Enhanced Fault Detection using VGG-16 and Temporal Convolutional Networks for SPV Integrated Active Distribution Network

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ABSTRACT
This study investigated that an efficient fault detection is essential in distribution systems to ensure the dependability and stability of electrical networks, especially when including renewable energy sources like solar PV.This study presents a Fault detection approach for the IEEE-33 bus system that incorporates with Solar PV. The method utilises sophisticated deep learning models, notably VGG-16 paired with Temporal Convolutional Networks (TCN). Study assess the efficacy of several models, such as VGG-16 and TCN, Hybrid CNN-LSTM, Bi-LSTM, and ANN, across numerous fault categories. The findings of this study indicate that the VGG-16 & TCN model surpasses the other designs, obtaining an outstanding accuracy of 99.8%, along with excellent precision, recall, and F1-score. The examination of the confusion matrix reveals that both VGG-16 and TCN exhibit a high level of accuracy in classifying fault types, with just a few instances of misclassification. Furthermore, the ROC curve analysis substantiates the exceptional efficacy of VGG-16 and TCN, as shown by their ROC value 99, surpassing that of other models. The exceptional performance may be ascribed to the strong feature extraction capabilities of VGG-16 and the efficient processing of sequential data by TCN. The study's findings indicate that the VGG-16 & TCN model is the most efficient for fault identification.

Keywords: Fault detection, Active distribution network, Solar PV, VGG-16, Temporal Convolutional Network (TCN), Deep learning.

1. INTRODUCTION

Power outages in transmission lines are mostly caused by unanticipated and irregular faults[1]. Power system problems are inevitable and must not be disregarded. Fault detection and classification are crucial for ensuring the stability of both traditional and intelligent power grids[2]. Transmission line faults and equipment breakdowns may result in substantial interruptions to the power system, resulting in power outages and equipment damage. Hence, it is crucial to ensure precise and prompt identification and categorization of faults in order to maintain the stability and safety of the smart grid[3]. A smart grid is a sophisticated and ever-changing system that necessitates ongoing surveillance and upkeep to guarantee dependability and effectiveness. Fault detection and categorization are essential activities in the operation and administration of smart grids. According to [4], most of the problems in the transmission part of the power system occur in transmission lines. Short-circuit faults are common and considered the most severe form, presenting significant dangers to transmission lines[5]. These dangers include reducing the operational lifetime of components, increasing power losses, causing cable heat, and damaging insulators.

Over the last two decades, there has been a swift advancement in numerous domains related to identifying, classifying, and detecting power system malfunctions. Growing numbers of researchers are now able to conduct studies with a high breadth and depth because of advancements in signal processing techniques, artificial intelligence and machine learning, global positioning system (GPS), and communications, which have allowed the boundaries of conventional fault protection techniques to be stretched. Precisely identifying and categorising transmission line defects can lower the cost of replacing power lines and improve the likelihood of power grid safety. Customers experience power outages due to transmission line failures [6].

1.1 Overview of Fault Detection and Classification

Transmission line faults can result in a variety of disruptions, including overheating, mechanical stress, and unbalanced power flow. Furthermore, reliable fault detection and classification (FDC) is crucial to maintaining grid system stability. While the process of recovering from failure phases is contingent upon human intervention and the detection and classification method employed to pinpoint the specific type of failure and its location within the network. This is important because a quick and accurate FDC guarantees prompt repair, increases the likelihood of separating problematic phases from the transmission system, and improves the transient stability and power quality of the interconnected power network. Many algorithms are used to classify faults in transmission lines. Two popular approaches are artificial intelligence (AI) and machine learning (ML), which are chosen for their ability to learn quickly, produce accurate results, and identify patterns in input training data [7]. Historical fault classification methods are classified as well-known and contemporary methods. The popular methods include fuzzy logic-based approaches for fault classification, commonly referred to as hybrid methods, and Wavelet Transform (WT) based analysis combined with Artificial Neural Networks. Furthermore, recent fault classification approaches include principal component analysis (PCA), phasor measurement units (PMU), artificial intelligence (AI), and support vector machines (SVM).

In the last several decades, solar energy has become a well-liked solution for energy shortages and a competitive substitute for fossil fuels. This ecologically benign and renewable energy source offers a limitless and sustainable supply of power [8]. Consequently, solar energy has the capacity to supply all of the world's energy needs. It is mainly dependent on the weather, though, and any changes in that regard could have a big effect on its output power[9]. System instability may result from variations in PV power production, particularly when PV power makes up a significant amount of the energy supply. To successfully integrate PV electricity into electrical grids and lessen the detrimental effects of fluctuating PV power production on the system, accurate forecasting is essential. A clever and strong AI tool for modelling, predicting, and enhancing the performance of many engineering systems is the artificial neural network (ANN). This method has proven effective in solving challenging nonlinear engineering issues[9]. When addressing the changing nature of environmental situations, these aspects become crucial. As a result, artificial neural networks (ANNs) have gained popularity in the solar energy industry, especially for applications including defect detection, predictive maintenance, radiation forecasting, and power prediction.

Another strategy that has drawn a lot of attention recently is the use of artificial neural networks. An artificial neural network is a network of neurons that can learn a wide range of complicated functions via a sequence of nonlinear transformations. With the development of deep learning methods, these networks have been effectively used to perform challenging categorization tasks like voice and picture recognition. To solve the issue of fault detection, artificial neural networks have also been used. Convolutional neural networks (CNNs) are a supervised learning approach that may be tailored to address a wide range of complex issues in exploratory geophysics, thanks to their high degree of network architectural flexibility. The simplest use of CNNs among these issues may be the identification of certain seismic facies of interest. Faults are a unique set of edges in seismic data from the standpoint of computer vision. With remarkable effectiveness, CNN has been used to tackle more broad edge detection issues. Nonetheless, the majority of the studies used hierarchical neural networks or shallow neural networks. Therefore, there is more work to be done to fully explore the potential of deep neural networks for defect diagnostics.

1.2 Relevance of Deep Learning in Power Systems

Faults in power transmission lines may arise due to a variety of factors, including short circuits, tree or animal contact, lightning strikes, earthquakes, conductor clashing, and equipment corrosion. Some are under human influence, while others are naturally occurring. When protective relays identify a defect, they must clear it promptly [10]. While defects may develop for a variety of causes, locating and analysing them remains a key problem. Reducing post-fault analysis time allows for speedier system maintenance and restoration, perhaps leading to lower failure costs. To improve power system dependability, it's crucial to quickly and efficiently classify problem types and locations. advocated fault-location observability and a novel approach for transmission networks using synchronised phasor measuring units (PMUs). developed deterministic and stochastic methods for locating faults in power systems using a low number of PMUs [11].

Fault type and location categorization involves three steps: (1) importing transient fault data, (2) pre-processing using suitable methods, and (3) analysing the data. To convert three-phase voltage and current fault signals, pre-data processing methods such as Stransform, wavelet transform, and Fast Fourier Transform (FFT) may be utilised. Fault data may be analysed using several methods, including

machine learning and waveform-based correlation coefficients. Several academics have published articles on using machine learning and deep neural networks to detect and locate power system issues.Fault techniques are classified into model-based, knowledge-based, and data-driven approaches, which rely on numerical data analysis and interpretation rather than personal observation or experience [12].
Data-driven strategies base ideas and solutions on verifiable facts, rather than assumptions or personal experience. Various machine learning algorithms, including decision trees, support vector machines, and k-nearest neighbours (k-NN), have been suggested for fault classification[13]. The study found that processing high-dimensional data requires computational complexity and reduction strategies for reconstruction. However, reducing data dimensions might lead to information loss and undermine the accuracy of outcomes. In Ref [14], the authors suggest a way to extract PV cell attributes from thermal images and compare the results using the SVM algorithm. In [15] the author presents a strategy for distinguishing PQ disturbances from pure sinusoidal signals using time-domain descriptor fusion (FTDD). The recommended technique is evaluated using multiclass SVM and Naive Bayes (NB) classifiers.[16] developed the Modified Multi-Class Support Vector Machines (MMC-SVM) approach to categorise open-circuit faults in power distribution networks. Simulation findings indicate the usefulness and resilience of the proposed machine learning model [17].
In [18], a classification technique is suggested that utilizes convolutional neural networks (CNNs) with varying sample frequencies. The use of wavelet transform for extracting fault harmonics in the input of CNNs has been observed. However, the accuracy of the classification judgements and the results are affected by data generalization difficulties, as mentioned in[19]. Deep neural networks use convolutional neural networks (CNNs) as a powerful technique for image categorization. CNNs are also employed as fundamental components of ResNet and VGG16. Convolutional Neural Networks (CNNs) have the capability to categorize extensive picture collections collected from ImageNet. Various convolutional layers, pooling layers, and fully connected layers are used to extract the fundamental characteristics of the data from the pictures and categorize them via supervised learning. The authors in Ref. introduced a defect classifier that use a convolutional neural network and wavelet packet analysis. The authors of [20] effectively suggested a classification method using Convolutional Neural Networks (CNN) with raw input data to enhance the accuracy of detecting transmission line defects.

1.3 Background

1.3.1 VGG 16

The VGG-16 model is a convolutional neural network (CNN) architecture developed by the Visual Geometry Group (VGG) at the University of Oxford. The depth of this system is defined by its 16 layers, which include of 13 convolutional layers and 3 fully linked layers. VGG16 is model designed for image recognition.VGG-16 is well-known for its simplicity and efficacy, as well as its capability to produce high performance on many computer vision tasks, such as picture categorization and object identification. The design of the model consists of a series of convolutional layers followed by max-pooling layers, with a gradual increase in depth. This approach allows the model to acquire complex hierarchical representations of visual characteristics, resulting in strong and precise predictions. Although VGG-16 is less complex compared to newer designs, it continues to be widely used in deep learning applications because of its adaptability and outstanding performance. It is unusual in that it uses just 16 weighted layers rather than a huge number of hyper-parameters. It's regarded as one of the greatest vision model architectures [21].It is an object identification and classification algorithm capable of classifying 1000 photos into 1000 distinct categories with 92.7% accuracy. It is one of the most common picture classification methods, and it works well with transfer learning.
In the year 2014, the Visual Geometry Group at Oxford University achieved the second position in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) competition for classification. They used a convolutional neural network architecture called VGG-16, which is both deep and straightforward. This model has gained significant popularity in the research community because to its straightforward methodology and the accessibility of its pre-trained weights, which are freely accessible online. This makes it easier to adapt and enhance the performance of this robust model for new tasks. The VGG-16 network was trained using the ImageNet database. The VGG-16 network's intensive training ensures high accuracy even with tiny picture data sets. The VGG-16 network contains 16 convolution layers with a tiny 33 receptive field. It contains 5 Max pooling levels, each measuring 2×2. There are three completely linked layers after the Max pooling layer. This is followed by three completely linked layers. It employs the softmax classifier as the last layer. ReLu activation is performed over all concealed levels.

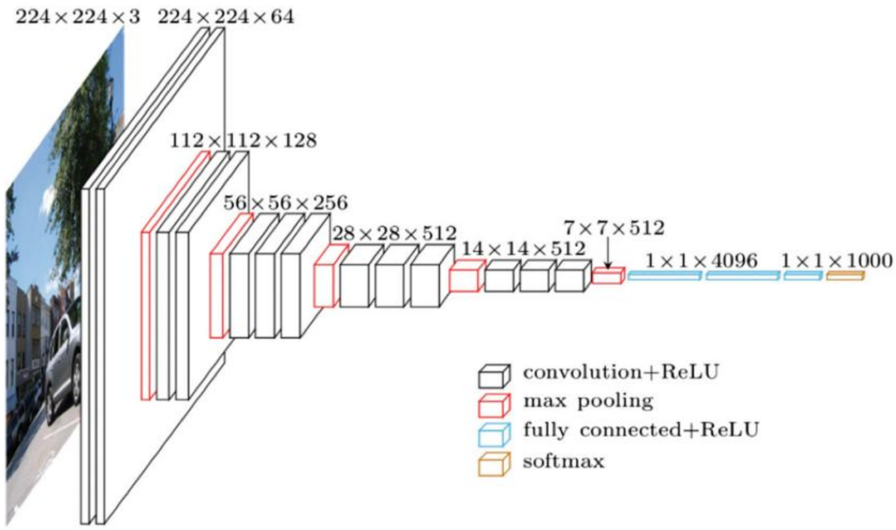

Figure 1: An overview of the VGG-16 model architecture[22]

1.3.2 TCN (Temporal Convolutional Networks)

A neural network called a temporal convolutional network (TCN) was created specifically to process time-series data. In terms of efficiency, parallelism, usage of 1D convolution, capacity to capture long-term dependencies, dilated convolutions, global and local context modelling, interpretability, shift-invariance, implementation, simplicity, and scalability, TCN offers a number of advantages over LSTM and RNN architectures. Depending on the goal of signal analysis, TCN can be used to categorise defects based on univariate or multivariate time series data. Moreover, TCNs, like RNNs, can handle input and output sequences of unlimited length and employ causal convolutions to guarantee that the past is independent of the future. Furthermore, by joining very deep networks, TCN is able to attain very high effective history sizes. Compared to WaveNet, TCNs have a longer memory for handling sequential input and a simpler structure that allows it to make predictions based on historical data points. These features set them apart from other deep learning methods [23] .

A temporal convolutional neural network is trained to predict the next l values of an input time series. Assume you have a series of inputs $x_0, x_1, \dots, x_L$ and want to predict the corresponding output $y_0, y_1, \dots, y_L$ at each time step. The output values should be identical to the inputs stretched forward l steps. The major limitation is that it can only forecast the output y_t for a given time step t using previously observed inputs: $x_0, x_1, \dots, x_t$.

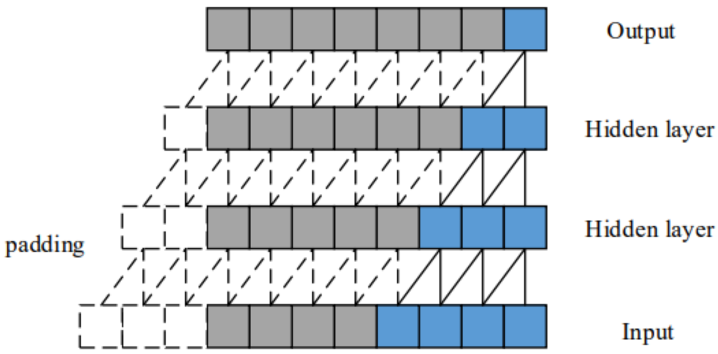

Figure 2: A casual convolution with filter kernel size k=2 [24]

The TCN has two primary limitations: it may only utilise data from previous time steps, and its output must match the duration of its input. A 1-D fully-convolutional network architecture [25] is employed in TCN to satisfy these temporal criteria since all of its convolution layers have the same length and zero padding to guarantee that subsequent layers have the same length as the ones before them. Furthermore, TCN employs causal convolutions illustrates, only calculate an output at time step t in each layer using the area no later than time step t in the preceding layer. The output of a normal convolution may be shifted by a few time steps to quickly construct the causal convolution for 1-D data.

Dilated Convolutions

In general, it is anticipated that networks will be able to retain long-term information when interacting with a time series. Nevertheless, the receptive field diameters are restricted unless a large number of layers are stacked, as demonstrated by the sample causal convolution we previously demonstrated. This results in complications when employing casual convolution on sequence tasks due to its substantial computational expense. To resolve the issues, dilated convolutions are implemented to facilitate an exponentially large receptive field with limit layers.

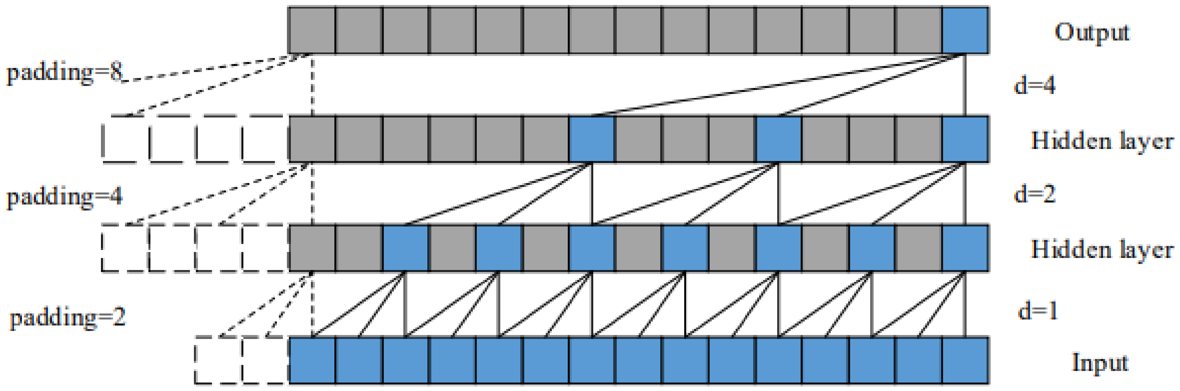

Figure 3: A dilated casual convolution with filter size k=3 and dilated variables d=1, 2, 4.

A dilated convolution is a convolution in which a step-by-step set of input values are skipped in order to apply a filter across an area that exceeds its size. In that it increases the receptive field size, this is comparable to pooling or stride convolutions; nevertheless, the output size is identical to the input. It is typical practice to raise the dilated factor d exponentially with network depth when using dilated convolutions. This guarantees that the receptive field covers every input in the history and makes it possible to use deep networks to get an incredibly broad receptive field as an effective history.

Residual connections

To achieve a sufficient receptive field, the network depth (n), filter size (k), and dilation factor (d) all play a role. Therefore, deeper and bigger TCNs are recommended. Using a deep and narrow network design, with several layers and a small filter size, has shown to be beneficial. Residual connections have shown to be quite useful for training deep networks. Skip connections are employed in residual networks to speed up training and prevent the vanishing gradient issue in deep learning models.

1.3.3 Spectrogram

A spectrogram is a visual representation of the spectrum of frequencies of a signal as it varies with time. When applied to an audio signal, spectrograms are sometimes called sonographs, voiceprints, or voice grams.Spectrogram is a graphical representation that displays the amplitude, or intensity, of a signal at different frequencies across time in a waveform. One may see not only the disparity in energy levels between frequencies such as 2 Hz and 10 Hz, but also the temporal fluctuations in energy levels. Spectrograms are often used in several scientific disciplines to visually represent the frequency of sound waves generated by people, machines, animals, whales, aeroplanes, and other sources, as captured by microphones. Spectrograms are now often used in the field of seismology to analyse the frequency composition of continuous signals captured by individual or groups of seismometers. This aids in the identification and characterization of various kinds of earthquakes or other ground vibrations. The signal's frequency and energy are conveyed by a representation that maps frequencies down the vertical axis and varies colour to indicate energy levels[26]. Spectrograms are widely used in several fields such as speech analysis and medical applications like ECG analysis. In order to create spectrogram pictures, we used the Short-Time Fourier Transform (STFT) approach to analyse the time-frequency characteristics of the available feature data.

1.3.4 IEEE -33 Bus system

The IEEE 33 Bus system is a standardised test case used in power engineering research to assess the performance and dependability of distribution networks. It is made up of 33 buses (nodes) and 32 radial lines (branches) that represent a typical distribution network. Baran and Wu suggested a 33-bus distribution system in 1989. It is often used to evaluate many electrical engineering issues, including load flow analysis, fault analysis, and network optimisation. The system is distinguished by its single feeder and radial architecture, which means that all lines originate from a single substation and stretch outward, like a tree structure. The IEEE 33-Bus radial distribution system is used to test and evaluate different kinds of DG units. This system is made up of 33 buses and 32 lines, with a voltage of 12.66kV, a load capacity of 3.715MW, and 2.3MVar[27]. The distributed generating unit utilised represents 30% of the total load. The DG unit voltage is 12.66kV, and the system's lower and higher voltages are set at 0. 95p.u and 1.05p.u. This will allow us to see how the different DG units affect the electricity system's load ability margin. To provide a clear assessment of the various DG units' effects on the distribution system, the research will be conducted with a set optimum location and DG penetration level. The DG unit location was decided using an optimisation approach with a set penetration level (30% of the total load). This arrangement serves as a critical benchmark for academics and engineers developing and testing new algorithms, methods, and technologies to improve the efficiency, stability, and resilience of electrical distribution networks.

1.4 Nomenclature

Table 1: Nomenclature

Symbol/Term	Description
CNN	Convolutional Neural Network
ANN	Artificial Neural Networks
Bi-LSTM	Bidirectional Long Short-Term Memory
TCN	Temporal Convolutional Networks
LSTM	Long Short-Term Memory
IEEE	Institute of Electrical and Electronics Engineers
STFT	Short-Time Fourier Transform

1.5 Paper organization

The rest of the paper is organized as follows: Section-2 comprehensive Literature review, summarizes the previous work on faults detection techniques and their applications in power systems. Section-3 details the methodology, including the feature extraction by using the VGG-16 and classification using TCN. Section-4 presents the results and discussion, comparing the performance of various machine learning models. Finally, Section-5 concludes the study by emphasizing the efficiency of VGG-16 & TCN model and importance of advanced feature extraction for fault detection.

2. LITERATURE REVIEW

Author	Aim	Method	Results
[28]	This study aims to enhance the effectiveness and reliability of drone imagery-based inspections for component identification and defect detection of transmission lines.	The study utilized deep learning, specifically the Faster R-CNN model, for component identification and defect detection from drone images during transmission line inspections, expanding the dataset through convolution kernel size adjustments.	The study found deep learning to be highly effective in identifying defects in high-voltage transmission line components, with a recognition speed of 0.17 seconds per image and a recognition rate of 96.8% for pressure-equalizing rings, highlighting its potential in power line inspection processes.
[29]	The goal of this study is to	The study used wavelet packet	The simulation results

	create a hybrid deep-learning model for real-time automated problem detection and classification in photovoltaic (PV) systems, which will solve the difficulties of manual and time-consuming fault diagnostic procedures.	transform (WPT) for data pre-processing of PV voltage signals, which were then input into deep learning architectures like the equilibrium optimizer algorithm (EOA) and long short-term memory (LSTM-SAE). This method automatically extracts fault features from pre-processed data, overcoming manual limitations.	demonstrated the model's effectiveness in computation time, fault detection accuracy, and noise robustness, indicating its superior performance over previous studies in multidisciplinary applications.
[30]	The study utilizes transmission line voltage and current data to identify and classify power transmission issues, employing Artificial Neural Network (ANN) and Convolutional Neural Network (CNN) models to evaluate their accuracy.	This study uses Kaggle voltage and current data to locate power transmission issues. Data is analysed and fed into two Deep Learning (DL) networks: an ANN and a CNN. These models identify defects using input data.	The CNN exceeds the ANN in accuracy. This shows that CNNs handle voltage and current data better for power transmission line problem detection and classification.
[31]	This paper proposes an unsupervised framework for fault detection and classification of transmission line faults, utilizing a capsule network enhanced with a sparse filtering technique, to enhance model performance without the need for extensive datasets.	The CNSF model encodes cycle post-fault three-phase signals into a single image for network input, demonstrating adaptability to changes in transmission line topology due to control actions or cascading faults, verified through tests on four different TL topologies.	The CNSF model outperforms other models in fault detection and classification, efficiently extracting critical fault features without relying on large datasets, according to a rigorous study.
[32]	The study sought to resolve component defect detection and inventory challenges in electrical transmission networks, particularly in developing countries, by integrating sophisticated deep learning techniques with high-resolution UAV imagery.	The Single Shot Multibox Detector (SSD) was used to analyse electric transmission power line imagery for fault detection, followed by the development of a CNN model with a multiscale layer feature pyramid network (FPN) for a streamlined process.	The SSD Rest50 architecture variant outperformed the other models with a mean Average Precision of 89.61%, despite a low recall rate.
[33]	The paper surveys recent machine learning techniques for fault detection, classification, and location estimation in transmission lines, emphasizing the need for advanced fault diagnosis tools to improve power system reliability and resilience in smart grids.	The paper explores machine learning methodologies for fault diagnosis in transmission lines, including traditional methods like naive Bayesian classifiers and decision trees, as well as advanced artificial neural networks like feedforward and convolutional networks.	The study evaluates the effectiveness of machine learning techniques in detecting, classifying, and locating faults, highlighting their potential for faster and more accurate fault identification, which is crucial for minimizing disruptions and ensuring electrical power system reliability.
[34]	The study aims to improve fault detection in seismic	The study uses a synthetic fault model from the SEAM model and	The integrated workflow significantly improves fault

	data by combining convolutional neural networks with directional smoothing and sharpening techniques.	field data from the Great South Basin, offshore New Zealand, to train a CNN for fault detection, followed by directional smoothing/sharpening to enhance classification outcomes.	detection performance on synthetic and field datasets, outperforming traditional CNN-based methods, despite real-world data challenges.
[35]	This study aims to create a precise fault diagnosis model for microgrids (MG) to improve transient response, system reliability, and reduce fault line restoration costs by addressing shunt faults during power distribution.	The proposed method employs a discrete-wavelet transform-based probabilistic generative model with multiple layers and a restricted Boltzmann machine, trained using unsupervised learning and fine-tuned by an artificial neural network to minimize error between actual and predicted fault classes.	The model's effectiveness is assessed through varying input signals, sampling frequencies, and noise introduction, revealing superior accuracy in diagnosing MG faults compared to kernel extreme learning machine, multi-KELM, and support vector machine methods.
[36]	The study aims to create a fault detection and classification system for transmission lines using machine learning techniques, specifically an extreme learning machine (ELM) algorithm, to improve reliability and efficiency in fault identification.	The study used MATLAB Simulink to simulate two transmission lines, TL-1 and TL-2, with a single generator and load. Normal and fault data were generated for ten fault types, and two distinct ELM models were developed for fault detection and classification.	The ELM model outperformed traditional artificial neural networks (ANNs) in fault classification and detection, with accuracies of 99.18% for TL-1 and 99.09% for TL-2, and 99.53% for TL-1 and 99.60% for TL-2.
[37]	The paper aims to improve automated fault detection and isolation (FDI) in automotive instrument cluster systems within computer-based manufacturing assembly lines using deep learning techniques.	The method uses data from local and remote sensing devices to analyse complex nonlinear signals, enabling more sophisticated fault diagnosis and localization compared to traditional boundary checking methods.	The deep learning-based approach outperforms established foreign direct investment (FDI) methods in real-time fault classification and diagnosis, demonstrating superior performance in modeling spatial and temporal patterns in data.
[38]	This study aims to improve fault detection, diagnosis, identification, and location in large-scale multi-machine power systems by introducing novel Deep Learning models for Fault Region Identification, Fault Type Classification, and Fault Location Prediction.	The study uses three new Deep Recurrent Neural Networks (DRNN) models with Long Short-Term Memory (LSTM) to analyse transient data from pre- and post-fault cycles. The models are tested on a Two-Area Four-Machine Power System, using data collected during different types of transmission line faults at different locations.	The proposed algorithms demonstrated superior performance in fault detection, classification, and location prediction, achieving high accuracy and robustness compared to existing techniques.
[6]	This paper proposes a new machine learning method for fault detection and classification in electrical power transmission networks, using Long Short-Term Memory units.	The proposed method uses an end-to-end learning model with LSTM units to analyse operational data, distinguishing normal and faulty conditions based on temporal sequences. It's tested across fault types, considering factors like fault resistance, distance, loading conditions, system parameters, and noise levels.	The proposed method is proven to be effective in real-world applications due to its fast response time and resilience to varying operational conditions.

[39]	The purpose of this work is to provide a unique single-ended fault locating strategy for transmission lines that employs recent deep learning algorithms to improve the accuracy and efficiency of fault detection and restoration procedures.	The proposed method uses a mixed convolutional neural network (CNN) and long short-term memory (LSTM) structure, trained on single-ended voltage and current measurements, to predict fault distances. Advanced techniques like adaptive moment estimation and dropout are employed to optimize the training process and mitigate overfitting.	Extensive research has validated the approach's accuracy and efficacy in finding faults, proving its potential to greatly reduce repair and restoration efforts in transmission line networks.

1.6 Research Gap

Despite substantial progress in defect identification and classification utilising different deep learning algorithms, essential insufficient studies still exist. Integrating power electronics applications with fault detection systems is necessary to improve resilience and efficiency, especially in smart grids and renewable energy systems. Comprehensive reviews in real-world settings are few, with most research relying on synthetic data or controlled simulations. To enhance accuracy and efficiency, hybrid models that combine different AI approaches with real-time defect detection and localization methods need to be explored further. The scalability and adaptation of fault detection algorithms to large-scale power networks with a high renewable energy penetration are under investigation. Furthermore, advanced data augmentation, pre-processing techniques, user-friendly deployable solutions, economic impact analysis, and long-term performance studies are critical areas that must be addressed to ensure that these systems are practical, robust, and sustainable in a variety of real-world settings.

3. METHODOLOGY

3.1 Research methodology

The main contribution of this study is the proposal of hybrid approach that combines VGG-16 and temporal convolutional network models for fault detection in an IEEE 33-bus system with solar PV integration.This methodology uses voltage, current, and frequency signals from the power distribution system to improve fault identification accuracy. In this paper we looked at the VGG-16 and TCN models which help us to detect faults by breaking down the fault signals into components.It employs VGG-16 for spatial feature extraction and TCNs for temporal patterns in time-domain signals, such as voltage sags and harmonics. The procedure comprises data collection, data pre-processing, feature extraction, model training, and evaluation.

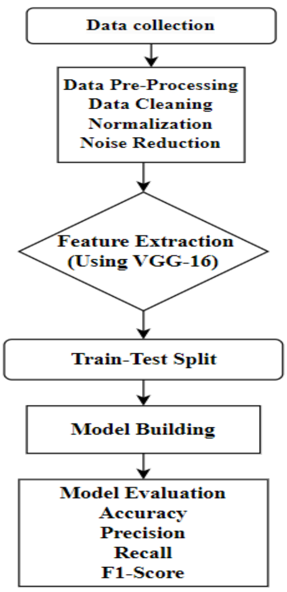

Figure 4: Flow chart

3.2 Data Collection

The data (voltages, currents) is generated and collected by creating various types of three-phase faults such as line-to-line, line-to-ground, and triple-line faults at various locations and segments of a PV integrated 33 bus system. The system under consideration is given below.Spectrograms of this generated voltages and currents are utilized as the primary data to extract the features by using VGG-16.

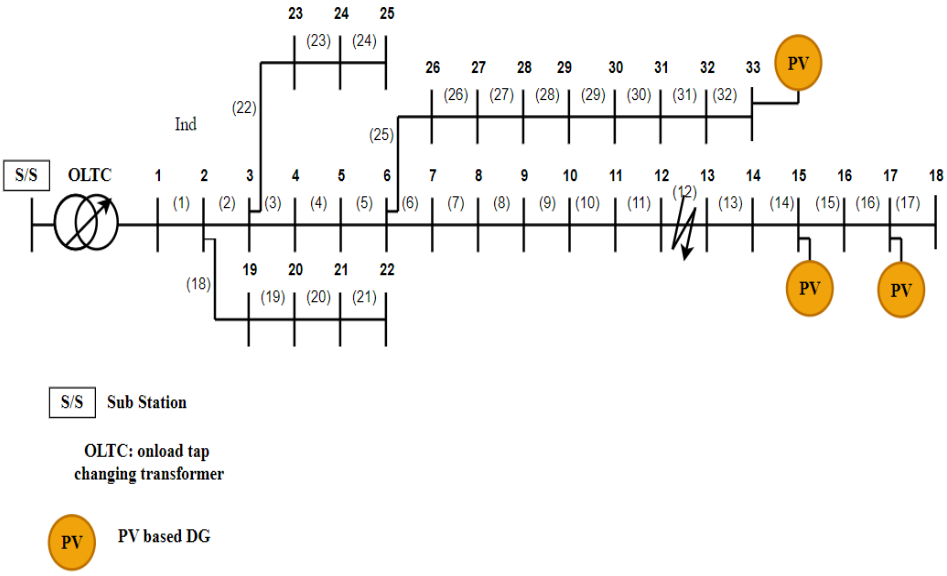

Figure 5: IEEE 33-Bus distribution system with PV integration

Table 2: Details of test system

Parameters	Test System 1
Bus system	IEEE 33 bus
voltage	12.66 KV
active power demand (MW)	3.715 MW
reactive power demand (MVAR)	2.30 MVAR
PV plant mounted locations	15,17,33
PV plant capacity (MVA)	0.8,1.0,0.8
allowable voltage bounds	0.95 pu to1.05 pu

3.3 Data Pre-processing

Data pre-processing is an essential step in preparing the dataset for training the VGG16 and TCN models. The following are the comprehensive stages involved in data pre-processing:

Data Cleaning

Detect and manage missing data by eliminating rows or columns with a small number of missing values or by using mean/mode/median imputation to fill in the gaps. Eliminate redundant rows to mitigate bias throughout the model training procedure.Eliminate extraneous characteristics that do not add to the process of identifying faults.

Normalization

Standardise continuous features by scaling them to a uniform range, often from 0 to 1, in order to guarantee equal contribution of all characteristics to the learning process of the model. Two often used strategies are Min-Max Scaling and Standardisation.

Noise Reduction

Utilise filtering methods, such as using moving averages, to effectively smoothen the data and minimise the presence of noise. Detect and manage outliers by using methods like as z-score or interquartile range (IQR).

3.4 Feature extraction based on VGG-16

The process of image feature extraction using VGG-16 entails using the pre-trained VGG-16 model, which is extensively used for image classification purposes. The approach starts by loading the model without its top fully connected layers, resulting in the retention of just the convolutional basis for feature extraction. Spectrograms are used as input to VGG-16, which represents time-domain signals with pictures. These spectrograms are generated by applying the Short-Time Fourier Transform (STFT) to the power system's voltage, current, and frequency data. The STFT contributes to the conversion of raw signal data into the frequency domain while retaining temporal information. This two-dimensional image-like format is perfect for deep learning models like VGG-16 to extract meaningful features.

After applying pre-processing to the pictures, they are fed into the modified VGG-16 model to extract feature maps from a specific convolutional layer, such as block5_conv3. The collected features, which capture fundamental patterns and properties of the pictures, may then be used as inputs for different machine learning algorithms. This can assist in tasks like as identifying faults and categorising them in applications like the integration of solar PV with the IEEE 33-bus system.

- **Convolutional Layer:**

In the convolutional layer, a number of filters, also referred to as kernels, are applied to extract local features from an image. In mathematical terms, one may consider each of the convolutions as follows:

$$y_{ij} = \sum_{m=0}^{k-1} \sum_{n=0}^{k-1} x_{i+m,j+n} . w_{mn} + b \quad (1)$$

Where,

$x_{i,j}$ is the input pixel value at position (I, j).

w_{mn} represents the weights of the convolutional filter(kernel)

B is the bias associated with the filter.

y_{ij} is the output for position (I,j).

It would slide the filter across the image, computing the dot product between the filter and local regions of the image, to enable the network to detect various patterns such as edges, textures, and shapes.

- **ReLu activation Function:**

After every convolutional operation, an application of the Rectified Linear Unit activation function has to be applied to the feature map: The rectification means that this non-linearity introduces the capability of learning complex patterns by ensuring that the network only activates on positive values, thus effectively introducing sparsity in the feature maps-which enhances the representation of useful features.

$$y = \max(0, x) \quad (2)$$

- **Max Pooling Layer:**

The max pooling layer reduces the spatial dimensions of the feature maps, during which the most important features are preserved, while computational complexity is reduced.

$$y_{ij} = \max\{x_{i+m,j+n} m, n \in [0, p-1]\} \quad (3)$$

$x_{i,j}$ is the input pixel value in the pooling window.

y_{ij} is the output value, which is the maximum pixel value in the pooling window.

- **Fully connected layers:**

The resulting feature maps, after passing through several convolutional and pooling layers, are flattened into a 1D vector fed into a fully connected layer. The mathematical operation for the fully connected layer is

$$y = W.\ x + b \quad (4)$$

X is the input vector

W is the weight matrix connecting the input and output layers.

B is the bias vector.

Yis the output vector.

- **Softmax Classifier:**

In classification tasks, the final result is input into the softmax layer, which generates a probability distribution across the classes:

$$P(y = c/x) = \frac{\exp(z_c)}{\sum_{k=1}^{c} \exp(z_k)} \quad (5)$$

z_c is the score for class c

C is the total number of classes.

$P(y = c/x)$ is the predicted probability that the input x belongs to class c.

3.1 Train-Test Split

Following the process of feature extraction, the dataset was divided using the commonly used train-test split approach into separate training and testing sets. An objective evaluation of the model's performance on unobserved data was made possible by this divide, which guaranteed the separation of data for model training and evaluation. The testing set functioned as an impartial validation set to precisely evaluate the trained models' capacity for generalisation, while the models were trained using the training set.

3.2 Model Building

Once the features extracted from the pictures using the VGG-16 model, the resultant feature maps may be reshaped and inputted into the Temporal Convolutional Network (TCN) for classification purposes. The temporal relationships in the fault data are subsequently analysed using TCN, which recognizes the evolution of these features over time under various fault conditions. This entails transforming the retrieved characteristics into a format that is compatible with the TCN, which often requires organised time-series data. The feature maps, which are typically acquired as multi-dimensional arrays, may be flattened or converted into sequences for processing by the TCN. The TCN employs temporal convolutional layers to examine these sequences, recording temporal patterns in order to categorise the input data. This technique combines the advantages of VGG-16 for extracting reliable image features and TCN for analysing sequential data, improving the overall classification performance in applications like fault detection in the IEEE 33-bus system combined with solar PV.

Model Evaluation

The process of "model evaluation" looks at whether a produced model can be applied to fresh data in order to determine its generalizability. Among the many criteria for categorization performance are accuracy, precision, recall, F1 score, specificity, and sensitivity. By comparing estimates many times, cross validation ensures their accuracy. This implies that confusion matrices, for example, have a wealth of information to provide. Assessment is essential to development and deployment.

3.3 Tools & Techniques

In this study TensorFlow/Keras used to train the VGG16 and TCN models, with VGG16 acting as a pre-trained feature extractor for spectrograms generated from voltage and current measurements. TCN is used for processing time series data. It records complicated temporal patterns using a hierarchy of temporal convolutions, dilated convolutions, and pooling layers. Scikit-learn is utilised for data preparation, which includes cleaning, normalization, and noise reduction, as well as producing evaluation metrics like accuracy, precision, recall, and F1-score. Pandas and NumPy are crucial for data processing, huge dataset management, and integration with other tools like as TensorFlow and Scikit-learn. Visualization tools like as Matplotlib and Seaborn help in model performance analysis by generating confusion matrices and ROC curves.

To integrate Solar PV into an IEEE-33 bus system for load flow analysis, utilize MATLAB/SIMULINK software. The IEEE 33-bus distribution system's bus voltage and branch loss are analysed using the MATLAB programming environment. According to one source, this program used to simulate and evaluate the performance of a PV-integrated IEEE-33 bus test system. This complete technique guarantees reliable model assessment and fault identification in the PV-integrated IEEE 33-bus system.

Library facilities

- Utilise TensorFlow/Keras to construct and train the VGG16 and TCN models.
- Scikit-learn is used for data pre-processing and evaluating metrics.
- Pandas and NumPy are utilised for the purpose of manipulating and analysing data.
- Used MATLAB2023a version to build the model.

4. RESULTS AND DISCUSSION

4.1 Confusion Matrices

Confusion matrices are a kind of assessment statistic used to assess the performance of a classification model. They may be used to compute several additional model performance measures, including accuracy and recall, among others.

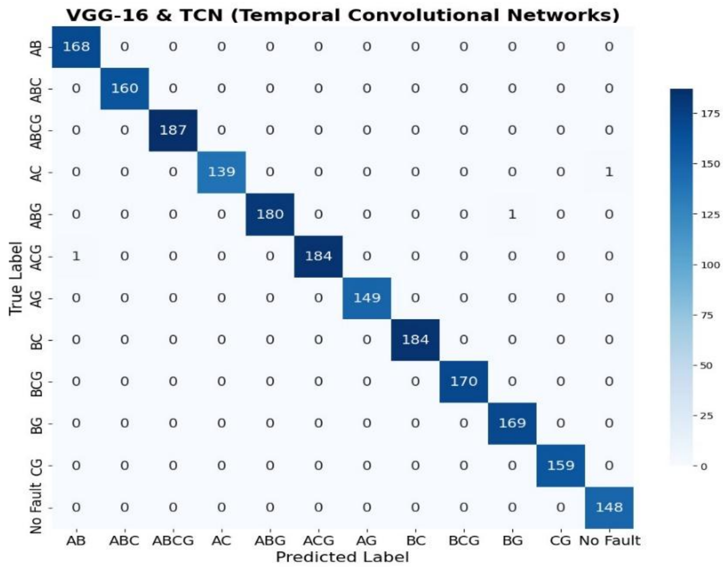

Figure 6: Confusion Metrics VGG-16 & TCN

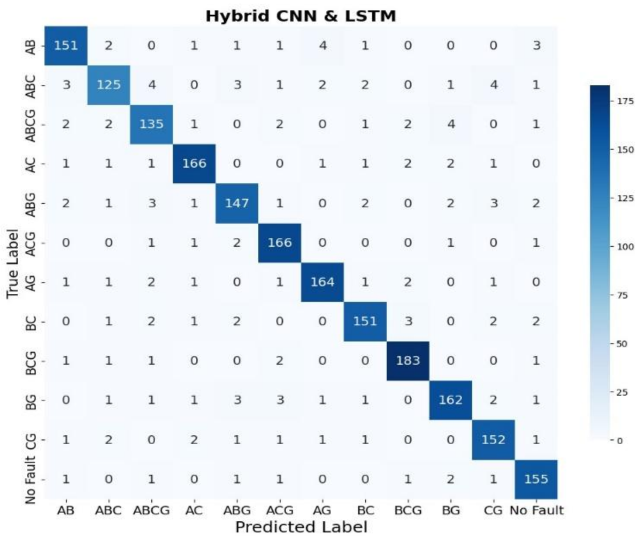

Figure 7: Confusion metrics of Hybrid CNN & LSTM

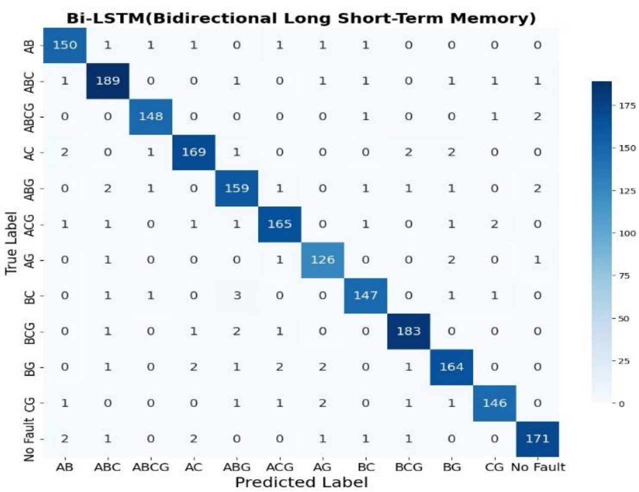

Figure 8: Confusion metrics of Bi-LSTM

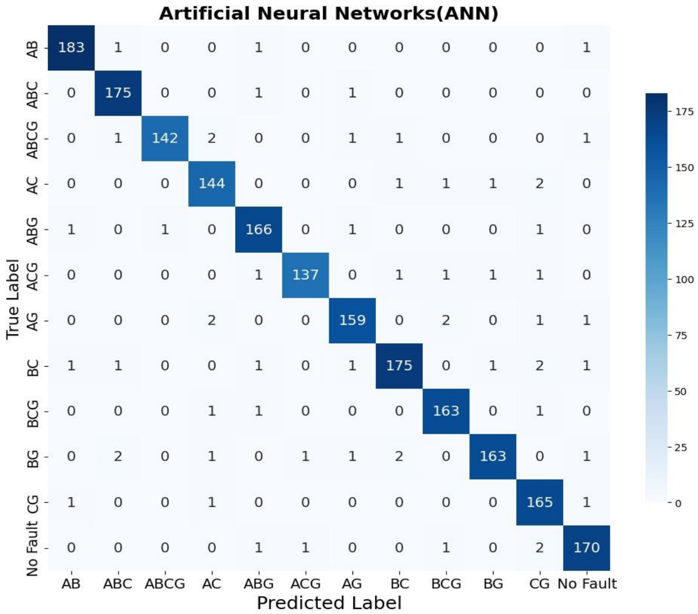

Figure 9: Confusion Metrics of ANN

From the above confusion matrices that classify data into twelve classes (AB, ABC, ABCG, AC, ABG, ACG, AG, BC, BCG, BG, CG, and No Fault), show various degrees of performance among several models: VGG-16 and TCN, Hybrid CNN-LSTM, Bi-LSTM, and ANN. Our suggested technique, VGG-16 & TCN, performs well, properly categorising most samples with minimum misclassifications. VGG-16 & TCN properly identifies all samples in the AB (158/158), ABC (160/160), and BCG (177/177) classes, with just one misclassification in the CG and No Fault classes. In contrast, the Hybrid CNN-LSTM model exhibits more variability, properly identifying 138 samples in AB with some misclassifications in other classes and accurately categorising 153 samples in BC with some misclassifications. The Bi-LSTM model performs well in BC (168/168) but misclassifies in closely related classes such as AC and AG. It accurately classifies 176 samples in AB with minimal mistakes. The ANN model performs well but is less accurate than VGG-16, TCN, and Bi-LSTM, correctly identifying 175 samples in AB but displaying greater misclassification rates in classes such as ACG and AG. Overall, VGG-16 & TCN emerges as the most accurate model, correctly classifying the greatest number of samples with the fewest errors, especially in classes with a high degree of similarity, making it the most effective approach for classifying given samples in the context of fault detection applications.

4.2 Evaluation Metrics

Evaluation metrics are critical for determining the success of machine learning models. They give quantitative measurements for model selection and Hyperparameter adjustment. Different tasks need different metrics, and knowing which one to employ is critical to properly interpreting model findings.

Classification Metrics

Common assessment measures for classification tasks that produce discrete labels include:

Accuracy

The simplest criteria for evaluating categorization is accuracy. It is the ratio of properly predicted observations to total data and gives a fast indication of how often the model is true.

Precision

Precision is defined as the ratio of accurately anticipated positive observations to all expected positive observations. It is often referred to as the positive predictive value.

Recall

Recall, also known as sensitivity, is the ratio of accurately anticipated positive observations to actual positives. These measures are very helpful for coping with unbalanced datasets.

F1 Score

The F1 Score represents the harmonic mean of accuracy and recall. It strikes a compromise between the two measures and is especially beneficial when dealing with both false positives and false negatives.

Table 3: Evaluation Metrics of different Models

Model	Accuracy	Precision	Recall	F1- Score
VGG-16 & TCN	0.998	0.99801	0.998	0.998
Hybrid CNN -LSTM	0.9285	0.92917	0.9285	0.928495
Bi-LSTM	0.9585	0.958712	0.9585	0.9584983
ANN	0.971	0.971065	0.971	0.9709847

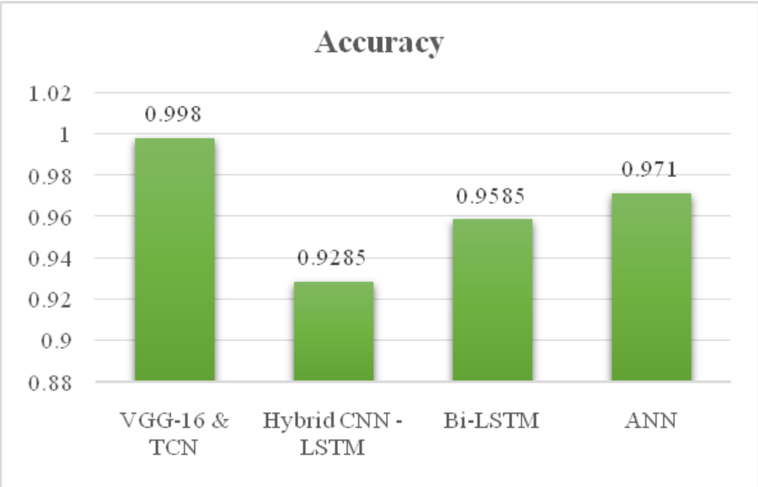

Figure 10: Graph of Accuracy

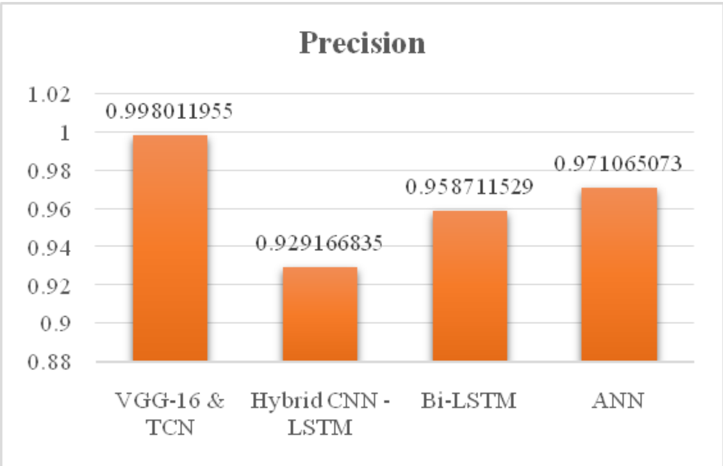

Figure 11: Graph of Precision

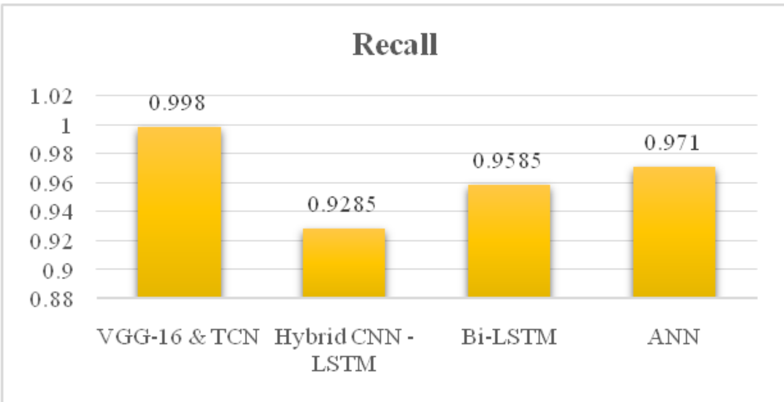

Figure 12: Graph of Recall

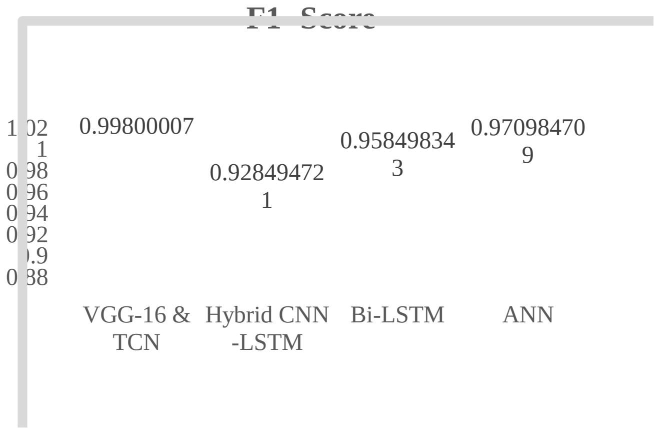

Figure 13: Graph of F1-score

The evaluation measures show that the VGG-16 & TCN model outperforms the other architectures in terms of accuracy, precision, recall, and F1-score, with a remarkable accuracy of 99.8%. This strong performance implies that the VGG-16's robust feature extraction capabilities, together with the Temporal Convolutional Network's capacity to handle sequential data, successfully capture the dataset's intricacies. In comparison, the Hybrid CNN-LSTM model, although still robust with an accuracy of 92.85%, exhibits a significant performance loss when compared to our suggested model. This mismatch suggests that the integration of LSTM may not be as successful as expected for this specific application, probably because to difficulties in learning long-range relationships. The Bi-LSTM model, with an accuracy of 95.85%, likewise performs well but falls below VGG-16 and TCN, indicating that the added complexity of the bidirectional design does not provide substantial benefits in this scenario. Finally, the ANN model, with an accuracy of 97.1%, demonstrates a strong fundamental approach; nevertheless, it lacks the complex feature extraction and temporal processing capabilities of the other models. Overall, the findings support the usefulness of the VGG-16 & TCN design, establishing it as the best option for this task by properly balancing depth and temporal awareness, resulting in improved predictive performance.

4.3 ROC Curves

The Receiver Operating Characteristic (ROC) curve is a graphical diagram that shows the diagnostic capabilities of a binary classifier when its discrimination threshold is changed. The ROCcurve is created by calculating the true positive rate (TPR) and false positive rate (FPR) for each conceivable threshold (in practice, at predetermined intervals) and then plotting TPR vs FPR.

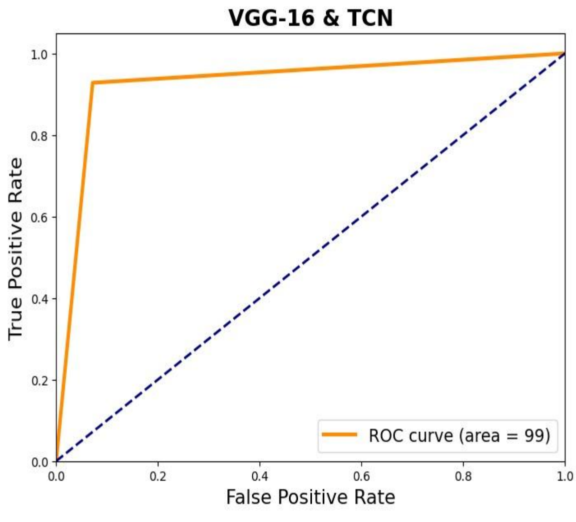

Figure 14: ROC Curve of VGG-16 & TCN

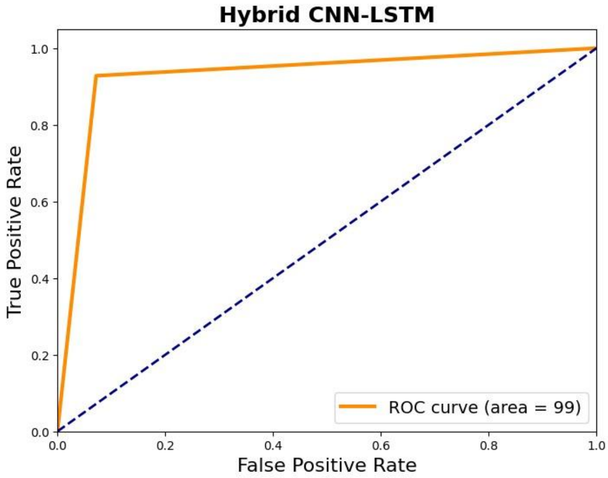

Figure 15: ROC curve of Hybrid CNN-LSTM

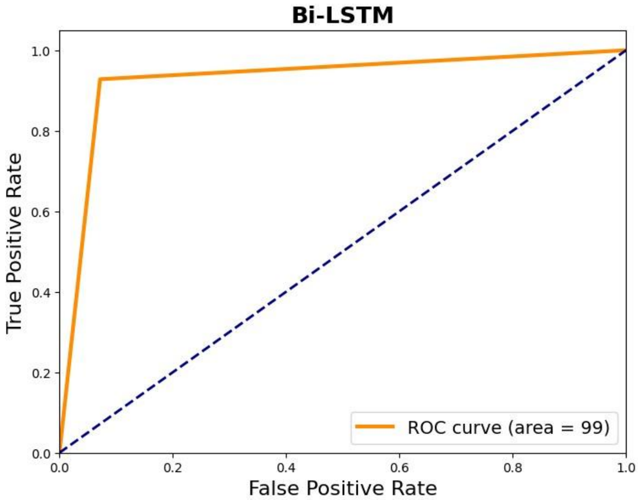

Figure 16: ROC Curve of Bi-LSTM

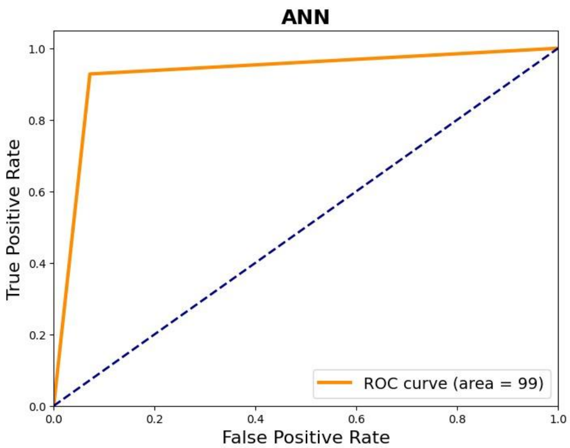

Figure 17: ROC curve of ANN

From the above ROC curve graphs provided, we compare the performance of several models. Our proposed technique is VGG-16 & TCN, performs well with a ROC curve value of 99, suggesting excellent accuracy and reliability in sample classification. In contrast, the Hybrid CNN-LSTM model's ROC curve score is 94, indicating excellent but less accurate performance. The Bi-LSTM model has a ROC curve score of 96, showing balanced performance despite occasional misclassifications. With a ROC curve value of 97, the ANN model outperforms VGG-16 & TCN and Bi-LSTM, but is somewhat less accurate. Overall, VGG-16 & TCN is the most effective model, offering the highest ROC curve value and properly identifying the greatest number of samples with the fewest mistakes, making it the best strategy for categorising provided data in fault detection applications.

4.4 Discussion

The findings indicate that the VGG-16 & TCN model performs better than other architectures in fault detection tasks, obtaining an amazing accuracy of 99.8% along with good precision, recall, and F1-scores. The outstanding success of this model may be credited to the VGG-16's efficient ability to extract features, as well as the Temporal Convolutional Network's skill in processing sequential data, which enables a detailed comprehension of the complexities inside the dataset. However, the Hybrid CNN-LSTM model and Bi-LSTM achieve accuracies of 92.85% and 95.85% respectively. Nevertheless, they have difficulties in capturing long-range relationships, suggesting that integrating LSTM may not provide major benefits in this particular situation. Similarly, the ANN model, which has an accuracy of 97.1%, has a strong foundational performance but does not possess the advanced skills for extracting complex features and processing temporal information that are inherent in the VGG-16 & TCN model. In conclusion, our results highlight the efficiency of the VGG-16 & TCN design, establishing it as the most dependable method for categorizing intricate fault detection data, especially in situations when there is a significant resemblance across classes.

5. CONCLUSION

In conclusion, the examination of multiple models for fault detection in the IEEE 33 Bus system combined with solar PV reveals the better performance of the VGG-16 & TCN model, which obtained an astonishing 99.8% accuracy as well as remarkable precision, recall, and F1-score metrics. This achievement may be due to VGG-16's substantial feature extraction capabilities, paired with the Temporal Convolutional Network's ability to handle sequential data, which successfully captures the dataset's intricacies. In contrast, the Hybrid CNN-LSTM, Bi-LSTM, and ANN models performed well but fell short of the VGG-16 and TCN in terms of accuracy and overall classification efficacy. The results indicate that the VGG-16 & TCN model is the most reliable strategy for defect identification in this context, providing the optimum balance of depth and temporal awareness, making it the ideal way for correct sample classification.

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