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INTELLIGENT ELECTRICAL FAULT DETECTION AND CLASSIFICATION USING ENSEMBLE DEEP LEARNING ARCHITECTURE

Mudasir Ali[1], Umer Farooq[2], Saima Noreen Khosa[3], Urooj Akram[4], Muhammad Faheem Mushtaq[*5]

[1]*Faculty of Computing, The Islamia University of Bahawalpur, 63100, Pakistan*
[3]*Faculty of Information Technology, Khwaja Fareed University of Engineering and Information Technology, Rahim Yar Khan 64200, Pakistan*

[1]mudasiralics786@gmail.com, [2]umer.dgk.se@gmail.com, [3]saimakhosa@yahoo.com, [4]urooj.akram@iub.edu.pk, [*5]faheem.mushtaq@iub.edu.pk

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Corresponding Author: *
Muhammad Faheem Mushtaq

Abstract
The electrical power transmission lines defect detection system uses deep learning algorithm techniques, taking with regard the rising need for electricity in contrast to the slow development of transmission capacity. This research introduces a unique solution to detect electrical faults utilizing an ensemble deep learning algorithm. This research proposed a deep learning-based ensemble ACG model that integrates Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), and Gated Recurrent Units (GRU) to combine feature compression, spatial feature extraction, and temporal pattern learning within a unified framework. In addition, several deep learning architectures, including Artificial Neural Networks (ANN), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), and Convolutional Recurrent Neural Networks (CRNN), are implemented and evaluated to analyze their effectiveness for electrical fault detection and classification. Sensor data collected from electrical systems are preprocessed, normalized, and encoded to assure the model has high-quality inputs. In particular, ACG model performance is examined using different datasets, including datasets comprising various fault types. The proposed ensemble ACG model obtained 99.66% accuracy, 99.54% precision, 99.72% recall, and 99.63% F1 Score. In addition, in order to validate ACG model performance, a K-fold cross validation was employed, and results indicated that ACG model performed better by obtaining 99.79% accuracy, 100% precision, 99.52% recall, and 99.76% F1 score. Experiment results indicate that proposed framework is more accurate, reliable, and precise than previous models utilized in the process of classifying and identifying faults.

INTRODUCTION

The electrical system has become increasingly important to our daily lives in recent years. They function in a state of equilibrium, fault analysis is the main issue that arises in a power system [1]. It is possible to work in a normal flow by analyzing, identifying, and controlling a transmission line fault. A power system can develop faults for a variety of causes, including short circuiting and natural disruptions like earthquakes and lightning. Fault categorization is one way to address this issue [2]. A machine learning method may be used to categorize various kinds of errors. Only when the system is in an imbalanced state can all of these various fault kinds be categorized. They fall into two categories: symmetrical and unsymmetrical defects. Transmission lines are usually the site of unsymmetrical faults like L-L (Line to Line Faults) and L-G (Signal to Ground Faults). When compared to the conventional and current procedures, the novel approach outlined below offers a significant benefit [3].

The electricity system stability is among the most significant factors in modern society due to the increase in the demand for power [4]. It can cause the entire electrical system to collapse. Thus, the rapid detection of faults has come up as a challenge in the operation of power systems [5]. Usually megger-based devices or physical inspection of the electrical system have been used to identify defects. These techniques, however, need more time to discover faults. Therefore, improving the power system dependability is crucial. Thermal imaging technology used to identify heat dissipation in electrical devices with high voltage. The thermal characteristics of High Voltage (HV) electrical devices can be obtained through the Infrared Thermal Imaging (IRT) technology [6].

This technology uses advanced infrared cameras to obtain images of the High HV electrical devices [7]. The obtained image by the camera has retained temperature profile and range. The various scales of different color tones represent different temperature range in electrical device [8]. Using the temperature profile, the modeling of images can be obtained by thermographs. These images are used to categories defective parts according to seriously they need to be maintained in electrical equipment [9]. These defective parts are inspected and repaired according to the electrical equipment priority. In addition to its rapid, inexpensive and non-intrusive manner, IR imaging is currently regarded as a key technique in predicting and avoiding the flaws of various substances in many areas [10]. Thus, in a study of the literature, the infrared imaging technique is important for a variety of applications and practical procedures in the functional operations of electrical equipment without interfering with the system's operation [11].

As the electrical devices, being of high voltage, age, they tend to produce more internal resistance, and hence, more internal heat. This increase in internal heat can lead to a breakdown in the electrical equipment, thereby setting them on fire, leading to a shutdown of the system [12]. Additionally, such as present a risk to the lives of the power substation employees. The damaged components may be found and the extent of the defect can be comprehended by employing the IR-based method for inspecting the electrical devices during periods of high load [13]. The cost of high-voltage equipment maintenance is subject to change depending on the degree of electrical equipment deficiency as well as the type of equipment required to carry out the maintenance operations on the electrical power grids [14].

The monitoring of HV equipment is vital in the initial prevention of the fault as well as the enhancement of the operation lifecycle of HV equipment [15]. In certain cases, the monitoring plan is created based on the electrical power networks records of malfunctioning devices [16]. The functioning of HV equipment in power substations is monitored by a variety of sensors using the infrared imaging approach [17]. This monitoring technique offers comprehensive information regarding the operation performance of high voltage devices, thus enabling the enhancement of the working life, elimination of unnecessary steps, prevention of breakdown, as well as the management of the maintenance cost of HV equipment [18].

The huge quantity of electrical equipment in power substations makes the evaluation of electrical equipment status is the time consuming operation since the traditional methods for assessing the condition of electrical equipment require skilled and knowledgeable individuals [19]. The autonomous thermal state analysis of electrical components has been the focus of study in recent years. The components analysis method is applied at several phases. At the first stage, a portion of the component in the thermal image is found [20]. The extraction of statistical characteristics and other pertinent data on the respective portion thermal status is the second step[21]. The computed statistical characteristics are examined for the decision-making process in the last phase. In this situation, identifying the precise area of the infrared picture is crucial for making decisions [22]. The major contributions of this work are as follows:

1. This research introduces a deep learning framework the proposed ensemble ACG, design to use electrical fault data to improve the results of electrical problem detection in power transmission systems.
2. This research provides a several kinds of deep learning models, such as convolutional neural networks, long short-term memory, gated recurrent units, artificial neural networks, recurrent neural networks, convolutional recurrent neural networks, and autoencoders, are implemented and analyzed to evaluate their effectiveness for fault detection and classification.
3. Data preprocessing approaches is applied, including handling missing value, transforming categorical features into numerical forms, and normalized the data to ensure reliable and efficient model training.
4. The proposed ensemble model accomplished an excellent position of identifying electrical defects, attaining high accuracy, recall, f1 score and precision while successfully lowering false detection and enhancing classification reliability.
5. The evaluation process incorporates robust validation method such as K-fold cross-validation, which confirms the proposed model generalization, stability, and consistency across the data.

The following sections comprise this study: The literature on recent research and advancements are explained in the Section 2. An overview of the study plan, including data collection methods, data processing techniques, and a proposed intrusion detection method, is given in Section 3. Section 4 presents the findings and discusses the proposed approach. The conclusion and potential paths for further study are discussed in Section 5.

2. Related Work

In research, clustering, mathematical techniques like Hough transformations and Gabon filters, knowledge-based techniques, and traditional pattern recognition techniques or low-level filters are the most often employed models for fault identification in power line components [23]. In this regard, a defective transmission line spacer was located using a combination of a Canny edge detector and a Hough transform. First, a scan window was made along the conductor route [24]. Potential spacers are present after the convolution; they will be found in every sliding window. Lastly, a shape configuration parameter was created based on the measurement of connected portions to ascertain if the discovered item was fractured [25]. An area where a detected insulator had a flashover was retrieved using a color channel in a lab color system. A 92.7% identification rate was obtained when this technology was evaluated on 100 flashover fault insulation photos. Using a similar idea, defects pertaining to a missing insulator cap were found using a combination of form and pattern factors based on Saliency and Adaptive Morphology (S-AM) [26]. Furthermore, such a methodology is not applicable to multiple classification, location, and identification of faults, particularly in a complex natural environment, as is applicable to EPTN components [27].

Utilized ANN and ML algorithms to solve transmission issues and enhance power quality [28]. Examining fault detection and fault classification, power quality may be enhanced. Fault detection and classification are developed using back propagation algorithms and feed forward networks [29]. The deduction mostly yields 96% accuracy and achieves 5.6 148 Mean Square Error (MSC) tolerance. The issue may be classified with ease because to the classification 0.893955 MSC tolerance and 70% perfection from this suggested approach [30].

Several kinds of techniques have been put forth to identify the precise position of a component in infrared thermal images. The study provide a method for insulators by integrating infrared and ultraviolet images using the Otsu method along with the PSO-BPNN approach [31]. The neuro-fuzzy technique was used in the research study to identify the components of the arresters. The detected characteristics and the infrared pictures are sent into the artificial neural network. The watershed approach is not suitable for images containing noise as well as non-uniform colors. This approach requires the initial points to be properly projected, and the components must be placed in the center of the thermal images to detect the components [32]. The color segmentation approach is used on the specific part of the infrared images as well as the pattern of the temperature distribution. Therefore, the fault detection in the electrical equipment can be fused with the other components in the substation [33]. The color segmentation approach is used only on the basis of the clustering of the pixels. The thresholding approach for the infrared images can result in the overfitting phenomenon in the segmentation approach [34]. Convolutional neural networks were used by the authors to identify insulators from infrared pictures using in recognition of two-class items, insulator and non-insulator equipment, a vector of locally aggregated descriptors approach was used [35]. The feature extraction algorithm was used by several researchers for the fusion of the thermal as well as the visible images of the electrical components by the scale-invariant feature transform approach [36].

Another research obtained state-of-the-art performance in visual image identification using the 2012 ImageNet ILSVRC dataset [37]. Object recognition issues have been significantly improved by object recognition approaches such as region-based fully convolutional Siamese network (R-FCSN), faster R-CNN, and single shot multi-box detector (SSMBD) [38]. Through improving classification performance, the CCN method may provide human-level recognition from the raw input picture pixel data [39].

This sequence of processes repeats multiple times depending on the domain [40]. A representation of the completely linked layers is the last step, after which the data classes are distinguished. Therefore, the max-pooling filter within every feature map can then perform an invariance to the small-scale distortions [41]. The identification of surface discoloration caused by some of the first instances of deep learning-based defect detection is flashover on the insulator utilizing a CNN classifier using an AlexNet model that has already been trained. The experiments were carried out by achieving a score of 98.71% mean Average Precision (mAP) on 1000 data samples [42]. Despite being restricted to insulator state inspection image categorization, which required a lot of feature engineering, the proposed approach performance was better than the conventional handmade method. Additionally, Faster R-CNN has been introduced for the identification of missing insulator caps [43].

3. Proposed Methodology

The study uses advanced deep learning methods to identify and categorize electrical defects by identifying intricate temporal and spatial patterns in electrical data. Several deep learning approaches have been explored for electrical fault detection, including ANN, RNN, CNN, LSTM, GRU, and CRNN) In addition, a proposed ACG ensemble model has been developed to improve detection accuracy and overall classification performance. Each of these models has its unique advantages; CNN models, for example, are useful for feature extraction in relation to the spatial characteristics of the measurements, whereas LSTM and GRU models can help in analyzing the sequential nature of signals by considering temporal dependencies. Other architectures built on top of RNN models have improved our understanding of dynamic data analysis, and autoencoders have also proven effective in detecting anomalies through their capability of capturing normal behavior and then finding deviations from it. Feature compression and noise removal tasks are performed by the autoencoder, while CNN learns the high-level characteristics of the input data, and GRU detects the time-dependent relationships among the electric signals. In addition to that, during the process of developing the models, certain data processing methods like normalization and label encoding are performed in order to encode categorical data into numeric values. Data splitting is done with the 80/20 training and testing ratio purposes, respectively. The experimental analysis, it is observed that the ensemble model constructed using the ACG architecture provides better accuracy and reliability than the standalone deep learning techniques for power grid network fault detection. The proposed ensemble model is illustrated in Figure 1.

3.1 Dataset Description

The dataset that has been employed in this experiment has been specifically created for solving binary classification problems. In this case, the target variable will be whether there is a fire alarm or not. The dataset has been developed on the basis of information gathered from a smoke detector system that has been designed using the Internet of Things technology along with artificial intelligence modeling. Smoke detectors serve an important function in detecting fires by detecting any smoke particles in the air. Photoelectric sensors detect smoke by measuring the scattering of light particles when they collide with smoke particles. Ionization sensors work through the measurement of any variations in electric current as ionized air particles are interrupted by smoke particles. These situations include common indoor and outdoor scenarios, controlled fires such as wood and gas fires within training environments, grilling in outdoor settings with various fuel sources, and high

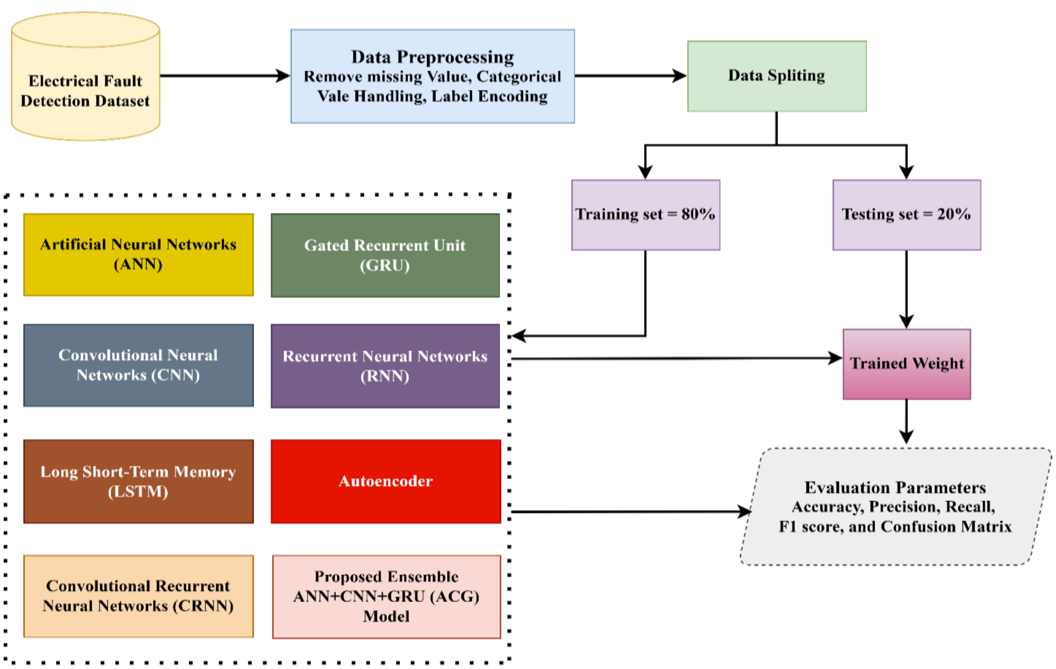

Figure 1. Architecture of Proposed System.

-humidity scenarios. With all of these scenarios included in the data collection process, the deep learning algorithm will be able to differentiate between regular environmental conditions and a fire situation. In total, there are about 60,000 samples collected every second. All samples are stamped with timestamps that use UTC in order to preserve the sequential nature of the collection process. Below is an illustration of the correlation matrix for the described dataset. Figure 2 show the Correlation Heatmap of Dataset Description.

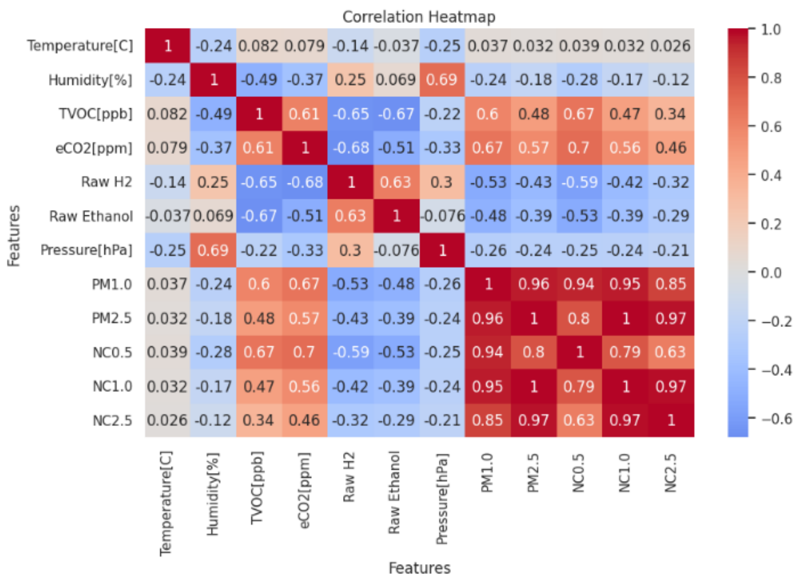

Figure 2. Correlation Heatmap of Dataset.

3.2 Preprocessing

The data preparation before implementation of the models, we made sure that the obtained data would give reliable and valuable results. Firstly, we cleaned the data set from all inconsistencies, including duplicates or missing observations. Sensor data had to be processed, and their scales had to be standardized, thus allowing the machine learning algorithm to obtain better predictions. Any categorical data had to be encoded numerically so as to be able to apply it in further computations. Moreover, the time stamp was ordered in such a way that the order of the measurements remained sequential. The former will be used to build a regression model while the latter would be used for validation.

3.3 Deep Learning Algorithms

A deep learning technique was utilized to examine the dataset and extract meaningful patterns associated with the target variable. Each model was selected based on its ability to handle different characteristics of the data. Some approaches were used to capture important features from the input signals, while others focused on learning relationships and dependencies within sequential data. In addition, a baseline method was included for comparison purposes, and an ensemble approach was considered to combine the strengths of multiple techniques. Furthermore, an unsupervised method was utilized to identify unusual or anomalous patterns by learning the normal behavior present in the data.

3.3.1 Convolutional Neural Network (CNN)

CNN use the methods of convolution and pooling for extracting valuable information in form of spatial features. These neural networks have the ability to automatically discover patterns including correlations and local neighborhoods without any need for explicit feature extraction. CNNs are suitable for structured data and signals since filters are applied to them in a scanning fashion. The operation of a layer of CNNs may be written as follows:

$$xj = f(\sum ixi * kij + bj)$$

3.3.2 Artificial Neural Network (ANN)

The ANN is composed of linked neurons laid out in layers, and each neuron takes input and then uses the activation function to compute an output. ANN is used as the basic algorithm that learns nonlinear connections between input and output data. The mathematical representation of a neuron is:

$$y = f(\sum_{i=1}^{n} w_i\, x_i + b)$$

3.3.3 Long Short-Term Memory (LSTM)

LSTM neural networks belong to the family of recurrent neural networks and are used to find long-range dependencies in data. In LSTM networks, memory cells and gates are used to manage the flow of information. LSTM neural networks are excellent at solving problems related to time series analysis and sequence predictions. One important element of LSTM networks is:

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t$$

3.3.4 Recurrent Neural Networks (RNN)

RNN use a hidden state to handle sequential data which contains information related to past inputs. In this way, the model learns certain temporal aspects. But traditional RNNs can have problems with learning long sequences because of gradient issues. The formula for updating a hidden state in RNN is:

$$h_t = tanh\,(Wx_t + Uh_{t-1} + b)$$

3.3.5 Autoencoder

Autoencoder is an unsupervised machine learning algorithm that learns how to encode input data in a compressed form. Autoencoder contains two subnetworks encoder and decoder which map the input to its compressed representation and back respectively. Applications like noise filtering and anomaly detection, which identify deviations from the predicted pattern, are good uses for autoencoders. An equation is represented as:

$$\hat{x} = g(f(x))$$

3.3.6 Convolutional RNN (CRNN)

CRNN leverage both spatial and temporal feature learning by combining CNN and RNN architectures. Important characteristics are extracted from the input by CNN layers and sent to recurrent layers for sequence modeling, such as RNN, LSTM, or GRU. This hybrid structure is effective for tasks involving sequential data with spatial dependencies. The combined operation can be expressed as:

$$h_t = RNN(CNN(x_t))$$

3.3.7 Proposed ACG-Based Ensemble Model

The proposed ACG ensemble model aims to achieve better prediction results since each of the three neural networks, namely the ANN, CNN, and GRU, contributes its own strengths to enhance prediction performance when used together. In particular, at the beginning of this architecture, the Autoencoder network is used to discover latent features and compress the input data to reduce the noise and focus on important patterns. Next, after receiving input data preprocessed by Autoencoder, CNN analyzes and identifies essential structures of the data. Then, the sequence of features generated by the CNN network will be analyzed by the GRU network to detect and exploit temporal information of features. Eventually, the final predictions are achieved by integrating outputs of all networks into the stacking process. Thus, with the use of stacking, the model can utilize feature extraction and learning advantages of each network. Prediction results using the stacked models will be better and more stable than using isolated models. Finally, with the help of stacking, the final predictions can be produced:

$$y = f_{stack}(h_t, F, z)$$

3.3.8 Validation Results

The validation procedure demonstrates how well the proposed models identify the target condition. This allows us to evaluate the model's performance using data that has been observed. Metrics including F1 score, recall, precision, and accuracy were used to evaluate the model's performance. The results showed that the better performance of ensemble ACG model than the other models in terms of both increased accuracy and the capability of recognize complex patterns in the data. This suggests that it is reliable to use the proposed ensemble architecture for real-time prediction tasks. The k-fold cross-validation using the proposed approach is shown in Figure 3.

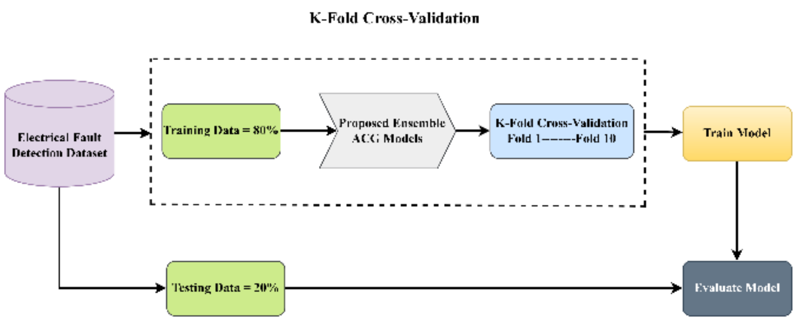

Figure 3. Proposed Model using K-Fold Cross-Validation.

3.3.9 Evaluation Parameters

The deep learning model performance is frequently evaluated using measures such as accuracy, recall, and precision, particularly in terms of categorization assignments. The evidence shows how well the model can estimate the various input data types or categories. Even though this statistic is often employed, precision is always enough, particularly when working with datasets that aren't balanced. The genuine positive rate, also referred to as sensitivity, it is the proportion of successfully predicted fulfilled events in memory that deals with responses to real happy experiences. It illustrates the model ability to identify every pertinent good scenario. The model effectively reduces false negatives, as seen by stronger recall scores. It illustrates why the model can detect positive samples and reduce false positives. A high-accuracy model generates minimal false positives.

Accuracy is a metric used in research that measures the extent to which the expected and actual numbers or observations match up. The mathematical formulation are:

$$Accuracy = \frac{(TP + TN)}{TP + TN + FP + FN}$$

Precision is also used to describe the level of conformity or consistency over repeated observations or measures. For measuring accuracy in classification tasks, the following formula is commonly applied:

$$Precision = \frac{TP}{(TP + FP)}$$

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A common statistic for evaluating a model's performance in classification challenges is recall. Determining whether the model can accurately identify positive observations or occurrences among all of the data that are actual positive instances is the main goal of this study. Recall is frequently produced using the formula below:

$$Recall = \frac{TP}{(TP + FN)}$$

In classification tasks, the F1 score is a performance
assessment statistic that combines recall and accuracy into a single number. It offers a fair assessment of a model correctness, particularly when working with unbalanced data, and is defined as the harmonic mean of precision and recall. The F1 score is calculated using the following formula:

$$F1\ score = \frac{2 * (Precision * Recall)}{(Precision + Recall)}$$

4. Results and Discussion

The performance improvement for the proposed framework base model comparison was measured through experiment results which used recall, precision, accuracy and f1 score as assessment metrics. The explanation highlights the advantages of the proposed model and illustrates the way it gets used to address the current challenge by overcoming the baseline shortcomings.

4.1 Performance of ANN Model

The ANN is trained on a dataset in order to determine the assessment standards. The Table 1 displays the ANNs model performance over a broad range of epochs, from 5 to 30. A recall of 0.9906, precision of 0.9954, accuracy of 0.9936, and F1 score of 0.9930, the method was able to anticipate a variety of fault kinds. Figure 4 show the confusion matrix of ANN model.

Table 1. Performance metrics for ANN Model.

Epoch	Accuracy	F1 score	Precision	Recall
5	0.9659	0.9647	0.9675	0.9624
10	0.9758	0.9756	0.9783	0.973
15	0.9832	0.9833	0.9857	0.9815
20	0.9885	0.9882	0.9945	0.9865
25	0.9912	0.9917	0.9934	0.9891
30	0.9936	0.993	0.9954	0.9906

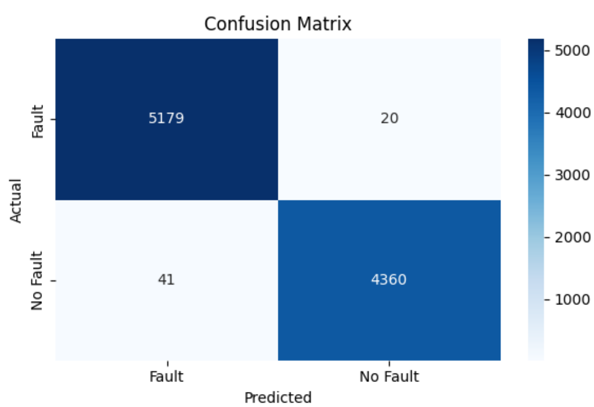

Figure 4. Confusion Matrix of ANN Model.

4.2 Performance of GRU Model

The GRU has been trained on a dataset; the evaluation metrics are computed. Table 2 displays the GRU model performance over a variety of epochs, from five to thirty. F1 score of 0.9942, accuracy of 0.9946, recall of 0.9940, and precision of 0.9943. It accurately and effectively predicted a variety of fault kinds. Figure 5 present the confusion matrix of GRU model.

Table 2. Performance metrics for GRU Model.

Epoch	Accuracy	F1 score	Precision	Recall
5	0.9821	0.9813	0.9815	0.9812
10	0.9875	0.9869	0.9871	0.9868
15	0.9902	0.9896	0.9898	0.9895
20	0.9925	0.9919	0.9921	0.9918
25	0.9936	0.9931	0.9933	0.9939
30	0.9946	0.9942	0.9943	0.994

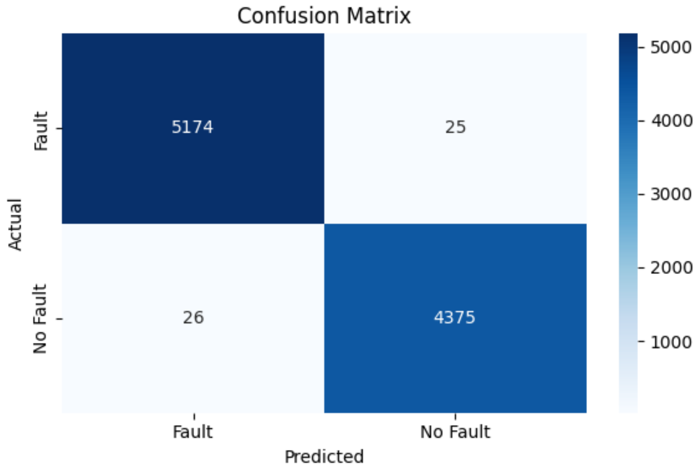

Figure 5. Confusion Matrix of GRU Model.

4.3 Performance of CNN Model

The CNN is trained using a dataset in order to calculate the evaluation metrics. The Table 3 displays the CNN model performance over a variety of epochs, from 5 to 30. With an accuracy of 0.9922, recall of 0.9859, F1 score of 0.9915, and precision of 0.9972, the test was able to forecast a variety of errors. Figure 6 show the confusion matrix of CNN model.

Table 3. Performance metrics for CNN Model.

Epoch	Accuracy	F1 score	Precision	Recall
5	0.9453	0.9459	0.9549	0.9471
10	0.9673	0.9638	0.9656	0.9552
15	0.9729	0.9723	0.9781	0.9677
20	0.9817	0.9811	0.9875	0.9753
25	0.9879	0.9873	0.9937	0.9815
30	0.9922	0.9915	0.9972	0.9859

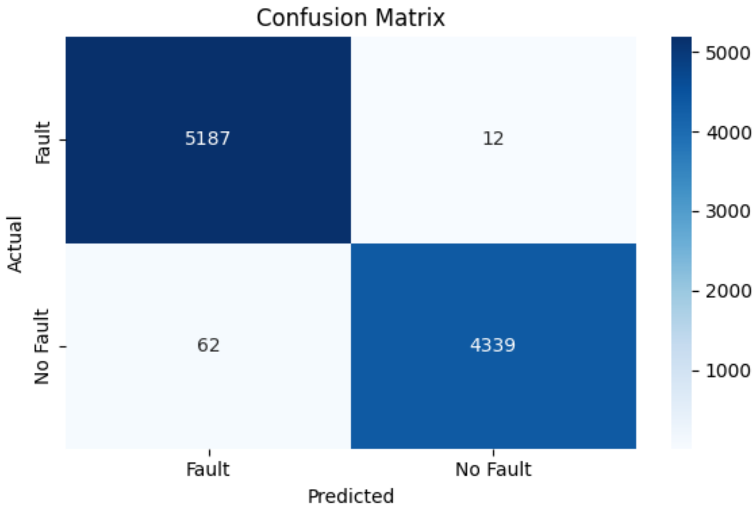

Figure 6. Confusion Matrix of CNNs model.

4.4 Performance of LSTM Model

The LSTM are trained on a dataset in order to compute the performance measures. The LSTM model performance over a range of epoch types, from 5 to 30, is shown in the Table 4. Since it was able to accurately anticipate a variety of fault with a precision of 0.9918, its accuracy was 0.9852, its F1 score was 0.9911, and its precision was 0.9970. Figure 7 show the confusion matrix of LSTM model.

Table 4. Performance metrics for LSTMs Model.

Epoch	Accuracy	F1 score	Precision	Recall
5	0.9421	0.9418	0.9503	0.9335
10	0.9617	0.9612	0.9672	0.9554
15	0.9735	0.9734	0.9791	0.9678
20	0.9824	0.9816	0.9875	0.9763
25	0.9879	0.9865	0.9921	0.9811
30	0.9918	0.9911	0.997	0.9852

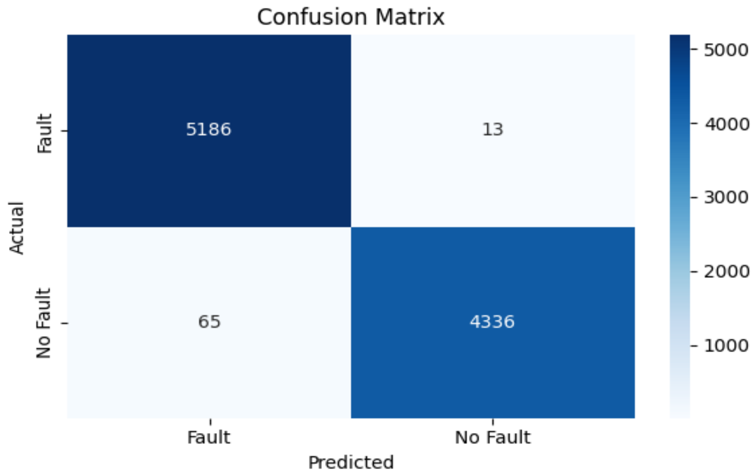

Figure 7. Confusion Matrix of LSTM Model.

4.5 Performance of RNN Model

The RNN is trained on one given dataset to calculate the measures of performance. The RNN model performance over various types of epochs, from epoch 5 to epoch 30, is presented in the Table 5. As it could predict a range of fault with a precision of 0.9979, its accuracy was 0.9916, its F1 score was 0.9908, and its recall was 0.9938. Figure 8 show the confusion matrix of RNN model.

Table 5. Performance metrics for RNN Model.

Epoch	Accuracy	F1 score	Precision	Recall
5	0.9458	0.9437	0.952	0.9353
10	0.9625	0.9627	0.9773	0.9559
15	0.9767	0.9741	0.9815	0.9683
20	0.9839	0.9823	0.9897	0.9765
25	0.9887	0.9871	0.9945	0.9813
30	0.9916	0.9908	0.9979	0.9838

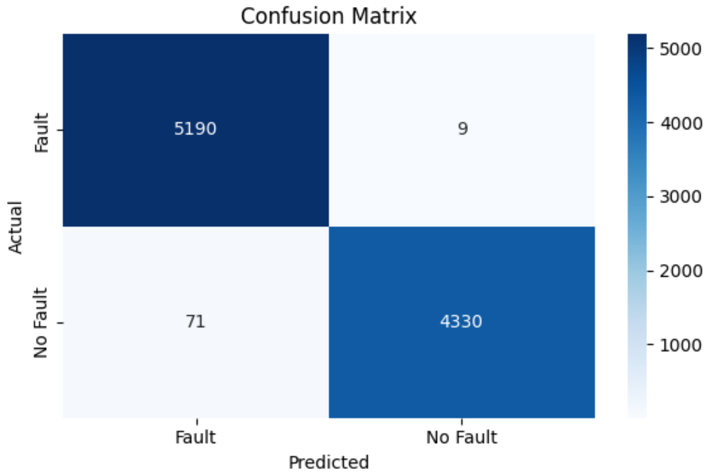

Figure 8. Confusion Matrix of RNN Model.

4.6 Performance of Autoencoder Model

The Autoencoder determines the performance metrics after being trained on a particular dataset. A test dataset is then used for testing. The Autoencoder model performance is shown in the Table 6 for a range of epoch types, from 5 to 30. It showed a great capacity to anticipate a wide variety of results a recall of 0.9856, F1 score of 0.9915, accuracy of 0.9922, and precision of 0.9974. Figure 9 display the confusion matrix of Autoencoder.

Table 6. Performance metrics for Autoencoder Model.

Epoch	Accuracy	F1 score	Precision	Recall
5	0.9453	0.9459	0.9536	0.9461
10	0.9628	0.9617	0.9675	0.9566
15	0.9757	0.9755	0.9815	0.9737
20	0.9846	0.9844	0.9981	0.9793
25	0.9891	0.9882	0.9943	0.9825
30	0.9922	0.9915	0.9974	0.9856

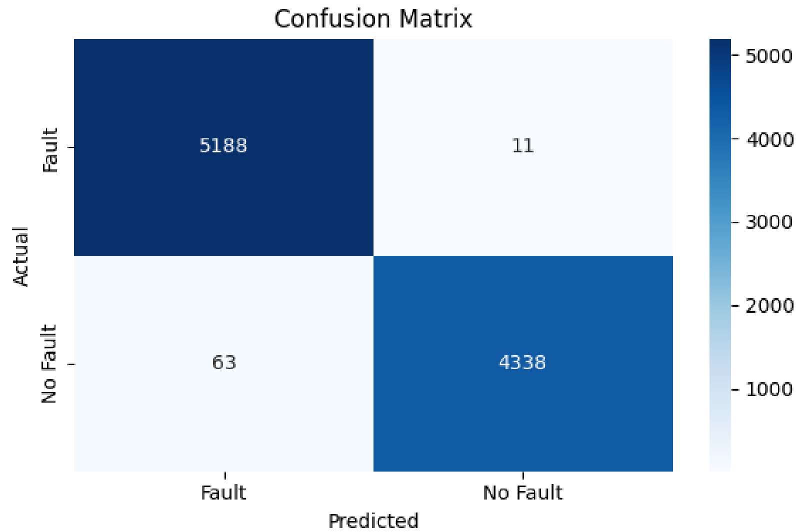

Figure 9. Confusion Matrix of Autoencoder Model.

4.7 Performance of CRNN Model

The performance measurements are estimated by training the CRNN using a specified dataset. The CRNN model performance is shown in the Table 7 for a variety of epoch types, ranging from 5 to 30. With accuracy, recall, and F1 scores of 0.9929, 0.9911, and 0.9976, as a result, it is able to forecast a broad range of faults. Figure 10 display the confusion matrix of CRNN model.

Table 7: Performance metrics for CRNN Model.

Epoch	Accuracy	F1 score	Precision	Recall
5	0.9148	0.9138	0.9250	0.9021
10	0.9453	0.9451	0.9556	0.9359
15	0.9663	0.9638	0.9727	0.9552
20	0.9785	0.9776	0.9851	0.9784
25	0.9861	0.9859	0.9923	0.9785
30	0.9911	0.9902	0.9976	0.9829

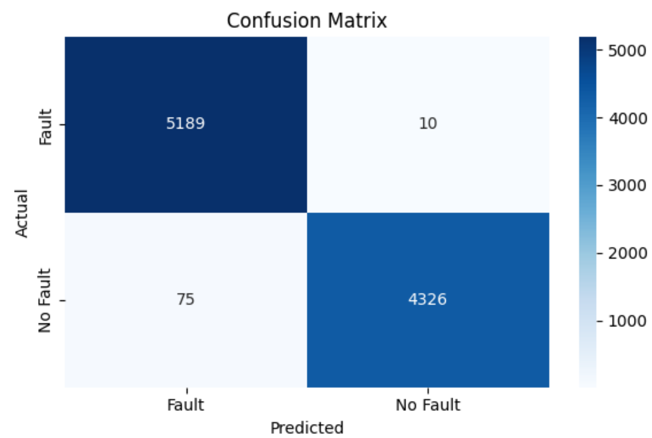

Figure 10. Confusion Matrix of CRNN Model.

4.8 Performance of proposed ANN+CNN+GRU Models

The most important elements of the work are the evaluation of deep learning models. The Table 8 displays the test results that were achieved with the proposed model. In the metrics of accuracy, precision, recall, and F1 score, 0.9966, 0.9654, 0.9972, and 0.9663 are the deep learning models that this study recommends outperforming the others. Figure 11 illustrate the confusion matrix of proposed model.

Table 8. Performance metrics for Proposed Model

Epoch	Accuracy	F1 score	Precision	Recall
5	0.9917	0.9907	0.9893	0.9925
10	0.993	0.9927	0.9915	0.9947
15	0.9945	0.9941	0.9939	0.9952
20	0.9955	0.9951	0.9942	0.9963
25	0.9962	0.9959	0.9959	0.9968
30	0.9966	0.9963	0.9954	0.9972

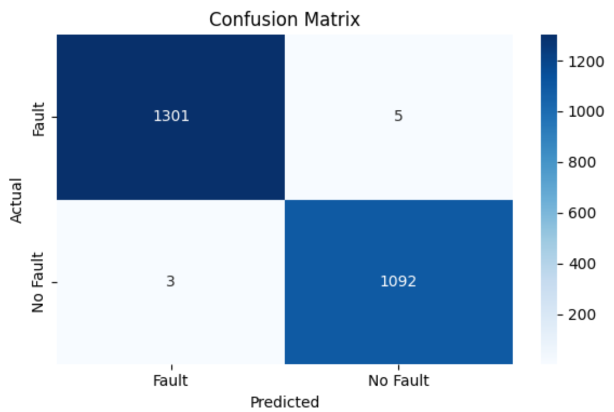

Figure 11. Confusion Matrix of Proposed Model.

4.9 K-fold Cross-Validation for the Proposed Model

The performance of the proposed approach is validated using K-fold cross-validation. Tables 9, 10, 11, and 12 present the results for k = 3, 5, 7, and 10 along with training time. The findings show that the proposed models outperform other models on average, although operating slightly differently for various folds.

Table 9: Model performance with k = 3.

Fold	Accuracy	F1 score	Precision	Recall
1	0.9928	0.9922	0.9925	0.9918
2	0.9938	0.9933	0.998	0.9887
3	0.9938	0.993	0.9944	0.9916

Table 10: Model performance with k = 5.

Fold	Accuracy	F1 score	Precision	Recall
1	0.9927	0.9922	0.9911	0.9933
2	0.9943	0.9936	0.9977	0.9896
3	0.9958	0.9955	0.9978	0.9933
4	0.9969	0.9967	0.9967	0.9967
5	0.9948	0.9941	0.9918	0.9965

Table 11: Model performance with k = 7.

Fold	Accuracy	F1 score	Precision	Recall
1	0.9898	0.9892	0.9892	0.9892
2	0.9942	0.9935	0.9951	0.9919
3	0.9927	0.9920	0.9904	0.9936
4	0.9942	0.9937	100	0.9874
5	0.9956	0.9955	0.994	0.9970
6	0.9927	0.9917	0.9869	0.9967
7	0.9920	0.9909	0.9950	0.9868

Table 12: Model performance with k = 10.

Fold	Accuracy	F1 score	Precision	Recall
1	0.9938	0.9935	0.9935	0.9935
2	0.9938	0.9931	0.9908	0.9954
3	0.9948	0.9942	0.9977	0.9907
4	0.9938	0.9931	0.9977	0.9885
5	0.9958	0.9957	0.9979	0.9936
6	0.9958	0.9953	100	0.9906
7	0.9958	0.9957	0.9957	0.9957
8	0.9958	0.9954	0.9954	0.9954
9	0.9885	0.9871	0.9859	0.9883
10	0.9979	0.9976	100	0.9952

4.10 Comparative analysis of all models

In this research, every model is used to show the results in Table 13. Results are shown for F1 scores, recall, accuracy, and precision. The proposed approach is shown to be more successful than even models like ANN, GRU, CNN, LSTM, RNN, RCNN, and Autoencoder that are intended to yield the best results with the given dataset. However, in terms of accuracy, the proposed approach exceeds all existing models.

Table 13: Analysis of all employed models.

Models	Accuracy	F1 score	Precision	Recall
CNN	0.9922	0.9915	0.9972	0.9859
ANN	0.9936	0.993	0.9954	0.9906
LSTM	0.9918	0.9911	0.997	0.9852
RNN	0.9916	0.9908	0.9979	0.9838
GRU	0.9946	0.9942	0.9943	0.994
Autoencoder	0.9922	0.9915	0.9974	0.9856
CRNN	0.9911	0.9902	0.9976	0.9829

ACG	0.9966	0.9963	0.9954	0.9972

4.11 Performance Comparison with Existing Approaches

The proposed ensemble GRU, CNN, and ANN model outperforms conventional models by combining the advantages of multiple deep learning structures into a single framework. A suggested technique allows the model to extract more characteristics and improve the classification accuracy of electrical issue detection. It finds subtle patterns in false positives that individual models would overlook. The validity of the results was ensured through the use of k-fold cross-validation. The data set was partitioned into k number of equal subsets. In each cycle, a particular subset was taken as a test subset, whereas the other subsets were considered as training sets. The entire process was performed k number of times. By preventing overfitting and ensuring that the model works correctly on all data, it strengthens and increases the reliability of the evaluation. The Table 14 provides a comparison of the study with its frame of existing research.

Table 14: Comparative Study with Existing Models.

Literature	Classifiers	Results
[44]	LSTM	Accuracy= 97.70%
[45]	ANN	Accuracy = 87%
[46]	ANN	Accuracy= 84.40%
[47]	ANN	Accuracy= 97.90%
[48]	HTT-CNN	Accuracy = 99.29
[49]	WT-CNN	Accuracy = 98%
[50]	ANN	Accuracy = 70%
[51]	CNN-LSTM	Accuracy= 98.60%
[52]	BRNN	Accuracy= 96.11%
[53]	SE-CDAE	Accuracy = 97.98%, Precision = 94.83%, Recall = 96.28%, F1- score = 97.35%
[54]	FCN	Accuracy= 99.57%
[55]	ANN	Accuracy= 99.33%
[56]	CNN	Accuracy= 99.52%
[57]	LSTM	Accuracy= 99.45%
[58]	MFF-GNN	Accuracy = 94.5% Precision = 83.1% Recall = 82.8% and F1 score = 81.9%
Proposed	ACG	Accuracy = 99.66, Precision = 99.54, Recall = 99.72, F1 score = 99.63
Proposed	ACG with K fold	Accuracy = 99.79%, Precision = 100% Recall = 99.52%, F1 score = 99.76%

5. Conclusion and Future Work

The defect is identified by applying deep learning techniques to power system model, while evaluating the correctness of the model using different data parameters. Accurate analysis is conducted on different models and then the most effective model is selected. The study provides a method for fault identification and classification in electrical power transmission systems based on the proposed ensemble ACG model. The three models of ANN, CNN, and GRU enable the identification of temporal and spatial patterns in the data. The experiments finding demonstrated that the ACG model had a precision 99.54%, accuracy 99.66%, recall 99.72%, and f1 score 99.63%. The performance rate has been improved by the K-Fold Cross-Validation, reaching a precision 100%, accuracy 99.79%, f1 score 99.76%, and recall 99.52%. The findings demonstrate the reliability and accurate the proposed technique is for real-time electrical fault identification. In future studies, the model could consider incorporating more parameters into the power system and use real-time streaming data.

REFERENCES

[1] M.-F. Guo, N.-C. Yang, and W.-F. Chen, "Deep-learning-based fault classification using Hilbert–Huang transform and convolutional neural network in power distribution systems," IEEE Sensors Journal, vol. 19, no. 16, pp. 6905-6913, 2019.

[2] N. A. M. Leh, F. M. Zain, Z. Muhammad, S. Abd Hamid, and A. D. Rosli, "Fault detection method using ANN for power transmission line," in 2020 10th IEEE international conference on control system, computing and engineering (ICCSCE), 2020: IEEE, pp. 79-84.

[3] A. Moradzadeh, H. Teimourzadeh, B. Mohammadi-Ivatloo, and K. Pourhossein, "Hybrid CNN-LSTM approaches for identification of type and locations of transmission line faults," International Journal of Electrical Power & Energy Systems, vol. 135, p. 107563, 2022.

[4] M. Rizwan et al., "Depression intensity classification from tweets using FastText based weighted soft voting ensemble," Computers, Materials & Continua, vol. 78, no. 2, pp. 2047-2066, 2024.

[5] S. F. Rubab et al., "The Comparative Performance of Machine Learning Models for COVID-19 Sentiment Analysis," in International Conference on Soft Computing and Data Mining, 2022: Springer, pp. 371-379.

[6] C. Khadse, A. A. Patharkar, and B. S. Chaudhari, "Electromagnetic field and artificial intelligence based fault detection and classification system for the transmission lines in smart grid," Energy Sources, Part A: Recovery, Utilization, and Environmental Effects, vol. 47, no. 1, pp. 9362-9376, 2025.

[7] Alrifaey, M., Lim, W. H., & Ang, C. K. (2021). A novel deep learning framework based RNN-SAE for fault detection of electrical gas generator. *IEEE Access*, *9*, 21433-21442.

[8] A. A. Ghaffar et al., "Refined Sentiment Analysis by Ensembling Technique of Stacking Classifier," in International Conference on Soft Computing and Data Mining, 2022: Springer, pp. 380-389.

[9] M. F. Mushtaq, U. Akram, A. Tariq, I. Khan, M. Zulqarnain, and U. Iqbal, "An innovative cognitive architecture for humanoid robot," International Journal of Advanced Computer Science and Applications, vol. 8, no. 8, 2017.

[6] T. Kiran et al., "Textile defect detection in the textile industry using deep learning," Journal of Computing & Biomedical Informatics, vol. 8, no. 02, 2025.

[7] Belagoune, S., Bali, N., Bakdi, A., Baadji, B., & Atif, K. (2021). Deep learning through LSTM classification and regression for transmission line fault detection, diagnosis and location in large-scale multi-machine power systems. *Measurement*, *177*, 109330.

[8] M. A. Shahid, U. Akram, M. M. A. Shahid, A. Samad, and R. Majeed, "A systematic approach towards compromising remote site HTTPS traffic using open source tools," in 2020 IEEE 23rd International Multitopic Conference (INMIC), 2020: IEEE, pp. 1-6.

[9] U. Iqbal, R. Ghazali, and A. Kanwal, "Functional expansions based multilayer perceptron neural network for classification task," Computación y Sistemas, vol. 22, no. 4, pp. 1625-1635, 2018.

[10] A. I. Khan *et al.*, "Intelligent Cloud Based Load Balancing System Empowered with Fuzzy Logic," *Comput. Mater. Contin.*, vol. 67, no. 1, pp. 519–528, 2021.

[11] M. Ali, M. Shahroz, S. Alfarhood, M. Safran, and I. Ashraf, "Hybrid machine learning model for efficient botnet attack detection in IoT environment," IEEe Access, vol. 12, pp. 40682-40699, 2024.

[12] M. F. Mushtaq, D. M. Khan, U. Akram, S. Ullah, and A. Tariq, "A cognitive architecture for self learning in Humanoid Robots," International Journal of Computer Science and Network Security, vol. 17, no. 5, p. 26â, 2017.

[13] M. Ali et al., "Botnet detection in internet of things using stacked ensemble learning model," Sci Rep, vol. 15, no. 1, p. 21012, 2025.

[14] oradzadeh, A., Teimourzadeh, H., Mohammadi-Ivatloo, B., & Pourhossein, K. (2022). Hybrid CNN-LSTM approaches for identification of type and locations of transmission line faults. *International Journal of Electrical Power & Energy Systems*, *135*, 107563.

[15] Lei, T., Lv, F., Liu, J., Zhang, L., & Zhou, T. (2022). Research on fault detection algorithm of electrical equipment based on neural network. *Mathematical Problems in Engineering*, *2022*(1), 9015796.

[16] Chen, H., Jiang, B., Zhang, T., & Lu, N. (2020). Data-driven and deep learning-based detection and diagnosis of incipient faults with application to electrical traction systems. *Neurocomputing*, *396*, 429-437.

[17] de Las Morenas, J., Moya-Fernández, F., & López-Gómez, J. A. (2023). The edge application of machine learning techniques for fault diagnosis in electrical machines. *Sensors*, *23*(5), 2649.

[18] M. Khalid, U. Akram, M. Safran, S. Alfarhood, and I. Ashraf, "Sentiment analysis for deepfake X posts using novel transfer learning based word embedding and hybrid LGR approach," Sci Rep, vol. 15, no. 1, p. 28305, 2025.

[19] S. A. S. Bukhari, M. F. Mushtaq, and M. A. Ahmad, "A Comprehensive Review of Novel AI Techniques and Applications in Bioinformatics," Technical Journal of University of Engineering & Technology Taxila, vol. 30, no. 1, 2025.

[20] M. Ali, M. Shahroz, R. Majeed, A. Samad, and U. Akram, "Elderly fall activity detection using supervised machine learning models," in International Conference on Soft Computing and Data Mining, 2022: Springer, pp. 331-340.

[21] M. Ali, S. Ramzan, S. Tahir, and M. Ahsan, "An ensemble approach for firewall log classification using stacked machine learning models," Journal of Computing & Biomedical Informatics, vol. 8, no. 02, 2025.

[22] M. Shahid, A. Ahmed, S. Ullah, Matiullah, and U. Akram, "Automatic patents classification using supervised machine learning," in International Conference on Soft Computing and Data Mining, 2019: Springer, pp. 297-307.

[23] M. A. Ahmad et al., "Sentiment Analysis of Urdu Text using Hybrid Deep Learning Techniques," Journal of Computing & Biomedical Informatics, vol. 8, no. 02, 2025.

[24] U. Akram et al., "Deep Learning-Based Ensemble Approach For Lung Disease Classification using Chest X-Ray Images," Spectrum of Engineering Sciences, pp. 955-967, 2025.

[25] Mohd Amiruddin, A. A. A., Zabiri, H., Taqvi, S. A. A., & Tufa, L. D. (2020). Neural network applications in fault diagnosis and detection: an overview of implementations in engineering-related systems. Neural Computing and Applications, 32(2), 447-472.

[26] A. Ali et al., "Smart stove automation using wireless network and mobile application," in Modern Industrial IoT, Big Data and Supply Chain: Proceedings of the IIoTBDSC 2020: Springer, 2021, pp. 369-388.

[27] Elmasry, W., & Wadi, M. (2022). Edla-efds: A novel ensemble deep learning approach for electrical fault detection systems. *Electric Power Systems Research*, *207*, 107834.

[28] M. Ali et al., "Improving Prediction Accuracy of Emotions from X (Twitter) Post Opinions with Enhanced Hierarchical Attention Model," International Journal of Computational Intelligence Systems, 2026.

[29] Gonzalez-Jimenez, D., del-Olmo, J., Poza, J., Garramiola, F., & Sarasola, I. (2021). Machine learning-based fault detection and diagnosis of faulty power connections of induction machines. *Energies*, *14*(16), 4886.

[30] Khandeparkar, V., Shreshtha, & Ramu, S. K. (2025). Effectiveness of supervised machine learning models for electrical fault detection in solar PV systems. *Scientific Reports*, *15*(1), 34919.

[31] U. Ismail et al., "Hybrid Machine Learning Models for Optimizing Retail Market and Inventory Forecasting," Journal of Computing & Biomedical Informatics, vol. 9, no. 01, 2025.

[32] Guo, M.-F., Yang, N.-C., & Chen, W.-F. (2019). Deep-learning-based fault classification using Hilbert–Huang transform and convolutional neural network in power distribution systems. *IEEE Sensors Journal*, *19*(16), 6905-6913.

[33] M. Ahmad et al., "Mental Health App Reviews Analyzer (MHARA) Using Logistic Regression and Tri-Gram," in International Conference on Soft Computing and Data Mining, 2019: Springer, pp. 274-282.

[34] Hoang, D. T., & Kang, H. J. (2019). A motor current signal-based bearing fault diagnosis using deep learning and information fusion. *IEEE Transactions on Instrumentation and Measurement*, *69*(6), 3325-3333.

[35] M. Mansab, T. B. Tariq, and U. Akram, "An Improved Fraud Detection System Using the LDX Ensemble Machine Learning Technique," Technical Journal, vol. 30, no. 02, pp. 31-39, 2025.

[36] M. Ali, S. N. Khosa, N. Kiran, H. Arshad, and U. Akram, "Deep Learning-Based Bone Age Growth Disease Detection (BAGDD) Using RSNA Radiographs," International Journal of Advanced Computer Science & Applications, vol. 16, no. 6, 2025.

[37] Hussain, M., Memon, T. D., Hussain, I., AhmedMemon, Z., & Kumar, D. (2022). Fault Detection and Identification Using Deep Learning Algorithms in InductionMotors. *Computer Modeling in Engineering & Sciences (CMES)*, *133*(2).

[38] T. B. Tariq et al., "Intelligent Cyber Security Framework for Threat Detection using Ensemble Learning Techniques," Journal of Computing & Biomedical Informatics, vol. 8, no. 02, 2025.

[39] Kosuru, V. S. R., & Kavasseri Venkitaraman, A. (2023). A smart battery management system for electric vehicles using deep learning-based sensor fault detection. *World Electric Vehicle Journal*, *14*(4), 101.

[40] S. N. Khan et al., "Comparative analysis for heart disease prediction," JOIV: International Journal on Informatics Visualization, vol. 1, no. 4-2, pp. 227-231, 2017.

[41] Kaplan, H., Tehrani, K., & Jamshidi, M. (2021). A fault diagnosis design based on deep learning approach for electric vehicle applications. *Energies*, *14*(20), 6599.

[42] Khadse, C., Patharkar, A. A., & Chaudhari, B. S. (2025). Electromagnetic field and artificial intelligence based fault detection and classification system for the transmission lines in smart grid. *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects*, *47*(1), 9362-9376.

[43] M. A. Abid, S. Ullah, M. A. Siddique, M. F. Mushtaq, W. Aljedaani, and F. Rustam, "Spam SMS filtering based on text features and supervised machine learning techniques," Multimedia Tools and Applications, vol. 81, no. 28, pp. 39853-39871, 2022.

[44] S. Zhang, Y. Wang, M. Liu, and Z. Bao, "Data-based line trip fault prediction in power systems using LSTM networks and SVM," Ieee Access, vol. 6, pp. 7675-7686, 2017.
[45] A. A. A. Mohd Amiruddin, H. Zabiri, S. A. A. Taqvi, and L. D. Tufa, "Neural network applications in fault diagnosis and detection: an overview of implementations in engineering-related systems," Neural Computing and Applications, vol. 32, no. 2, pp. 447-472, 2020.
[46] S. R. Fahim, Y. Sarker, O. K. Islam, S. K. Sarker, M. F. Ishraque, and S. K. Das, "An intelligent approach of fault classification and localization of a power transmission line," in 2019 IEEE International Conference on Power, Electrical, and Electronics and Industrial Applications (PEEIACON), 2019: IEEE, pp. 53-56.
[47] S. K. Padhy, B. K. Panigrahi, P. K. Ray, A. K. Satpathy, R. P. Nanda, and A. Nayak, "Classification of faults in a transmission line using artificial neural network," in 2018 International conference on information technology (ICIT), 2018: IEEE, pp. 239-243.
[52] V. Veeramachaneni, S. O. Husain, V. Khanna, P. K. Pareek, and P. Bhuvaneshwari, "Fault detection and classification in power grids using Shannon entropy with convolution distributed autoencoder," in 2024 4th International Conference on Mobile Networks and Wireless Communications (ICMNWC), 2024: IEEE, pp. 1-5.
[53] A. Tikariha, N. D. Londhe, B. Bag, and R. Raj, "Classification of faults in an IEEE 30 bus transmission system using fully convolutional network," International Transactions on Electrical Energy Systems, vol. 31, no. 11, p. e13134, 2021.
[54] A. Abdullah, "Ultrafast transmission line fault detection using a DWT-based ANN," IEEE Transactions on Industry Applications, vol. 54, no. 2, pp. 1182-1193, 2017.
[55] P. Rai, N. D. Londhe, and R. Raj, "Fault classification in power system distribution network integrated with distributed generators using CNN," Electric Power Systems Research, vol. 192, p. 106914, 2021.
[56] F. Rafique, L. Fu, and R. Mai, "End to end machine learning for fault detection and classification in power transmission lines," Electric Power Systems Research, vol. 199, p. 107430, 2021.
[57] V. Veeramachaneni, M. I. Habelalmateen, P. K. Pareek, A. Pavithra, and M. Suganya, "Arc fault detection in electrical systems based on multi-feature fusion with graph neural network," in 2024 4th International Conference on Mobile Networks and Wireless Communications (ICMNWC), 2024: IEEE, pp. 1-5.
[58] C. R. Borra, R. V. Rayala, P. K. Pareek, and S. Cheekati, "Optimizing security in satellite-integrated IoT networks: A hybrid deep learning approach for intrusion detection with JBOA and NOA," in 2025 International Conference on Intelligent and Cloud Computing (ICoICC), 2025: IEEE, pp. 1-8.