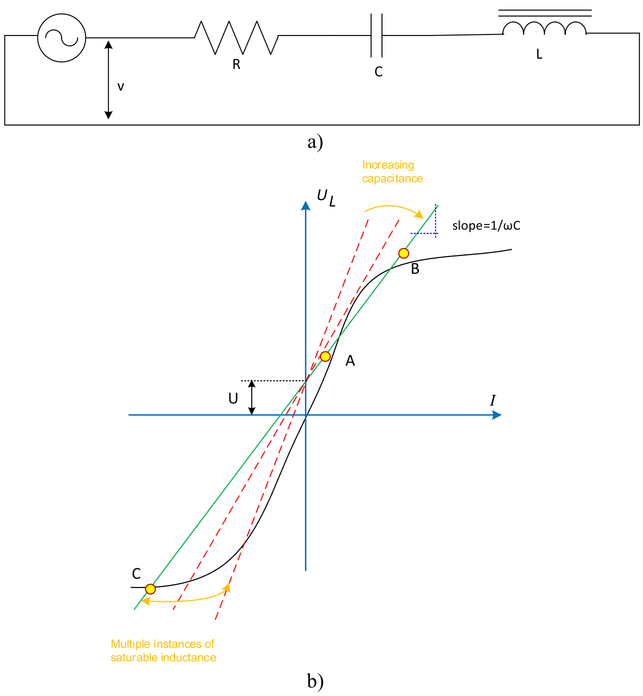


FIGURE 1. Schematic ferroresonance circuit and its curve [10], [11], [12].

ferroresonance are characterized by non-periodic behavior. Transitions between these modes can result in abrupt surges and oscillations in the network voltage [4], [5], [6].

Chaotic ferroresonance can damage power system insulators and continuous monitoring of the power system signal is necessary to eliminate harmful effects [7], [8]. To investigate the impact of ferroresonance on power quality and detect disorders, various methods have been employed, including fuzzy expert systems, wavelet analysis, Bayesian, and artificial neural networks. Case studies have been conducted to reduce the effects of ferroresonance on power quality and distribution networks [9].

In Figure 1, an alternating current circuit is shown schematically with elements represented as linear inductance (L), resistance (R), and capacitance (C). When the natural frequency of L and C is equal to the source frequency, high-frequency over-voltages can occur between the components, making the solution difficult due to the saturation of nonlinear circuits. The frequency of harmonics in a transmission line or electrical circuit varies based on the degree of saturation of the core. In non-linear systems, mathematical analysis can be used to obtain a system approach.

Figure 1 provides the schematic diagram and characteristic curve to depict the ferroresonance event. Figure 1a shows the free resonance of the circuit, while Figure 1b displays the magnetization curve (Φ). The voltage at the ends of the capacitor is represented as Vo. According to Equation 1, the inductive voltage is composed of a fixed component and a variable component. In the context of an iron core transformer, as the value of X_L (inductive reactance) undergoes variation, the probability of X_C (capacitive reactance) closely aligning with X_L notably enhances. Equation 1 gives ω, equation 2 gives magnetic flux (Φ), and equation 3 gives V [10], [11], [12].

$$\omega V_C = \frac{1}{C}, \quad \omega V_L = V_s + \frac{1}{C} \tag{1}$$

V voltage at the ends of the capacitance element,

$$\Phi = V\omega(V_o.\omega).sin\omega t \tag{2}$$

$$V_L = \omega f(I) \tag{3}$$

A review of recent studies on ferroresonance has been summarized as follows: Valverde et al. used Fourier transform to examine the characteristic properties of ferroresonance in electrical energy systems [12]. Akinrinde et al. studied the dynamic behavior of a wind turbine generator under high voltage ferroresonance conditions [13]. Negara and colleagues analyzed ferroresonance phenomena using wavelet analysis in a typical single-phase ground fault scenario for transformer ferroresonance stimulation [14].

Although there are many scientific studies on the investigation of ferroresonance voltage, ferroresonance problems and properties, the number of investigations about the identification of ferroresonance is very limited. With the development of the protection of power systems, the importance of ferroresonance detection research is increasing. Different new techniques proposed by researchers to analyze and predict ferroresonance phenomena. Nowadays, scientists aim to improve methods that can predict and differentiate ferroresonance from other temporary situations. Sharbain et al. propose the use of artificial neural networks (ANN) with wavelet transform to discriminate between ferroresonance and capacitor switching. In the study, ferroresonance was determined with an average accuracy of 97% [15]. In [16], wavelet transform and an ANN were used to identify the ferroresonance and distinguish it from other transient events. The proposed algorithms can distinguish other transient phenomena such as transformer, capacitors and load switchings with ferroresonance. The authors chose Daubechies as the main wavelet with level 6 decomposition and the powers of the detailed signals were used as input. The algorithm achieved a recognition rate of 93% on average. Besides, researchers increased the recognition rate to 94.8% using the Kernel Principal Component Analysis (KPCA) [17]. In another study by Mokryani et al., a ferroresonance detection method is introduced combining S-Transformer and Support Vector Machine (SVM). Ferroresonance data were collected from a 20kV radial distribution feeder in a real network. Transient data is generated by simulation. As a result, 97.5% accuracy was achieved with S-Transform and SVM [18]. Ferroresonance effects of faults in power transformers as a result of deformation of windings were investigated by Mikhak-Beyranvand et al. [19]. In another study, a new strategy for the determination of ferroresonance was attempted by utilizing the vibration of the inductive voltage transformer exposed to ferroresonance. In the laboratory environment, the ferroresonance conditions have been established and the ferroresonance detection strategy from the transformer's differences in vibration has been demonstrated and succeeded [20].

The primary objective of power system studies is to identify and analyze potential risks associated with ferroresonance phenomena. These investigations are typically carried out using laboratory experiments involving simplified circuit models or numerical models. In order to comprehend the diverse manifestations of ferroresonance, it is crucial to develop a comprehensive understanding of the behavior of soft magnetic materials within nonlinear inductors. Neglecting certain factors and assuming idealized magnetic properties may result in inaccurate simulation outcomes if full modeling is not performed. In particular, relying solely on simulations based on idealized transformer and capacitance conditions may not yield realistic results when dealing with chaotic ferroresonance. In a previous study, a simulation of a chaotic ferroresonance circuit was carried out, and an elimination algorithm was developed and implemented to iteratively eliminate ferroresonance by considering relevant parameters [21].

In various studies, the impacts of ferroresonance have been explored by analyzing the behavior of phase transformer models in nonlinear transient operations within a laboratory setting [22]. Another study used software simulation to analyze a ferroresonance event in a 0.4/22 kV distribution transformer powered by a photovoltaic source [23]. Additionally, another study highlighted the importance of protection against overcurrent during ferroresonance events and discussed relevant overcurrent protection and delay solutions [24].

The identification and monitoring of chaotic ferroresonance is crucial for taking timely measures to prevent it. In recent years, smart networks with online monitoring have been considered as a promising solution to address ferroresonance. Electric load estimation is an essential aspect of smart grids for efficient electrical power planning and operation. Deep Convolutional Neural Network (DCNN) is one of the popular deep learning methods used for electric load estimation. In a study, a DCNN model was trained and tested using two-dimensional photographs of long and short-term load charts as the data set. Additionally, a Cycle-based Long-Short Term Memory Network (C-LSTM) was applied to enhance the short-term load estimate performance [25]. The study successfully achieved short-term electric load estimation. Another study used a Smart Solid-State Ferroresonance Limiter to stabilize the chaotic behavior of a voltage transformer. The effectiveness of the proposed method in reducing ferroresonance over-voltages was evaluated through simulation and laboratory testing [26].

Identification systems always have two parts. The first one is the feature extraction and the other is the classification. If numerical data is to be used, these two parts are inevitable. In many studies for feature extraction and voltage signal analysis, wavelet transform (WT) and short-term Fourier transform (STFT) are commonly used time-frequency analysis algorithms [27], [28], [29]. However, in DCNN models where feature extraction is performed automatically based on image data, feature extraction is not performed separately. Deep convolutional neural networks in which graphical images are used to detect ferroresonance may close this gap at this point. Deep convolutional neural networks have been successfully applying in many classification problems. It is especially successful in the recognition or classification of image data in applications where online data flow is available, especially with the use of too much data. In another study that exemplifies the use of image data, wind power, which is the most influential factor in the electrical grid power in wind power plants, has been estimated for an ultra-short-term with DCNN. In the final phase of the study, a combined system with LightGBM classification algorithm was obtained. The system was compared with the support vector machine and a more successful result was observed [30]. Similarly, DCNN is used in solar power estimation [31]. After reviewing the previous works, at this point, the ferroresonance continues to be a serious problem of the electricity grid. Studies on the detection and classification of ferroresonance are still in progress, and other satisfactory studies and alternative solutions are still needed. Our study has three important originalities in terms of both being complementary to previous studies and contributing to the solution of the problem. We can list them as follows:

1. Using two-dimensional graphical image data, which was not used in any of the previous studies, we were able to instantly detect the chaotic ferroresonance state with DCNN.

2. In previous studies, the way to use two-dimensional (2d) DCNN could not be opened because the idea of reaching a conclusion using graphical image data often did not seem realistic due to some reasons such as the difficulty of feature extraction. Instead of designing a DCNN algorithm from scratch in order to use the (2d) DCNN method, which was not used in previous studies, more effectively and actively we implemented a pre-trained DCNN model by making use of the transfer learning (TL) approach. For this, we revised some layers in the AlexNet pre-trained model. Thus, we think that we are the first to use and apply a pretrained 2d-DCNN model in the detection of ferroresonance as far as we know. Also, this approach can contribute to the development of a fully automatic smart grid system by defining input-output parameters and integrating it into a fully automatic smart grid system as part of the sub-module.

3. In previous studies, the classification of chaotic ferroresonance phenomenon into subclasses was mostly neglected. We have designed, implemented and proposed a robust and powerful automatic detection method that can detect subtypes of chaotic ferroresonance thanks to DCNN trained with graphical image data.

The use of Deep Convolutional Neural Networks (DCNNs) such as AlexNet for analyzing ferroresonance data in power systems presents several advantages. Ferroresonance is a nonlinear and complex phenomenon, and detecting and classifying ferroresonance events accurately is crucial for maintaining power system stability and reliability. The potential advantages of using a DCNN AlexNet model for ferroresonance analysis are as follows:

- High Accuracy: DCNNs like AlexNet have shown exceptional performance in image classification tasks. Ferroresonance data can be transformed into spectrograms or other visual representations, which can be fed into the AlexNet model for classification. This approach has the potential to achieve high accuracy in detecting and classifying ferroresonance events.
- Reduced Complexity: Ferroresonance events are complex and nonlinear, making them challenging to detect. Traditional signal processing techniques are computationally expensive and time-consuming. However, using a DCNN AlexNet model can reduce the complexity of the ferroresonance analysis process since the model can automatically learn and extract features from the input data.
- Improved Efficiency: Traditional manual analysis methods require expert knowledge and significant time and effort. Using a DCNN AlexNet model can improve the efficiency of ferroresonance analysis, as the model can quickly classify ferroresonance events and reduce the need for manual analysis.
- Scalability: The DCNN AlexNet model can be trained on large datasets, making it scalable for use in large power systems. Additionally, the model can be easily retrained or adapted for new data or different power system configurations.

Using a DCNN AlexNet model for ferroresonance analysis provided the benefits of improved accuracy, reduced complexity, improved efficiency and scalability.

The rest of the article is organized as follows: In the second section, the method used in the study, the data set, the architecture of the DCNN models are explained. In the third section, the results obtained from the study are given. In the fourth section, the results are discussed and compared with previous studies. In the last section, the fifth one, the results of the study and what can be done in the future are explained.

II. INTRODUCTION ALGORITHM AND MATHEMATICAL BACKGROUND

The study is comprised of two distinct phases. The objective of the first phase is to identify chaotic ferroresonance, while the goal of the second phase is to categorize chaotic ferroresonance into four subclasses. To achieve these objectives, two separate deep convolutional neural network (DCNN) models were employed. The first model, referred to as "Model 1," was utilized for identification purposes, while the second model, "Model 2," was used for classification.

A. OBTAINED AND ARRANGING THE DATA SET

To create a data set and provide real solutions for ferroresonance, it is necessary to make real electricity network modelling in accordance with reality.

TABLE 1. Parameters in seyitomer-isiklar power network.

Components	*Parameters*
Transformers	362 MVA, 1.75 kV/380kV
Generators	362 MVA, 1.75 kV, 50 Hz
Line Length	284.341 km
Load	361 MW, 6 MVAr

The main objective of this study was to investigate the occurrence of ferroresonance in the "380 kV Seyitomer-Isiklar, Turkey Electrical Power System" by simulating sudden power cuts using cutters. To achieve this, we developed a simulation model of the system using the MATLAB-Simulink©environment, which was based on real parameters. The model was designed to represent the system as accurately as possible, and its effectiveness was verified by comparing the simulation results with the actual system behavior.

The modeled system is shown in Figure 2 and was based on the parameters presented in Table 1, which were obtained from the Seyitomer-Isiklar electrical grid. The fault line break in the network was symbolized to simulate the sudden power cuts induced by the cutters. The simulation was conducted by running the model with different fault scenarios, and the results were analyzed to determine the occurrence and characteristics of ferroresonance in the system.

Overall, the study presented a comprehensive investigation of ferroresonance in the Seyitomer-Isiklar electrical grid, which was accomplished through the development and analysis of a detailed simulation model. The findings of this study provide valuable insights into the behavior of power systems under sudden power cuts, which can help in improving the design and operation of electrical grids.

To generate medium to high voltage ferroresonance, it is necessary to connect the load to the medium to the long transmission line. In our system, the development of the ferroresonance event is simulated realistically. The graph of phase voltages before and after ferroresonance is shown in Figure 3.

For the training and testing of Model 1, short-term snapshots of the R-S-T phase voltages were obtained. In Figure 4, two sample data sets are randomly selected from the data used in the training and testing of Model 1, which include both ferroresonance and normal cases. Model 1 used 720 images, with 320 of these images representing instances before ferroresonance and the rest representing instances after ferroresonance. 85% of each group of this data set was used for training Model 1, while the remaining 15% was used for validation.

The purpose of Model 1 is to determine whether a ferroresonance event is present for any three-phase voltage curve. For Model 2, only the R-phase curve after the ferroresonance of the R-S-T phase voltages, shown in Figure 3, was used.

The ferroresonance in the R-S-T three-phase graph is known to be of the chaotic ferroresonance class, but it also differs from time to time. Model 2 aims to classify these

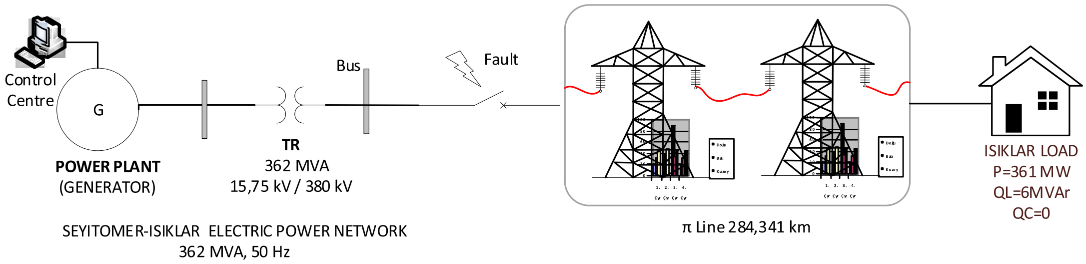


FIGURE 2. Seyitomer-isiklar schematic block model.

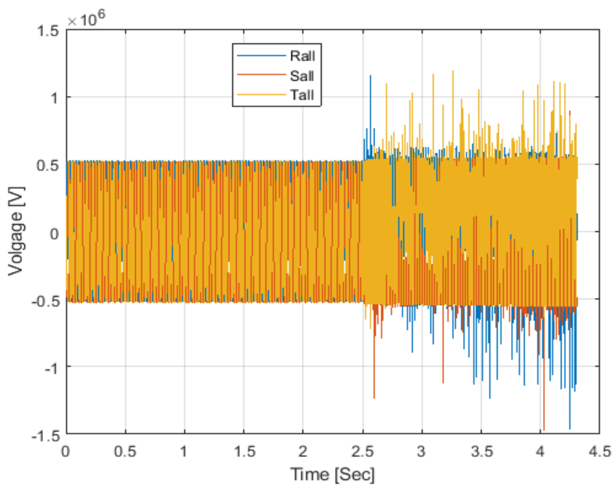
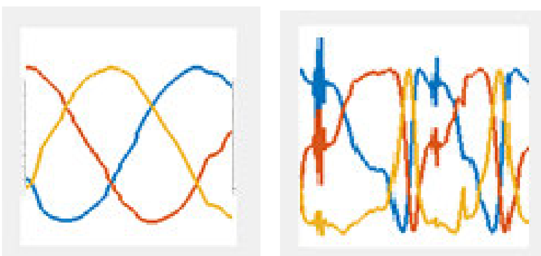


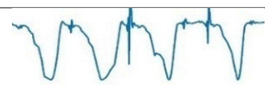
FIGURE 3. Overall data of the voltage variation for the three-phase.



a) Before ferroresonance b) After ferroresonance

FIGURE 4. Sample images from data set for model 1.

TABLE 2. Classification of chaotic ferroresonance.

Chaotic classes	Chaotic graphs
C1	
C2	
C3	
C4	

differences in chaotic ferroresonance. Table 2 shows the different chaotic ferroresonance classes in the voltage curve used in the study.

To obtain the data set for Model 2, a total of 880 short-term images were taken from each chaotic class in Table 2. 75% of each class data set was used for training Model 2, and the remaining 25% was used for validation. Figure 5 shows randomly selected sample image data from the data set used for the training of Model 2, regardless of their subclasses.

All data in the data set for model 1 and model2 are initially 547 × 1110×3 dimensions. These data were rearranged for both model1 and model2 with dimensions of 227 × 227 x 3.

B. ARCHITECTURE OF THE MODELS

In this study, we used pre-trained AlexNet DCNN models to the identification and classify chaotic ferroresonance event.

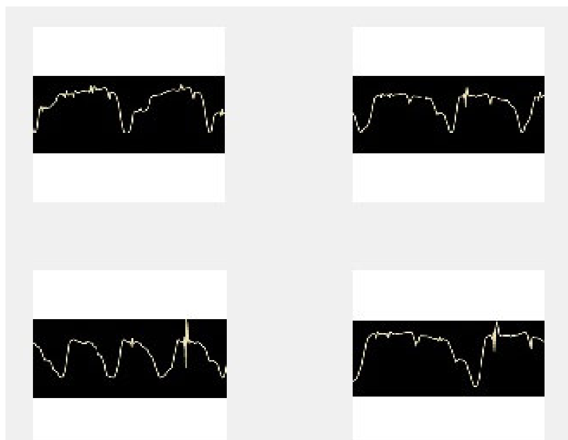


FIGURE 5. Sample images from data set for model 2.

We used the transfer learning approach for DCNN architecture. Transfer learning is a type of machine learning method in which a model trained for a particular task can be used to learn the new task by transferring information. The input images for AlexNet were colour images with a resolution of 227 × 227×3 pixels.

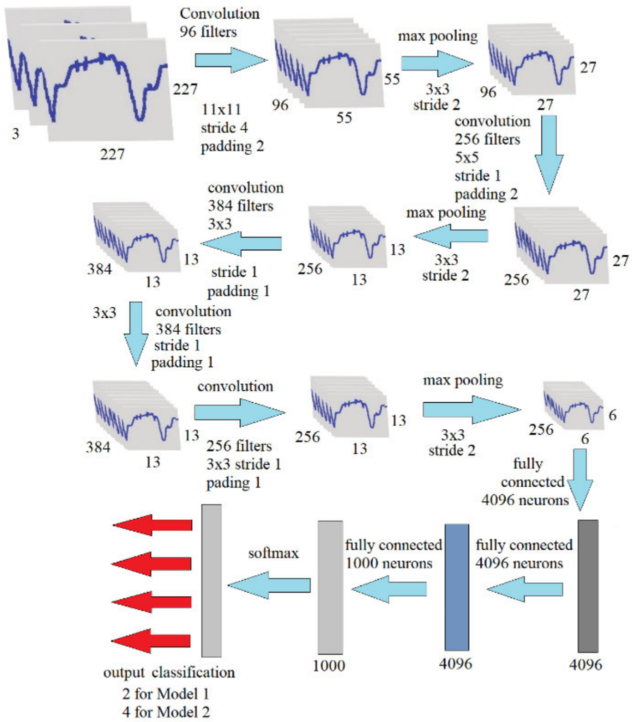


FIGURE 6. AlexNet architecture for chaotic ferroresonance identification and classification.

The AlexNet model consists of 5 convolution layers and 3 max-polling layers. Each convolution layer in AlexNet architecture is followed by a rectified linear unit (ReLU). All parameters including filter sizes for each layer are shown in Figure 6. In the pre-trained Alexnet model for transfer learning, we have removed the fully connected layer, the softmax layer and the classification layer, which are the last three layers, which are trained to classify 1000 categories. After removing these layers, we arranged this architecture for two tasks: the detection and classification of chaotic ferroresonance. To this end, in order to identification chaotic ferroresonance (CF), another "fully connected layer" with 2 neurons was placed instead of "fully connected layer" with 1000 neurons, which was removed. Before the "Fully connected" layer, there is a "softmax" function where all units are fully connected to two outputs.

The softmax function layer for both model1 and model2 has been replaced with a new one. Thus, we have arranged model1 to realize our first goal. Our second goal was to classify the chaotic ferroresonance phenomenon to their subtypes, namely C1, C2, C3 and C4, respectively. For this purpose, we changed the last link layer of the architecture to the probability of output from 2 classes to 4 classes, so we obtained model 2. The rest of the layers were the same as the CF identification. For Model 1 and model 2, the architecture for CF identification and subtype classification, respectively, is shown in Figure 6.

The network change rate is usually carried out with the training rate. The study was carried out with the NVIDIA GeForce 940MX, 6040 MB GPU notebook for both models. Model 1 training took about 1 minute and model 2 training took about 4 minutes. For model 1, mini batch size 22 and maximum epoch are set to 3. For model 2, mini batch size 22 and maximum epoch are set to 10. In this study, pre-trained AlexNet convolutional neural network model was reorganized with transfer learning method. Figure 6 shows the pretrained model AlexNet and the changes made.

TABLE 3. Accurancies (%) for DCNN models.

DCNN Models	Training Samples	Accuracies (%)
Identification (Model 1)	720	100.00
Subtype classification (Model 2)	880	100.00

III. RESULTS

Pretrained DCNN models were used to automatically detect and classify chaotic ferroresonance. Model 1 was used for the identification of chaotic ferroresonance and Model 2 was used for classification. With the data set of Model 1 and the data set of models 2, we analysed the results obtained from different training results. The number of training samples and the accuracy rates of the models are given in Table 3. Both models have provided a fair accuracy for the classification and detection of data sets. The accuracy rate for both models and data sets was 100%.

Figure 7 shows the process of accuracy rate for training and validation obtained according to iteration for model 1. Figure 8 shows the error curve of model 1 in the training process. For Model 2, the training process accuracy rate and loss graphs can be observed from Figures 9 and 10. Figure 11 and 12 show confusion matrixes, respectively, for the chaotic ferroresonance identification and subtype classification. As can be seen from both confusion matrix, it is understood that there is not an incorrectly predicted image for both classification and identification. The success of both models can be easily seen from both the confusion matrices and the accuracy graphs showing the training processes.

IV. DISCUSSION

Our study presents an automatic detection system for chaotic ferroresonance and classifies the subtype into 4 classes using deep learning techniques. Unlike previous classification methods that required numerical data of voltage and current information, our proposed method utilizes short-term graphical images, eliminating the need for extra processing such as feature extraction. Our system uses convolutional layers and other hidden layers in a deep convolutional neural network (DCNN), which can automatically detect and classify the graphic image dataset with superior accuracy compared to standard methods.

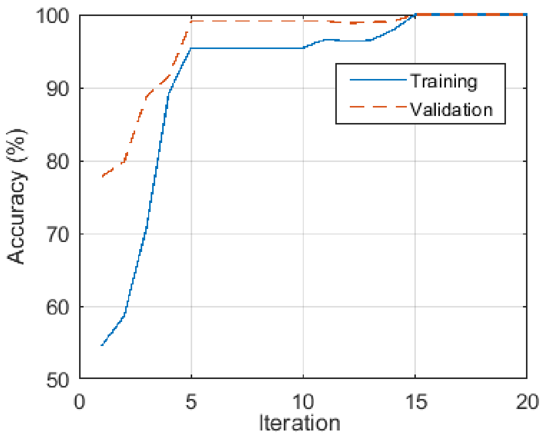


FIGURE 7. Accuracy per iteration for model 1.

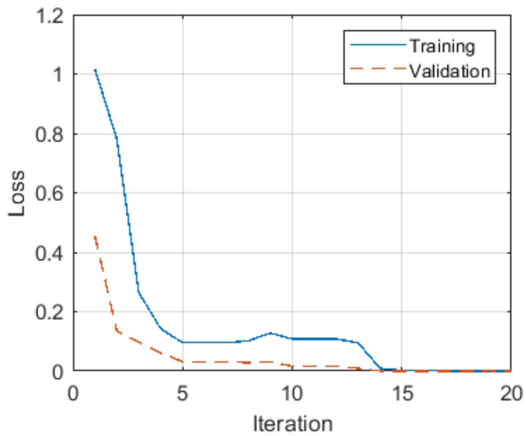


FIGURE 8. Loss per iteration for model 1.

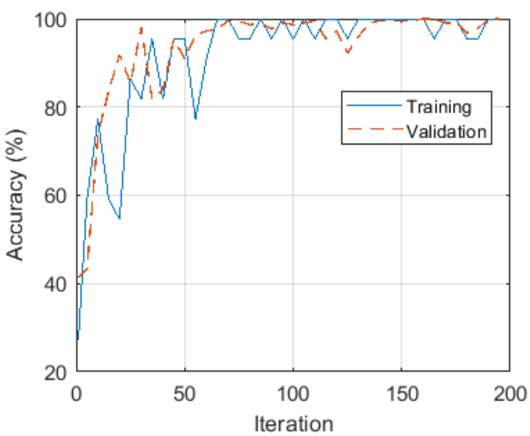


FIGURE 9. Accuracy per iteration for model 2.

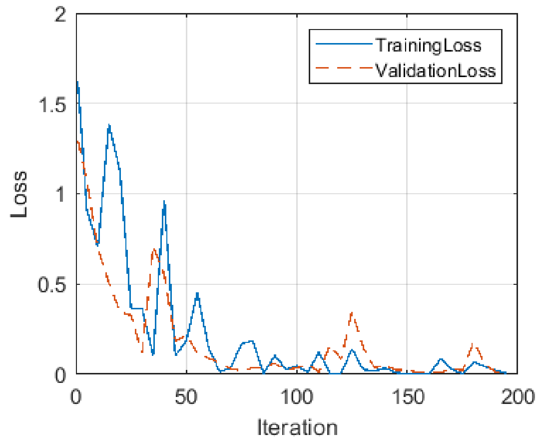


FIGURE 10. Loss per iteration for model 2.

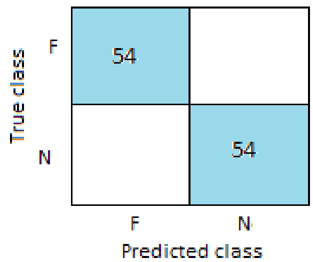


FIGURE 11. Confusion matrix for model 1.

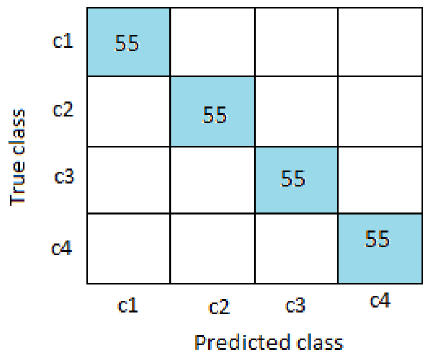


FIGURE 12. Train and test results of the ANFIS models.

Deep neural networks often required large amounts of data for training. However, in this study, we were able to obtain 100% accuracy in the determination of ferroresonance and 100% accuracy in the chaotic ferroresonance subtype classification using the short-term graphic image data and fine-tuning of the pre-trained DCNN despite our limited data set. The highest accuracy rate was obtained for the definition and classification of ferroresonance with 2 data sets. The absence of a difference in the accuracy ratio between model 2 and model 1 indicates that the deep neural networks are strong enough to detect both the subtypes of chaotic ferroresonance and the identification of chaotic ferroresonance. Abundant studies in the literature suggested different ferroresonance detection techniques, but most studies neglected the classification of subtypes due to inter-class similarity and intra-class variability of chaotic or other type ferroresonance.

Although these subtypes are difficult to use, they are of great importance in the case of chaotic ferroresonance.

In this preliminary study, the automatic determination of chaotic ferroresonance was performed and the subtypes were classified into 4 classes based on the instant graphical images. In a similar way to our study, each of the events that cause ferroresonance can be obtained by simulation. Therefore, the ferroresonance event can be obtained by simulation and classification can be performed by using this simulation data. However, if the materials such as inductance and capacitor used in the simulation are modelled by taking into consideration their ideal conditions, then the contribution of the solution remains limited. In Mokryani and Haghifam studies, they used multilayer perceptron to differentiate ferroresonance from the distribution transformer from other transients by using the data of ferroresonance and other transient events obtained as a result of a simulation. Other transient events simulated in the study are capacitor switching, transformer switching and load switching. In the study, the wavelet transform was used for the decomposition of the signals and the feature extraction. In general, they achieved a classification with a 93% accuracy [32]. In a study in which artificial neural networks were used to classify different overvoltage events in power transformers, in every overvoltage event the secondary winding current of the transformer was analysed using the discreet wavelet transform. Different load scenarios were considered. As a result, the overvoltage classification and ferroresonance classification were performed separately. As a result, the overvoltage classification and ferroresonance classification were carried out separately. Accuracy rate detection of ferroresonance was 100% and overall, 98.75% accuracy was achieved. In this study, however, the subtypes of chaotic ferroresonance were neglected, just as in previous studies [33]. The identification of ferroresonance phenomena is also extremely important for smart grid systems such as online monitoring. In a study in which a smart tracking and suppression system based on a fuzzy logic approach was examined and applied, the ferroresonance were defined by diversifying as low frequency or high frequency according to the frequency. In this study, according to the numerical data, classification and identification was made by the fuzzy logic algorithm based on frequency limits 0 or 1 judicial approach. In the study, 8 different events were taken into consideration and those who were known as ferroresonance were identified with 100% accuracy [34].

In an article, a system based on the Sparse Autoencoder (SAE) is proposed for the detection and classification of overvoltage in power distribution systems caused by ferroresonance. The system uses single-layer and stacked Sparse Autoencoders (SSAEs) to extract automatic features and reduce the dimensionality of ferroresonance overvoltage waveforms, without requiring feature engineering. The different modes of ferroresonance are then classified using a softmax classifier, achieving a high accuracy rate of 97% [35]. In another study, Djebli et al. investigated the sensitivity of ferroresonance to eddy currents in the iron core [36], while Majka and Klimas designed hardware for diagnosing ferroresonant circuits [37]. Negara et al. investigated the influence of special transformer core types on the formation of ferroresonance modes. Through a comprehensive cumulative energy analysis, significant distinctions were determined among normal waves, harmonics, and ferroresonances [38]. Heidary et al. recommended the use of ferroresonance for dual function protection element limiting by fault currents [39]. Abdel-Hamed et al. conducted a study on ferroresonance in integrated distribution systems with multiple distributed generations. They proposed a new method utilizing an RLC shunt limiter to mitigate ferroresonance in distribution networks. The study investigated ferroresonance in an IEEE-33 bus radial distribution system with multiple distributed generations. Their findings demonstrated the superior effectiveness of the shunt limiter, which was connected using a negative sequence detector, when compared to existing methods [40].

TABLE 4. Comparison of modern classifiers and classification accuracy.

	Classifier	Identific. Accur. (%)	Subtype of Cf Classification Accuracy (%)
Sharbain et al. [13]	WT+ANN	97	Neglected
Mokryani et al. [14]	WT+ANN	93	Neglected
Mokryani et al. [15]	KPCA	94.8	Neglected
Mokryani et al. [16]	S-Trfm + SVM	97.5	Neglected
Mokryani et al. [30]	WT+MLP	93	Neglected
ElNozahy et al. [31]	DWT+ANN	98.75	Neglected
Wang et al. [32]	Fuzzy Logic	100	Neglected
Chen et al. [33]	SAS + SSAS	97	Neglected
Proposed	DCNN	100	100

In this study, we conducted an investigation into the use of a Deep Convolutional Neural Network (DCNN) model for the identification and classification of chaotic ferroresonance phenomena and subtypes. The proposed model utilized instantaneous waveform images, eliminating the need for additional processing such as feature extraction. Our experimental results demonstrated that the DCNN model achieved the highest classification accuracy compared to all previously reported methods in the literature. Unlike previous studies, we utilized image data instead of digital data.

Table 4 compares the performance of the proposed method with other methods presented in the literature. It should be noted that the training and testing processes were performed on a limited amount of data. Therefore, our future goal is to develop algorithms that provide more generalizable solutions by utilizing a larger amount of image data.

V. CONCLUSION AND FUTURE DIRECTION

In this study, we investigated the application of a DCNN using pre-trained AlexNet to identify and classify chaotic ferroresonance phenomena and subtypes. We achieved 100% accuracy for sub-type classification and 100% accuracy for the identification of chaotic ferroresonance phenomena by using a dataset created from short-time graphical images. The automatic identification and classification system can help in the early detection of ferroresonance phenomena, providing opportunities for effective prevention. In the future, researchers may use different deep learning architectures to classify and identify any type of ferroresonance, and compare these architectures to determine the best network for ferroresonance detection. Additionally, deep learning models can be trained from scratch using larger image datasets, making the detection system usable in everyday life in the industry and helping researchers and industry workers identify the phenomenon of ferroresonance more effectively. Such deep learning studies need to be generalizable to be usable in real life. Therefore, it is necessary to use more image data. It should not be forgotten that our study should be done with more image data in this sense and should be more generalizable. In the future, we aim to go further in this regard and to carry out more generalizable studies. This approach can also be developed into a fully automatic intelligent grid system by defining input-output parameters, and integrated as a submodule into a fully automatic smart grid system. Another direction for researchers is to develop an automatic detection system for the phenomenon of ferroresonance, so that all types can be automated.

REFERENCES

[1] S. O. Koledowo, E. C. Ashigwuike, and A. Bawa, "A study of ferroresonance in underground distribution network for 15 MVA, 33/11 kV injection substation," *Nigerian J. Technol.*, vol. 39, no. 1, pp. 219–227, Apr. 2020.

[2] M. Yang, W. Sima, P. Duan, M. Zou, D. Peng, Q. Yang, and Q. Duan, "Electromagnetic transient study on flexible control processes of ferroresonance," *Int. J. Electr. Power Energy Syst.*, vol. 93, pp. 194–203, Dec. 2017.

[3] S. Boutora and H. Bentarzi, "Ferroresonance study using false trip root cause analysis," *Energy Proc.*, vol. 162, pp. 306–314, Apr. 2019.

[4] M. Yang, W. Sima, Q. Yang, J. Li, M. Zou, and Q. Duan, "Non-linear characteristic quantity extraction of ferroresonance overvoltage time series," *IET Gener., Transmiss. Distrib.*, vol. 11, no. 6, pp. 1427–1433, 2017.

[5] O. Akgun, T. C. Akinci, G. Erdemir, and S. Seker, "Analysis of instantaneous frequency, instantaneous amplitude and phase angle of ferroresonance in electrical power networks," *J. Electr. Eng.*, vol. 70, no. 6, pp. 494–498, Dec. 2019.

[6] M. Pejic, A. Tokic, M. Kasumovic, and T. C. Akinci, "Laboratory ferroresonance measurements in power transformers," *Elektrotehniski Vestnik-Electrochem. Rev.*, vol. 84, no. 4, 2017, pp. 195–199.

[7] A. M. Abdel-Hamed, M. M. El-Shafhy, and E. A. Badran, "High ohmic reactor as a shunt limiter (HOR-SL) method for ferroresonance elimination in the distribution system," *IEEE Access*, vol. 10, pp. 134217–134229, 2022, doi: 10.1109/ACCESS.2022.3231190.

[8] V. Grim, P. Ripka, and J. Bauer, "DC current sensor using switching-mode excited in-situ current transformer," *J. Magn. Magn. Mater.*, vol. 500, pp. 1–6, May 2020.

[9] R. Martínez, M. Manana, J. I. Rodríguez, M. Álvarez, R. Mínguez, A. Arroyo, E. Bayona, F. Azcondo, A. Pigazo, and F. Cuartas, "Ferroresonance phenomena in medium-voltage isolated neutral grids: A case study," *IET Renew. Power Gener.*, vol. 13, no. 1, pp. 209–214, Jan. 2019.

[10] T. C. Akinci, E. Ayaz, S. Y. Unnu, and S. Seker, "A review study on ferroresonance phenomena in power systems," in *Proc. Int. Conf. Technics, Technol. Educ. (ICTTE)*, Oct. 2014.

[11] M. Kutija and L. Pravica, "Effect of harmonics on ferroresonance in low voltage power factor correction system—A case study," *Appl. Sci.*, vol. 11, no. 10, p. 4322, May 2021, doi: 10.3390/app11104322.

[12] V. Valverde, A. J. Mazón, I. Zamora, and G. Buigues, "Ferroresonance in voltage transformers: Analysis and simulations," *Renew. Energy Power Quality J.*, vol. 1, no. 5, pp. 465–471, Mar. 2007, doi: 10.24084/repqj05.317.

[13] A. Akinrinde, A. Swanson, and R. Tiako, "Dynamic behavior of wind turbine generator configurations during ferroresonant conditions," *Energies*, vol. 12, no. 4, p. 639, 2019.

[14] I. M. Y. Negara, D. A. Asfani, I. G. N. S. Hernanda, D. Fahmi, Verdiansyah, and B. K. Aji, "Wavelet transformation selection for detection of ferroresonance behaviour," *Proc. Int. Seminar Intell. Technol. Appl. (ISITIA)*, Aug. 2019, pp. 253–258.

[15] H. A. Sharbain, A. Osman, and A. El-Hag, "Detection and identification of ferroresonance," in *Proc. 7th Int. Conf. Model., Simul., Appl. Optim. (ICMSAO)*, Apr. 2017, pp. 1–4.

[16] G. Mokryani, M. R. Haghifam, and J. Esmaeilpoor, "Identification of ferroresonance based on wavelet transform and artificial intelligence," *Eur. Trans. Elect. Power*, vol. 19, no. 13, pp. 474–486, 2009.

[17] G. Mokryani, M.-R. Haghifam, H. Latafat, P. Aliparast, and A. Abdolahi, "Wavelet based kernel Fisher classifier for ferroresonance identification," in *Proc. 15th Int. Conf. Intell. Syst. Appl. Power Syst.*, Curituba, Brazil, Nov. 2009, pp. 8–12.

[18] G. Mokryani, P. Siano, and A. Piccolo, "Identification of ferroresonance based on S-transform and support vector machine," *Simul. Model. Pract. Theory*, vol. 18, no. 9, pp. 1412–1424, Oct. 2010.

[19] M. Mikhak-Beyranvand, B. Rezaeealam, J. Faiz, and A. Rezaei-Zare, "Impacts of ferroresonance and inrush current forces on transformer windings," *IET Electr. Power Appl.*, vol. 13, no. 7, pp. 914–921, Jul. 2019.

[20] A. Arroyo, R. Martinez, M. Manana, A. Pigazo, and R. Minguez, "Detection of ferroresonance occurrence in inductive voltage transformers through vibration analysis," *Int. J. Electr. Power Energy Syst.*, vol. 106, pp. 294–300, Mar. 2019.

[21] M. Yang, W. Sima, L. Chen, P. Duan, P. Sun, and T. Yuan, "Suppressing ferroresonance in potential transformers using a model-free active-resistance controller," *Int. J. Electr. Power Energy Syst.*, vol. 95, pp. 384–393, Feb. 2018.

[22] J. A. Corea-Araujo, J. A. Martinez-Velasco, F. González-Molina, J. A. Barrado-Rodrigo, L. Guasch-Pesquer, and F. Castro-Aranda, "Validation of single-phase transformer model for ferroresonance analysis," *Electr. Eng.*, vol. 100, no. 3, pp. 1339–1349, Sep. 2018.

[23] N. Thanomsat, B. Plangklang, and H. Ohgaki, "Analysis of ferroresonance phenomenon in 22 kV distribution system with a photovoltaic source by PSCAD/EMTDC," *Energies*, vol. 11, no. 7, p. 1742, Jul. 2018.

[24] S. Rezaei, "Adaptive overcurrent protection against ferroresonance," *IET Gener. Transm. Distrib.*, vol. 12, no. 7, pp. 1573–1588, 2018.

[25] L. Han, Y. Peng, Y. Li, B. Yong, Q. Zhou, and L. Shu, "Enhanced deep networks for short-term and medium-term load forecasting," *IEEE Access*, vol. 7, pp. 4045–4055, 2019.

[26] A. Heidary and H. Radmanesh, "Smart solid-state ferroresonance limiter for voltage transformers application: Principle and test results," *IET Power Electron.*, vol. 11, no. 15, pp. 2545–2552, Dec. 2018.

[27] Y. H. Gu and M. H. J. Bollen, "Time-frequency and time-scale domain analysis of voltage disturbances," *IEEE Trans. Power Del.*, vol. 15, no. 4, pp. 1279–1284, Mar. 2000.

[28] Z.-L. Gaing, "Wavelet-based neural network for power disturbance recognition and classification," *IEEE Trans. Power Del.*, vol. 19, no. 4, pp. 1560–1568, Oct. 2004.

[29] M. Kezunovic and Y. Liao, "A novel software implementation concept for power quality study," *IEEE Trans. Power Del.*, vol. 17, no. 2, pp. 544–549, Apr. 2002.

[30] Y. Ju, G. Sun, Q. Chen, M. Zhang, H. Zhu, and M. U. Rehman, "A model combining convolutional neural network and LightGBM algorithm for ultra-short-term wind power forecasting," *IEEE Access*, vol. 7, pp. 28309–28318, 2019.

[31] H. Zang, L. Cheng, T. Ding, K. W. Cheung, Z. Liang, Z. Wei, and G. Sun, "Hybrid method for short-term photovoltaic power forecasting based on deep convolutional neural network," *IET Gener. Transm. Distrib.*, vol. 12, no. 20, pp. 4557–4567, Nov. 2018.

[32] G. Mokryani and M.-R. Haghifam, "Application of wavelet transform and MLP neural network for ferroresonance identification," in *Proc. IEEE Power Energy Soc. Gen. Meeting Convers. Del. Electr. Energy 21st Century*, Jul. 2008, pp. 20–24.
[33] M. S. ElNozahy, R. A. El-Shatshat, and M. M. A. Salama, "A robust technique for overvoltages classification in power transformers," in *Proc. IEEE Power Energy Soc. Gen. Meeting*, Jul. 2012, pp. 1–8.
[34] J. Wang, Q. Yang, W. Sima, T. Yuan, and M. Zahn, "A smart online overvoltage monitoring and identification system," *Energies*, vol. 4, no. 4, pp. 599–615, Apr. 2011.
[35] K. Chen, J. Hu, and J. He, "A framework for automatically extracting overvoltage features based on sparse autoencoder," *IEEE Trans. Smart Grid*, vol. 9, no. 2, pp. 594–604, Mar. 2018.
[36] A. Djebli, F. Aboura, L. Roubache, and O. Touhami, "Impact of the eddy current in the lamination on ferroresonance stability at critical points," *Int. J. Electr. Power Energy Syst.*, vol. 106, pp. 311–319, Mar. 2019.
[37] Ł. Majka and M. Klimas, "Diagnostic approach in assessment of a ferroresonant circuit," *Electr. Eng.*, vol. 101, no. 1, pp. 149–164, Apr. 2019.
[38] I. M. Y. Negara, I. G. N. S. Hernanda, D. A. Asfani, D. Fahmi, L. L. Hakim, and I. G. A. P. Putra, "Identification of ferroresonance on transformer using wavelet transformatio," in *Proc. 2nd Int. Conf. High Voltage Eng. Power Syst. (ICHVEPS)*, Oct. 2019, pp. 1–6, doi: 10.1109/ICHVEPS47643.2019.9011098.
[39] A. Heidary, H. Radmanesh, A. Bakhshi, S. Samandarpour, K. Rouzbehi, and N. Shariati, "Compound ferroresonance overvoltage and fault current limiter for power system protection," *IET Energy Syst. Integr.*, vol. 2, no. 4, pp. 325–330, Dec. 2020.
[40] A. M. Abdel-Hamed, M. El-Shafhy, and E. A. Badran, "A new method for ferroresonance suppression in an IEEE 33-bus distribution system integrated with multi distributed generation," *Sci. Rep.*, vol. 13, no. 1, p. 3381, Feb. 2023, doi: 10.1038/s41598-023-30268-w.

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