A Comparative Study of AI-Based and Signal Processing Techniques for Condition Monitoring of Power Transmission Networks

By

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A thesis submitted to the Department of Electrical & Electronic Engineering (EEE) in partial fulfillment of the requirements for the degree of Master of Science in Electrical & Electronic Engineering

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Declaration

It is hereby declared that

1. Thesis has been my own work and prepared by me during a study period at BRAC University.
2. The thesis nor any part of it has been previously submitted, or written in collaboration with another person, for a degree or diploma other than where previous publication is acknowledged through full and accurate referencing.
3. The thesis is not being submitted for any degree or diploma from any other university or similar institution.
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Ethics Statement

I hereby declare that this Thesis on " A Comparative Study of AI-Based and Signal Processing Techniques for Condition Monitoring of Power Transmission Networks" has met the research criteria for completing the degree which has been written and completed without any copy. All the information and data are the reflection of my work. Also, the systems and software coding used here are being done by me. I sometimes have collected some information from other papers where it is properly cited. There is nothing in this paper that can be related to any project or paper. I have completed total work with my own effort, and this unique work is done by taking assistance from supervisor and university.

Abstract

Transmission lines are essential for transporting power over long distances as far as it is not always effective and it may also fail thus putting the flow of power at risk and the people who depend on power at risk as well. This is why the maintenance of their reliability and efficiency is of paramount importance in energy infrastructure of the contemporary world. This research aims at exploring the detection and classification of faults in power networks. Here, a novel hybrid model, DWT- CNN-BiLSTM, is presented which combines signal processing and deep learning and compares it with the classic machine-learning and deep learning approach. A dataset of 11,000 current and line-voltage samples that were provided in MATLAB SimPowerSystem evaluated the proposed model. Wavelet transform breaks down the signals by time-frequency, which represents transient faults as well as attenuating noise. The resulting coefficients are then inputted into a CNN, which produces spatial features, which are then inputted into a BiLSTM that yields bidirectional time information. One last Softmax layer allows fault detection and classification of multiple classes reliably. It is a robust, high-accuracy end-to-end pipeline that can be deployed in real time, and the accuracy of fault-detection is 99.86 %, and the accuracy of classification is 93.75%. Further proof of the effectiveness of the hybrid model is that the hybrid model surpasses single-method machine-learning and Deep learning baselines in terms of precision, accuracy and recall. Such findings show that the model can be applied in practice in real-time as a way of enhancing system stability in power-generation, predictive maintenance, or operational resiliency.

Keywords: Transmission line faults; Fault classification; BiLSTM; Machine learning; Time–frequency analysis.

Dedication

This work is dedicated with deepest love and gratitude to my lovely sister Aisha, my dear mother Amina, and all my beloved family members. Your unwavering support, encouragement, and sacrifices have been the foundation of my journey. Thank you for always believing in me, for pushing me to aim higher, and for standing by my side through every challenge — emotionally, financially, and spiritually. Your faith in me has been my greatest source of strength and motivation to keep moving forward toward my goals.

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List of Acronyms

AI – Artificial Intelligence

ANN – Artificial Neural Network

ANFIS – Adaptive Neuro-Fuzzy Inference System

BPNN – Backpropagation Neural Network

CBM – Condition-Based Maintenance

CNN – Convolutional Neural Network

DL – Deep Learning

DT – Decision Tree

DWT – Discrete Wavelet Transform

FDOST – Fast Discrete Orthogonal S-Transform

FIS – Fuzzy Inference System

FFT – Fast Fourier Transform

GRU – Gated Recurrent Unit

KNN – K-Nearest Neighbours

LDA – Linear Discriminant Analysis

LR – Logistic Regression

LSTM – Long Short-Term Memory

MAE – Mean Absolute Error

MRA – Multi-Resolution Analysis

ML – Machine Learning

MLP – Multi-Layer Perceptron

MSE – Mean Squared Error

NB – Naïve Bayes

PCA – Principal Component Analysis

PV – Photovoltaic

QTA – Qualitative Trend Analysis

RBF – Radial Basis Function

RBM – Risk-Based Maintenance

RBFNN – Radial Basis Function Neural Network

RF – Random Forest

RMSE – Root Mean Squared Error

RNN – Recurrent Neural Network

RCM – Reliability-Centered Maintenance

SVM – Support Vector Machine

SMOTE – Synthetic Minority Over-sampling Technique

SOM – Self-Organizing Map

VMD – Variational Mode Decomposition

WT – Wavelet Transform

WPT – Wavelet Packet Transform

WPD – Wavelet Packet Decomposition

WOA – Whale Optimization Algorithm

Chapter 1: Introduction

1.1 Introduction

Electrical systems, ranging from small consumer devices to large-scale industrial equipment, play a key role in modern society. Among these systems, power systems are responsible for the large-scale generation, transmission, and distribution of electricity. A reliable power supply is an essential factor that supports economic activity, infrastructure development, and societal progress [1]. However, as energy demand increases, power networks become more complex and increasingly susceptible to faults. A fault is an abnormal event within the system that causes a change in one or more critical components [2]. Faults do not always lead to complete system failure, but they can disrupt normal operation. In contrast, a malfunction occurs when the system cannot perform its intended function under certain conditions and remains inoperative until repaired. Even minor unresolved issues can increase maintenance costs and, in severe cases, contribute to system collapse [3].

Power systems are exposed to risks such as mechanical wear, corrosion, human error, natural disasters, and aging equipment. These issues may result in frequent failures that have a severe impact on transmission and distribution networks [4]. Monitoring the conditions of the power systems can be used to enhance reliability as well as facilitate easier maintenance and avert such problems [5]. Transmission lines are especially vulnerable and do not cause less than 85% of the failure in the power system [6].

In electrical transmission networks, open circuit and short circuit defects are the most prevalent issues. A disruption in the electrical circuit may result in open circuit faults or series faults, subsequently disrupting power continuity, unbalancing loads, and inducing voltage fluctuations. Mechanical stress, environmental factors, infrastructure aging, and operational errors, such as improper manipulation of switches or breakers, are among the reasons. A short circuit occurs when two components of a circuit inadvertently connect, creating a low-impedance pathway that leads to a rapid surge in current flow. These may arise from insulation failure, mechanical damage, or installation errors that let conductors make direct contact with one another [5-7].

Figure 1.1 shows that transmission lines can experience two main types of failures: short circuits and series faults, also called open-conductor faults. These problems may be caused by accidents, lightning strikes, unexpected short circuits, or even human error [7]. The faults of short circuits may be symmetrical, asymmetrical, Single-line, double-line, or double-line-to-ground faults. Asymmetrical faults fall in the category of asymmetrical faults. These issues can render the power supply unreliable, leading to grave failures of the system and its users [8]. The detection of faults should be done quickly and in the most efficient manner, and this can help in minimizing the disruptions. Smart systems are used to detect, identify, and locate faults in order to reduce outages, enhance reliability, and accelerate repairs [7,9].

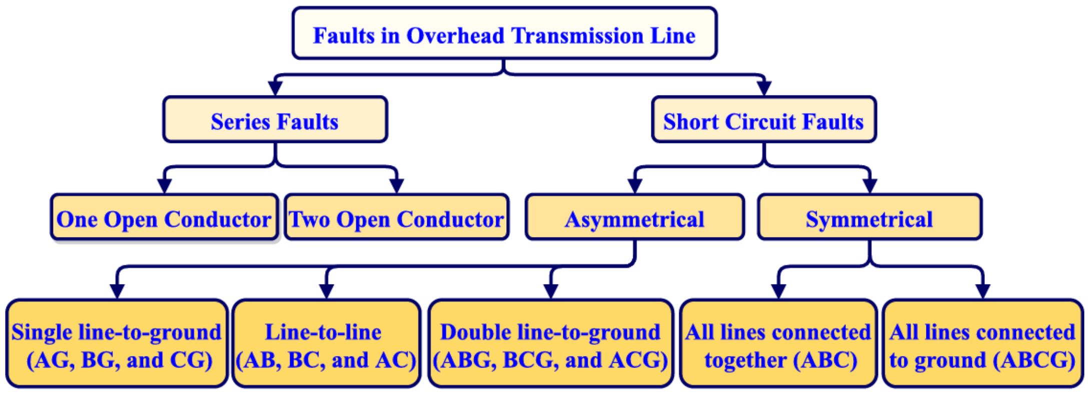

Figure 1.1: Faults in Overhead Transmission Lines

The methodologies used in traditional approaches strongly rely on signal processing to obtain useful information from sensors that detect temperature, vibration, current, and voltage [10]. Signal processing is useful in deconstructing stored signals to identify concealed attributes [11, 12]. Common methods include statistical, wavelet, and Fourier methods, which are also used to predict the lifespans of long components in power systems and to identify faults and other problems. Meanwhile, the complexity of power systems makes it difficult to employ the traditional condition monitoring tools. Recent developments show that deep learning and machine learning prove very beneficial to contest such challenges [13]. These tools can discover patterns in big data, adjust themselves to dynamism, and present more precise and timely information on power systems assets [14]. It has also been demonstrated that AI can be used to assist in optimization, classification, regression, and exploring data structure throughout the power electronic system lifetime [15].

Faults in transmission networks have been detected and solved through several approaches that have been developed by researchers. These approaches can be divided into three groups, namely classical, signal-processing-based, and AI-based. Conventional techniques for locating and categorizing faults in transmission lines include impedance measurement and the travelling-wave method [16]. The single-end or two-end impedance technique employs the change of voltage and current at the ends of the transmission line to precisely locate high-resistance faults. Nonetheless, this technique is not easily applicable to practice since it is costly, computationally involved, and the sampling rate must be high [17].

Key methodologies in signal processing of this study encompass the discrete wavelet transform (DWT) . Wavelet transforms can exploit the frequency components of an erroneous waveform after decomposition to determine fault characteristics with high precision [18]. Compared to the Fast Fourier Transform it requires a signal that is mainly stationery in order to get accuracy of determination of the coefficients. On the other hand, power system signals are not fixed, but can change in their properties with time [19].

1.2 Problem Statement

Transmission lines play a critical role in reliable power delivery but are vulnerable to failures due to aging infrastructure, environmental challenges, and operational complexity. Conventional fault detection techniques are not always sufficient to support modern dynamic power systems, resulting in longer response times, greater maintenance effort, and system downtime. Thus, superior, intelligent fault-detection and classification tools are required so that faults may be detected and categorized in a more precise and efficient way in real-time.

1. **High fault exposure in transmission lines:** Transmission lines operate in harsh environments (weather, aging, mechanical stress), making them highly vulnerable to frequent and diverse fault conditions.

2. **Conventional methods struggle in real operating conditions:** Traditional approaches such as Impedance/traveling-wave and classical signal-based methods are not up to the mark or impractical due to requirements like high sampling frequency, high computational cost, and sensitivity to changing system conditions.
3. **The purpose** is therefore to develop and validate a robust, accurate, and computationally feasible AI-based framework for real-time fault detection and multi-class classification under diverse and noisy operating conditions.

1.3 Research Objectives

To address the identified gaps, this thesis pursues the following objectives:

1. To systematically evaluate existing approaches (ANFIS, ANN, ML, DL, and hybrid models) for identifying and categorizing power transmission system faults, contrasting their computational efficiency and accuracy advantages and disadvantages and compare it with proposed DWT-CNN-BiLSTM approach.
2. To develop hybrid deep learning models, specifically DWT-CNN-BiLSTM, that combine time–frequency domain analysis with sequential learning, aiming to minimize errors and maximize fault classification accuracy and compare it with Baseline and existing hybrid approaches.
3. To propose a comprehensive comparative framework that identifies the most accurate, reliable, and computationally efficient models, among all the techniques thus providing practical guidelines for utilities and industries implementing fault monitoring systems.

1.4 Research Contributions

This thesis contributes to the field of defect detection and classification in power systems in the following ways:

1. **Comprehensive Comparative Study**
    - Provides an in-depth comparison of signal processing, ANN, ANFIS, classical ML, and modern DL approaches under identical datasets and performance metrics, creating a benchmark reference for future research.
2. **Validation of Hybrid Deep Learning**
    - Demonstrates that DWT-CNN-BiLSTM significantly outperforms other deep learning approaches, achieving highest accuracy (93.75%) and lowest error rates. This validates the superiority of combining wavelet-based feature extraction with BiLSTM sequence learning.
3. **Perform multi-metric evaluation**
    - Using accuracy, precision, recall, F1-score, MAE, MSE, and RMSE, ensuring that performance assessment captures not only correctness but also robustness against misclassification and noise.
4. **Hybrid Benchmarking Framework**
    - Introduces a novel benchmarking framework for hybrid and ensemble approaches, enabling systematic comparison across AI, ML, and DL techniques. This fills a gap in prior literature where hybrid approaches were rarely compared at equal footing.
4. **Comprehensive Evaluation of RMS vs. Time–Frequency Features**
    - The thesis provides a detailed comparative analysis between RMS-based features and DWT-based time–frequency features, highlighting the limitations of steady-

state descriptors and the superiority of wavelet-derived features for transient fault analysis.

5. **Practical Real-Time Relevance**

    - Emphasizes the practical utility of the proposed models for real-time condition monitoring and predictive maintenance in power systems. By reducing misclassification rates and improving reliability, the research offers direct contributions to grid stability, downtime reduction, and operational safety.

6. **Guidelines for Model Selection in Industrial Applications**

    - Based on extensive experimental results, the thesis provides clear, evidence-based guidelines for selecting appropriate AI models depending on accuracy requirements, computational complexity, and deployment constraints.

Chapter 2: Literature Review

This literature review focuses on transmission lines in the power system structure, which account for most issues. Focusing on fault detection and Classification

2.1 Maintenance Strategies Evolution

Technologies for planning power system maintenance have significantly expanded during the last 20 years. With more reliance on grid, it is critical to establish the best maintenance measures to ensure reliable operation [20]. The maintenance strategies have shifted towards being reactive to proactive in order to increase their reliability and efficiency and reduce costs. **Figure 2.1** illustrates how the practice of maintenance has changed over the years [21].

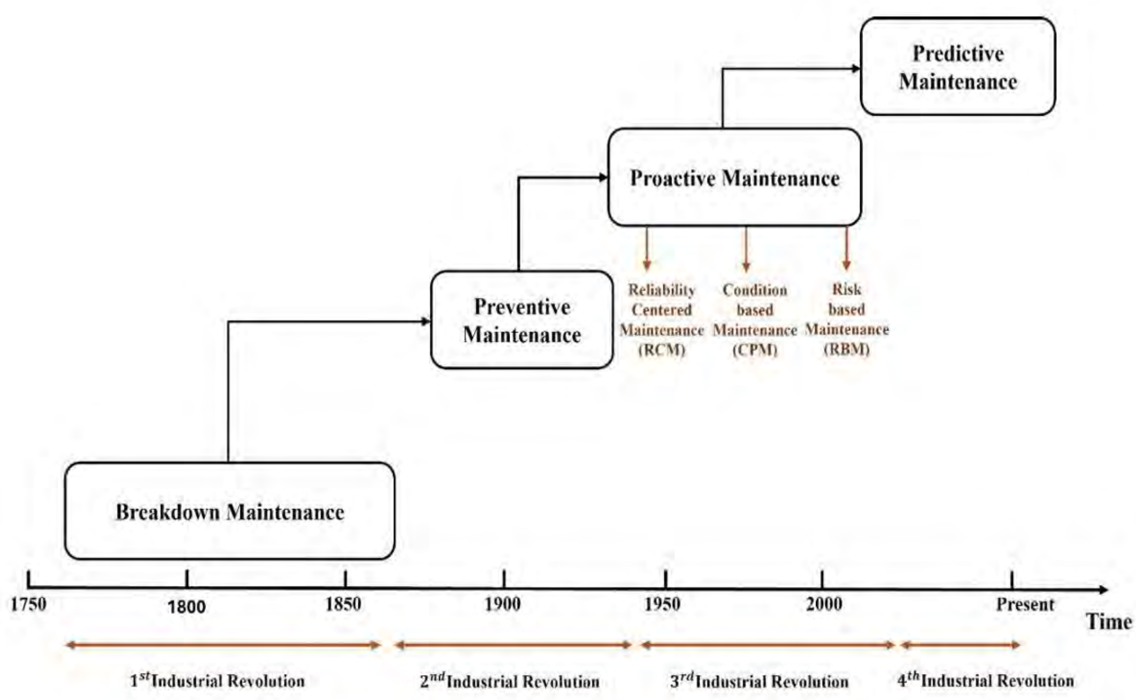

Figure 2.1: Advancements in Maintenance Over the Past Few Decades [21]

Initially, power systems primarily employed failure-based maintenance, also referred to as corrective or reactive maintenance. This type of maintenance necessitated resolving issues that had already occurred, resulting in significant outages and financial expenditures [22]. This reactive strategy, which prioritized resolving issues as soon as they occurred, was characterized by economic inefficiencies. Consequently, the Second Industrial Revolution resulted in a shift in emphasis towards preventive maintenance. This method involves planning maintenance based on equipment life cycles to prevent malfunctions [22-24]. This enhancement was revolutionary in reducing unscheduled downtime and maintaining operational integrity.

In the third industrial revolution, advanced methodologies were used, including Reliability-Centered Maintenance (RCM), Conditions-Based Maintenance (CBM), and Risk-Based Maintenance (RBM) [23]. RCM was first introduced by Nowlan in 1978. It aims at making sure that the equipment is reliable, by making sure to identify meaningful failure modes, and changing maintenance practices to adapt to them [25-26].This approach provides the least expensive solutions to businesses that suffer failures, which represent 20% to 25% of the total business maintenance duties [26].CBM also maximizes maintenance time, improves operational efficiency, minimizes expenses, and prolongs the life of equipment through real-time sensor data [27].

Risk-Based Maintenance (RBM) is a development of RCM that was initially implemented in power systems by Vittal in 1997 under the name "operation risk assessment" [28]. RBM optimizes resource allocation by prioritizing maintenance tasks based on the probability and impact of failures by integrating risk assessment with maintenance planning [28-30]. According to Manninen et al. [31], RBM is employed in numerous sectors, including electricity transmission, to ascertain the urgency and magnitude of the overhead wire replacement required.

Predictive maintenance that optimizes the maintenance schedules, minimizes downtime, and prolongs the life of the equipment. Equipment life is a new concept in maintenance strategies [32-33][24] [34-36]. These condition monitoring systems support and enhance the approach through data measurement and analysis. real-time to monitor and notice any problems prior to their impact on the power grid [31-36]. This enhanced maintenance must include procedures for condition-monitoring systems. The proper assessment of a system's health and operation depends on real-time data from continuous monitoring, delivered by various technologies. Specifics regarding defect-detection and classification methodologies and condition-monitoring systems will be addressed in subsequent sections.

2.2 Integration of Fault Detection and Classification in Condition Monitoring Frameworks

It is evident that transmission lines are essential for the reliability and efficacy of power networks, as they account for over 85% of all defects. Essential components of these lines include conductors, insulators, towers, ground wires, and other substation components. The fact that each component is susceptible to a variety of malfunctions affects both the power supply and significant safety concerns. Substation faults account for 32% of all transmission line problems, while line faults account for 58%.

Continuous condition monitoring systems are the sole solution to these issues. The objective of these systems is to identify early warning signals of degradation, malfunctions, or failures in electrical infrastructure and equipment by continuously or routinely monitoring their performance and physical condition. Predictive maintenance solutions depend on them to resolve potential issues before they develop into significant problems, thereby enhancing system reliability and preventing unforeseen disruptions. Researchers [24] [37-38] assert that condition monitoring not only reduces maintenance costs but also extends equipment lifespan by preventing premature failure and prioritizing predictive maintenance over reactive maintenance, which often requires costly, time-consuming restorations.

For the successful execution of these strategies, it is essential to possess a comprehensive understanding of the fundamental architecture of condition-monitoring systems. Each of the numerous levels that comprise these designs, illustrated in **Figure 2.2**, is indispensable to the entire surveillance process.

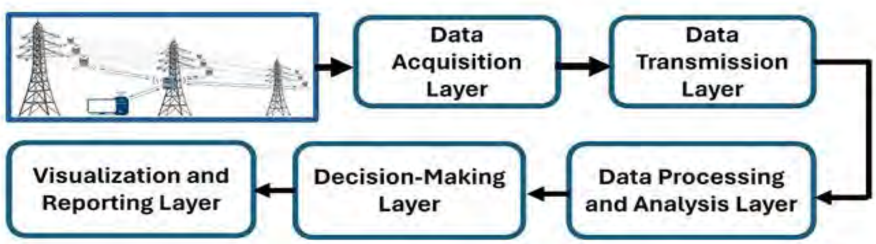

Figure 2.2 : Condition Monitoring Flow Chart

Figure 2.2 shows a condition-monitoring flowchart that is commonly used in power systems to enable Fault identification and Categorization. The Data Acquisition Layer collects real-time data from sensors installed in the transmission infrastructure at the beginning of the process. The information is subsequently passed to the Data Transmission Layer, which performs the operation to ensure the transmission of safe, trustworthy information to other modules. When information is transferred to this Layer, it is processed within the Data Processing and Analysis Layer, where more advanced techniques, such as signal processing or machine learning, can be applied to identify abnormalities or trends. This chart provides a conclusion or decision: the development of a layer that chooses the right response or maintenance. The third layer, the Reporting Layer, which displays diagnostic interpretations on easy-to-use dashboards and reports, enables engines and operators to quickly assess system health and make informed decisions. This pyramid design will ensure that the monitoring system is productive, automated, highly reliable, and minimizes the risk of breakdowns of crucial infrastructure. After that, data collection for monitored systems using various technical sensors is carried out. Processing and analysis of data. It is a layer applied during data decoding and collected through various means to detect and classify defects. This layer relies on the latest analytical methods and algorithms to turn raw data into insights that support early maintenance operations and detect potential issues. Fault detection within electrical power networks is a highly important issue due to its critical and complex nature. Practical solutions play a very important role in the safety, dependability, and effectiveness of power supply. The second way to rectify the identified faults is to organize them. There are three major frameworks for classifying these strategies: data-driven, model-based, and signal-based.

2.3 Power System Condition Monitoring Methodologies

This section will showcase the most recent research on power system status monitoring, as well as machine learning, deep learning, and hybrid methods, along with the results of each approach.

2.3.1 Machine Learning Methods

Firos et al. [39] examined the transmission line fault detection based on three machine learning models (Naive Bayes (NB), Support Vector Machine (SVM), and Random Forest (RF). The highest accuracy was 97.78% based on Naive Bayes classifier. Similarly, Janarthanam et al. [40] tested the effectiveness of machine learning methods in detecting and classifying power transmission line faults through voltage and current measurements recorded in faulty and normal operating conditions. The implementation and training of the four classifiers, which included SVM, K-Nearest Neighbours (KNN), Decision Tree (DT), and Random Forest, were done using the Python based Spyder IDE. The SVM model was found to be better with the highest accuracy of classification of 99.7 percent, which shows that it is effective in detecting faults in the power system

Fonseca et al. [41] suggested the use of a Random Forest-based solution with notch filtering as the preprocessing to differentiate various forms of faults in transmission lines. It was observed that the RF model performed better than the neural network, in which RF had an accuracy of 91.96% and the ANN achieved accuracy of 89.59%. K-fold cross-validation was used to evaluate all the models. Moreover, Sapountzoglou et al. [42] proposed a gradient boosting tree-based model of the detection of faulty phases, defective branches, and general system deficiencies through voltage and current measurements and delivered a high success with a 89 percent accuracy.

Chuan et al. [43] effectively classified power distribution systems (PDS) using the IEEE-34 and the IEEE-123 bus systems using support vector machines (SVMs). This has significantly enhanced the ability of distribution and transmission networks by successfully detecting defects and segments in real time. Similarly, Singh et al. [44] presented an astute approach that is predicated on machine learning. It employs KNN classifiers with different values of k (1, 3, and 5) to categorize defects in power networks using a series-compensated method. The proposed method achieved high classification accuracy, ranging from 99.404% to 99.553%, depending on the selected k values.

Patel et al. [45] proposed a fault detection, classification and localization framework for both overhead and underground transmission lines using Fast Discrete Orthogonal S-Transform

(FDOST) with entropy-based feature extraction. Support Vector Machines and regression models were used for fault type and location identification. The method gave a fault classification accuracy of 99.53% under noisy conditions with a signal-to-noise ratio of 30 dB, with average localization errors of 0.098 km for underground cables and 0.061 km for overhead lines. Despite its high accuracy and fast relaying response time of less than 17 ms, the approach was limited to one-way fault measurements. Aker et al. [46] also used a Naive Bayes Classifier with DWT-based feature extraction using the voltage and current signals for transmission line fault characterization.

Da Silva et al. [47] suggested a way of diagnosing multiple transmission line faults by using harmonic components of experimental and simulated leakage current signals as residual. Qualitative Trend Analysis (QTA) was used to extract the features, and a Naive Bayes Classifier was used to classify the features. The technique showed fault accuracies of 95 to 100 percent; nevertheless, the technique could not find fault locations properly. Discrete Fourier Transform (DFT) and Discrete Wavelet Transform (DWT) signal processing methods were necessary in extracting features and the frequencies of sampling ranged between 1 and 20 kHz in the studies.

2.3.2 Deep Learning Methods

Kanwal et al. [48] compared the performance of four models to detect, diagnose and locate faults in the transmission lines based on the IEEE 9-bus system data. Despite the fact that all models performed satisfactorily, the Adaptive Neuro-Fuzzy Inference System (ANFIS) had a high performance that showed low error rates. The hybrid DWT-ANFIS and Self-Organizing Map (SOM) methods provided the best overall performance so that it is possible to conclude that hybrid and ANFIS based methods are quite suitable in the case of protecting electrical systems in real-time. Similarly, Rajashekar et al. [49] created a deep learning model that has been implemented on the Long Short-Term Memory (LSTM) networks to detect and classify faults in power transmission lines. The model was used on three phase current values in the IEEE 9-bus system with measurements produced in the presence of different fault initiation angles, resistances, location, and fault conditions. The LSTM-based network had a classification accuracy of 96.7% among ten types of faults, which proves its consistency in detecting faults in power systems fast and accurately.

Shukla et al. [50] suggested a Convolutional Neural Network (CNN)-based algorithm that can both differentiate between symmetrical and asymmetrical power faults and identify, categorize, and locate transmission line faults. The suggested method was very strong as it produced the maximum accuracy of 99.94% with low false excursions and the classification accuracy of over 98% in all types of faults. In the same way, Alhanaf et al. [51] examined the use of Deep Neural Networks (DNNs) to detect faults, classify them, and localize faults using the IEEE 6-bus system. The ANN based model proposed had a detection accuracy of 99.99%, classification accuracy of 99.75% and localization accuracy of 98.25%. Similar results were also found to be achieved with the one-dimensional CNN architectures.

An experiment by Arafat et al. [52], examined several deep learning approaches to predictive maintenance of photovoltaic-based DC microgrids with the concentration on LSTM and Gated Recurrent Unit (GRU) versions of Recurrent Neural Networks (RNNs). The findings showed that LSTM was better than other models and had a lower Mean Absolute Error (MAE) of 8.263 and coefficient of determination (R) of 0.971, which justified its application in the continuity of distributed renewable energy systems. Similarly, Sundaram et al. [53] suggested an LSTM model to forecast smart grid stability with an accuracy of 96.3%, thus making it possible to mitigate grid instability proactively.

Devi et al. [54] explored how CNNs, RNNs, and LSTMs can be used to deal with interoperability issues in smart grids. Their results proved that deep learning models make it possible to detect errors in real-time, share data, and normalize processes that are essential to electric vehicles and distributed energy resource integration. Furthermore, Kaplan et al. [55] also investigated the application of LSTM networks in fault detection and load demand in smart grids and found higher accuracy than standard artificial neural network models and the importance of LSTM in enabling the grid to become more reliable and stable.

Dofia and Kalu [56] suggested a hybrid fault detection and localization method of transmission lines of 132 kV and 100 km by combining Discrete Wavelet Transform (DWT)-based feature extraction with ANFIS classification. The ANFIS model was trained based on root mean square (RMS) characteristics that were obtained by wavelet multi-level decomposition. The suggested approach was able to detect faults in 8 ms and with an accuracy of 99.78% which proved its suitability in real-time power system protection. Moreover, Goyal et al. [57] contrasted the GK networks with the traditional ones, including the Random Forest and the Support Vector Machines in a smart grid maintenance setting. The findings demonstrated that LSTM was more accurate in detection since it has the capability of capturing a temporal relationship, which minimizes unforeseen downtime and contributes to an adaptive maintenance schedule.

2.3.3 Hybrid Methods

A power transmission line fault detection and classification using ensemble-based methodology was introduced by Anwar et al. [58] through the combination of the Random Forest (RF), Long Short-Term Memory (LSTM), and K-Nearest Neighbours (KNN) models. Voltage and current data gathered under fault conditions were used in the study. Normalization and Principal Component Analysis (PCA) as a dimensional reduction technique and Synthetic Minority Oversampling Technique (SMOTE) to deal with class imbalance were all considered data preprocessing. Hyperparameter tuning was done using particle Swarm Optimization. The RF-LSTM stacked KNN ensemble showed greater stability and accuracy than single models, reaching accuracy values of 99.85% on binary fault detection and 99.96% on training multi-label fault classification, which further evolves the usefulness of ensemble learning in providing reliable power system diagnostics.

Rafi et al. [59] suggested a mixed-method fault detection system that integrates Support Vector Machines (SVM) and Artificial Neural Networks (ANN). MATLAB SimPowerSystem was used for voltage and current signal collections under different simulated fault conditions. In the ANN part, the number of dense layers was several with ReLU activation and dropout regularization to learn features and classify them by using SVMs. The hybrid ANN-SVM model was compared to the performance of several classifiers such as the Logistic Regression, random forest, SVM, and ANN. The findings established that ANN-SVM hybrid was more accurate, precise and recalled more transmission line faults.

Mishra et al. [60] gave an extensive overview of online and offline techniques of fault detection, classification, and localization of the transmission line. The paper has discussed modern signal processing techniques such as S-transform, Discrete Wavelet Transform (DWT), Wavelet Packet Transform (WPT) as well as impedance-based and travelling-wave techniques. Moreover, the artificial intelligence methods used to include ANFIS, fuzzy logic, SVMs, and ANNs were studied. It was observed in the analysis that AI-based procedures with wavelet characteristics showed more consistent performance in comparison to traditional procedures, which have classification accuracies of fault over 95 percent when used in a variety of working conditions.

Hosseinzadeh et al. [61] suggested a hybrid fault-detection model which employed Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) in the extraction of features and K-Nearest Neighbours (KNN) classification. The approach was effective to identify time-varying smart grid faults and feature management was simplified by increased separation in classes.

Alrifaey et al. [62] proposed a hybrid deep learning implementation to real-time fault identification in grid-connected photovoltaic (PV) systems to overcome the drawbacks of the traditional approaches in terms of computational complexity and sensitivity to noise. The suggested structure involved the use of Wavelet Packet Transform (WPT), Stacked Autoencoder, Equilibrium Optimizer Algorithm, and Long Short-Term Memory (LSTM) networks to pre-process the features, optimize them and classify them respectively. Using the method on a 250 kW PV plant with 264 faults, the method had an accuracy of 99.93 and noise resilience of greater than 96.57 at 20 dB signal-to-noise ratio.

Jawad et al. [63] discussed the fault detection in PV systems and presented a hybrid CNN-BiLSTM that is optimized with the help of the Whale Optimization Algorithm (WOA). In this model, CNN component, BiLSTM, and WOA optimized model parameters were learned. The suggested method proved to be more resistant in different working conditions with an accuracy of 99.9 percent among various types of faults and irradiance intensities.

Narasimhulu et al. [64] suggested a hybrid system of 1D-CNN and Gated Recurrent Unit (GRU) to identify the fault in PV system under the influence of partial shading and varying irradiance to detect the faults in the PV system. The algorithm reached a classification rate of 99.1 which was more accurate than the traditional methods. Equally, Alhanaf et al. [65] introduced a hybrid VMD-

DBN-SVM architecture, with Variational Mode Decomposition (VMD) working at signal decomposition, Deep Belief Networks (DBN) to extract the features, and SVM to classify the faults. The model proposed had an accuracy of 99.4, and this improves on the conventional methods of accuracy.

Mbey et al. [66] offered a strategy of fault classification that was a combination of Discrete Wavelet Transform (DWT) as a signal denoising tool, Principal Component Analysis (PCA) as a dimensionality reduction method, and Deep Neural Networks (DNN) as a classification tool. The method remained accurate with 98.86 percent during the noisy ones. On the same note, Gao et al. [67] proposed a hybrid photovoltaic fault detection model using Variational Mode Decomposition (VMD) to preprocess, the use of Gray Wolf Optimization (GWO) to optimize parameters and the use of DNN to classify faults and reported a corrected accuracy of 99.45% in varied operating conditions.

Table 2.1 below provides a brief summary of different studies for fault detection and classification of transmission line of power network.

Table 2.1: Summary of Fault Detection and Classification Studies

Ref	Methods Compared	Best Model	Accuracy [Detection]	Accuracy [Classification]	Key Notes	Research Gap
[39]	Naïve Bayes, SVM, RF	Naïve Bayes	97.78%	-	High accuracy for multivariable data	No classification done
[48]	ANFIS, Hybrid DWT-ANFIS, SOM	ANFIS	Highest	-	Lowest error, best performance	No classification done
[40]	SVM, KNN, DT, RF	SVM	99.7%	-	Reliable defect identification	No classification done

[49]	LSTM	LSTM	100%	96.7%	Accurate for 10 fault categories	Limited evaluation on multi-fault and real-world noisy conditions
[58]	RF, LSTM, KNN (Ensemble)	RF-LSTM Stacked KNN	-	96.55%	Outperforms individual models	Multi-fault handling limited.
[59]	ANN, SVM	Hybrid ANN-SVM	94.43%	93%	High precision, recall, and accuracy	Fault severity not addressed. and Weak under load variations
[60]	ANN, SVM, Fuzzy, ANFIS	AI with wavelet	-	95%	Comprehensive method review	High computational complexity and No fault detection is done
[41]	RF, NN	RF	-	91.96%	Higher than NN	Ground-related faults underexplored
[44]	k-NN	k-NN	99.55%	-	DWT feature extraction	Limited system scalability and No fault classification is done
[50]	CNN	CNN	99.47%	-	Distinguishes symmetrical/asymmetrical swings	The Hybrid faults not explored and No fault classification is done
[56]	DWT-ANFIS	DWT-ANFIS	-	99.78%	Fast (8ms), high reliability	Single-fault only and no fault detection is done
[55]	LSTM	LSTM	97.25%	-	Predicts faults before they occur	Multi-fault detection

						limited and No fault classification is done.
[65]	ANN, 1D-CNN	ANN/1D-CNN	99.74%	99.75%	High classification accuracy	Noise robustness not evaluated
[52]	LSTM, GRU	LSTM	97.25%	93.1%	Best performance for DC microgrids	Multi-fault scenarios unaddressed
[57]	LSTM vs. RF/SVM	LSTM	92%	91%	Effective in equipment failure	Hybrid/multi-fault classification missing.
[53]	LSTM	LSTM	97%	-	Predicts smart grid stability	Limited model diversity and fault classification is done
[54]	CNN, RNN, LSTM	Hybrid DL	93.8%	92.6%	Interoperability in smart grids	Accuracy–efficiency trade-off unresolved
[61]	PCA, LDA, KNN	Hybrid	-	95.9%	Accurate for temporal smart grid data	Limited generalization to rare faults and fault detection is not done.
[43]	SVM	SVM	100%	86.7%	Accurate classification in IEEE 34 & 123 bus systems	Weak classification
[42]	GBT	Gradient Boosting Tree	**fault detection** method's performance is tested using fault simulations based on voltage data	81.21%	Identifies phases, branches, and defects	Weak detection and classification ability

			collected via smart meters.			
[45]	RF-LSTM Stacked Tune KNN Random Forest (RF) K-Nearest Neighbors (KNN) Long Short-Term Memory (LSTM)	RF-LSTM Stacked Tune KNN Ensemble Model	99.96%	99.27%	RF–LSTM ensemble outperforms traditional models with high AUC.	Training time not optimized.
[46]	Naïve Bayes Classifier MLP (Multilayer Perceptron)	Naïve Bayes Algorithm	92%	87%	Naïve Bayes outperforms MLP, and STATCOM integration improves fault detection robustness.	Zone-3 protection limitation.
[47]	Qualitative Trend Analysis (QTA) Naïve Bayes (NB) Classifier	**Naïve Bayes (NB) Classifier** integrated with **QTA**	**84%**	95%	Uses LC residuals with QTA analysis and Naïve Bayes for reliable fault classification.	Multi-fault diagnosis limited
[51]	The ANNs are one -dimensional convolutional neural networks (1D-CNN).	1D-CNN (One-Dimensional Convolutional Neural Networks)	99.98%	99.99%	ANN and 1D-CNN models achieve high fault detection and classification performance.	Image-based processing costly
[62]	RF, LSTM, KNN and RF-LSTM Stacked Tune KNN ensemble model	RF-LSTM Stacked Tune KNN ensemble model	99.85%	99.85%	The study emphasizes the advantages of using a combination of RF and LSTM models in an ensemble framework.	Complex data handling limited

[63]	Support Vector Machine (SVM) Decision Tree (DT) K-Nearest Neighbor (K-NN) Ensemble Classifier Artificial Neural Network (ANN) with Ant Colony Optimization (ACO) and Discrete Wavelet Transform (DWT)	ANN-DWT-ACO-DT	**99.60%**	99.25%	The proposed method combined ACO for feature selection and DWT for preprocessing, significantly improving the ANN model's performance.	Inefficient feature selection
[64]	DWT-ANFIS DWT-RBFFN MWT-ANFIS MWT-FLC based GA Proposed Hybrid Method (ANN + GSA)	Hybrid Method (ANN + GSA)	-	**95%**	Combines ANN with GSA to enhance feature extraction and fault classification	Conventional techniques inefficient
[66]	Long Short-Term Memory (LSTM) Adaptive Neuro Fuzzy	A Novel Method for Combining LSTM and ANFIS	**99.99%**	**99.99%**	Uses smart meter data with a hybrid LSTM–ANFIS model for fault detection and classification.	Large-scale data handling inadequate

	Inference System (ANFIS) Hybrid Model combining LSTM and ANFIS					
[67]	Artificial Neural Network (ANN) Extreme Learning Machine with Kernel Function (KELM) Fuzzy C-Means (FCM) Clustering Using a ResNet network and a multi-class exponential loss function based on a classification and regression tree, SAMME-CART performs stage-wise additive modelling.	Convolutional Neural Network (CNN) and Residual Gated Recurrent Unit (Res-GRU)	98.61%	98.61%	Hybrid and single faults detected	Generalization to unseen PV conditions untested
Proposed study	DT GB KNN LG NB RF SVM	DWT-CNN_BiLSTM	**99.86%**	**93.75%**	Overfitting and imbalance data are handled	Imbalanced sequential data handling limited

	ANN ANFIS CNN LSTM CNN+LST M DWT-ANN DWT-CNN DWT- LSTM DWT- CNN_BiLS TM					

2.4 Key Limitations Identified in Existing Research

Regardless of major improvements in power system fault detection and condition monitoring, several enduring issues remained, especially concerning the precise categorization of fault severity in transmission lines. The principal constraints recognized in current research are highlighted below:

1- **Limited Handling of Multi-Fault and Hybrid Fault Scenarios:** Most studies deal with single fault conditions (e.g., L-G, L-L) and neglect simultaneous or hybrid faults, which are more relevant to the real-world systems.

2- **Imbalanced and Noisy Data Handling:** Most models are based on the assumption that data sets are clean and balanced, but fault data tends to be imbalanced and is usually noisy.

3- Lack of unified evaluation against classical and modern methods: Existing studies often compare only a limited set of models, making it difficult to justify the superiority of new approaches**.**

Chapter 3: Methodology

3.1 System Modeling and Feature Extraction Framework

The system's data is comprehensively illustrated in **Table 3.1**. The transmission line under investigation is situated between transmission lines 1 and 2. The system is composed of two buses, two transmission lines, one load, and a single three-phase power generator. The interconnection of all of these utilities is shown in **Figure 3.1**. The proposed approach to defect identification and classification is executed through simulations of this system using MATLAB/Simulink version 2021a.

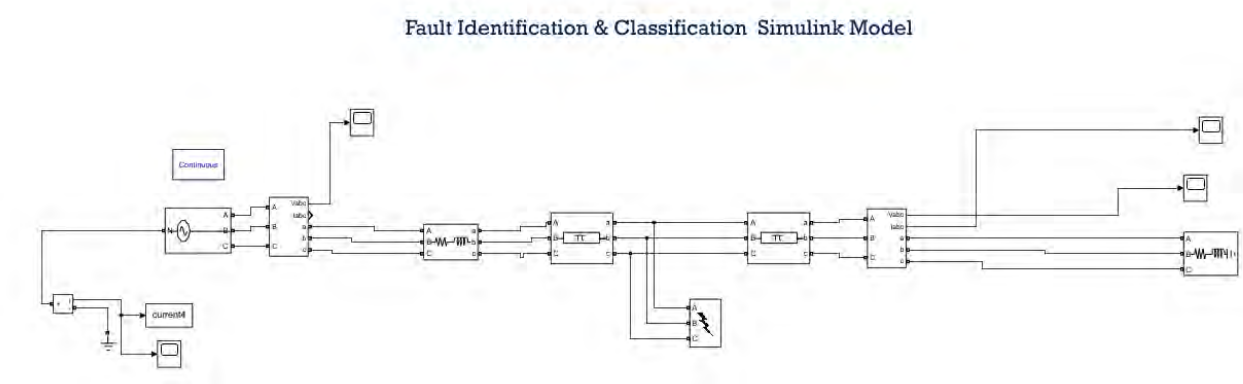

Figure 3.1: Simulink Model

Table 3.1 below illustrates the electrical system parameters used for modeling the three-phase power network and generating fault data in this study.

Table 3.1: Model Specification

Block	**Parameter**	**Specification / Value**
	Source	
Three-Phase Source	Frequency	50 Hz
Three-Phase Source	Phase-to-Phase Voltage	250 kV
Three-Phase RL Block	Resistance ®	6 Ω
Three-Phase RL Block	Inductance (L)	0.053052 H
	Transmission Line	
Three-Phase PI Section	Line Length / Distance	Variable
Three-Phase PI Section	Frequency	50 Hz
Three-Phase PI Section	Positive- & Zero-Sequence Resistance	[0.01273, 0.3864] Ω/km
Three-Phase PI Section	Positive- & Zero-Sequence Inductance	[0.9337e-3, 4.1264e-3] H/km
Three-Phase PI Section	Positive- & Zero-Sequence Capacitance	[12.74e-9, 7.751e-9] F/km
	Load	
Three-Phase Load	Active Power (P)	304.8 MW
Three-Phase Load	Inductive Reactive Power (QL)	228.6 MVAr

Three-Phase Load	Nominal Phase-to-Phase Voltage	220 kV

The figure below, **Figure 3.2**, depicts the thesis work, presenting a comprehensive and structured model for defect detection and classification in power system signals by analysing and comparing traditional machine learning, deep learning, and adaptive neuro-fuzzy models.

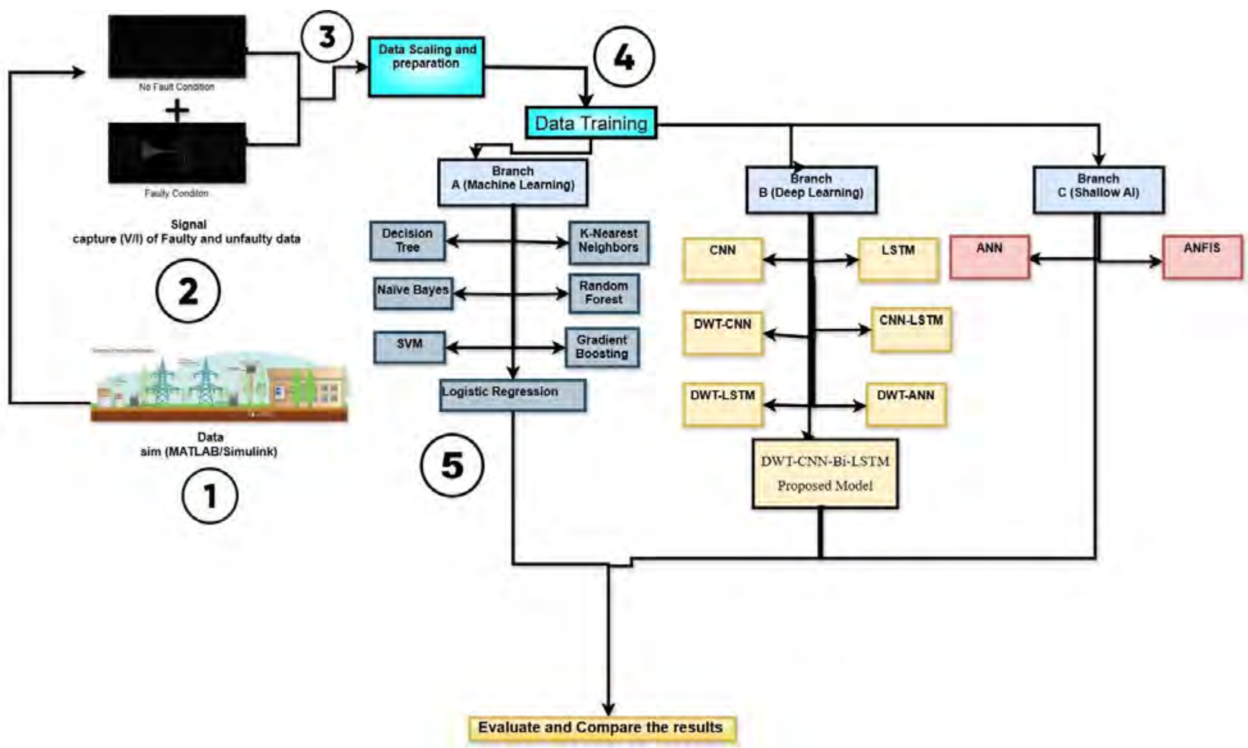

Figure 3.2: Schematic Illustration of the Study

Figure 3.2 illustrates the thesis work, which provides a unified, organized model for fault identification and classification in power system signals by analyzing and comparing traditional machine learning, deep learning, and adaptive neuro-fuzzy models. First, a MATLAB/Simulink power system model is used to generate voltage and current signals during healthy and faulty operation. These are captured and labeled to create the raw dataset, which is then processed through data scaling and preprocessing to guarantee numerical stability and optimize the learning process. The trained computational intelligence models are then utilized to predict the processed data, and they are organized into three primary branches: **classical machine learning algorithms** (such as Decision Tree, Naive Bayes, Support Vector Machine, K-Nearest Neighbors, Random Forest, Gradient Boosting, and Logistic Regression), **deep learning models** (such as CNN, LSTM, ANN, and their hybrid variants, which include **Discrete Wavelet Transform**, i.e., DWT-CNN, DWT-LSTM, DWT-ANN, CNN-LSTM, and proposed model **(DWT-CNN-BiLSTM)**. The proposed model is the essence of this work's contribution, combining time-frequency feature extraction with the ability to learn temporal aspects, leveraging powerful artificial intelligence to achieve the highest possible accuracy in fault discrimination. Lastly, the results of each model are compared and analyzed using conventional classification metrics, enabling us to conduct a comprehensive evaluation of their effectiveness and to demonstrate that the proposed hybrid model is the best choice for reliable power system fault diagnosis.

The below **Figure 3.3** demonstrates the feature extraction process utilising the Discrete Wavelet Transform (DWT) for hybrid deep learning models.

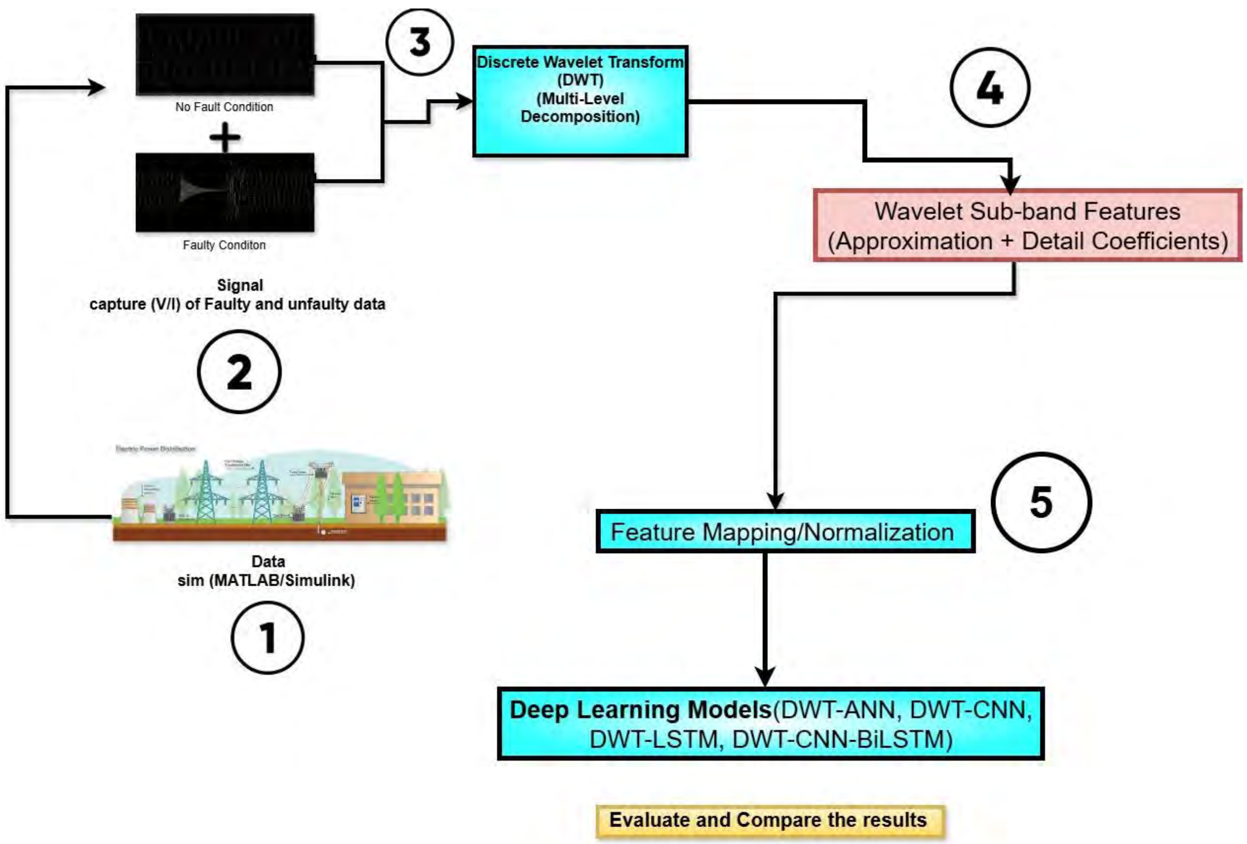

Figure 3.3 : Feature Extraction for DWT Deep Learning Approach

Figure 3.3 illustrates the extraction process of the features based on the Discrete Wavelet Transform (DWT). The extraction in this thesis aims to determine the time-domain and frequency-domain properties of power system signals under healthy and faulty conditions. First, voltage and current signals (Va, Vb, Vc, Ia, Ib, and Ic) are generated in the MATLAB/Simulink power system model and recorded under normal and fault conditions. These raw signals are non-stationary in nature, i.e., the frequency content of these signals' changes with time, so the traditional Fourier-based analysis will not be adequate to characterize faults correctly.

To counter this, the recorded signals are decomposed using a multi-level Discrete Wavelet Transform, in which each signal is subjected to a pair of low-pass and high-pass filters and down-sampling. The result of this process is a separation of the signal into approximation coefficients, which reflect the system's low-frequency content related to its basic behavior, and detail coefficients, which reflect high-frequency transients that can be attributed to faults (short circuits, switching events, disturbances). Through multi-level decomposition, the DWT gives a hierarchical time-frequency representation which displays fault signatures at various levels of resolution.

Wavelet sub-band coefficients (both approximation and detail) are then formed to make discriminative feature vectors. These characteristics are mapped and normalized to create equalized scaling as well as the dominance of a specific set of coefficients. Normalization enhances the rate of convergence in model training and stability without losing the necessary fault-related information. Lastly, the normalized wavelet-based features are input into deep learning models, which include: - DWT-ANN, DWT-CNN, DWT-LSTM, and the proposed DWT-CNN-BiLSTM. Such a feature extraction via wavelets contributes greatly to the classification performance since the localized time-frequency fault attributes are used in the learning models, and as such, the accuracy and strength of the fault diagnosis of the power systems become better and more reliable.

The RMS-based feature-extraction framework used for training both the baseline machine learning and deep learning models in this thesis is shown in **Figure 3.4.**

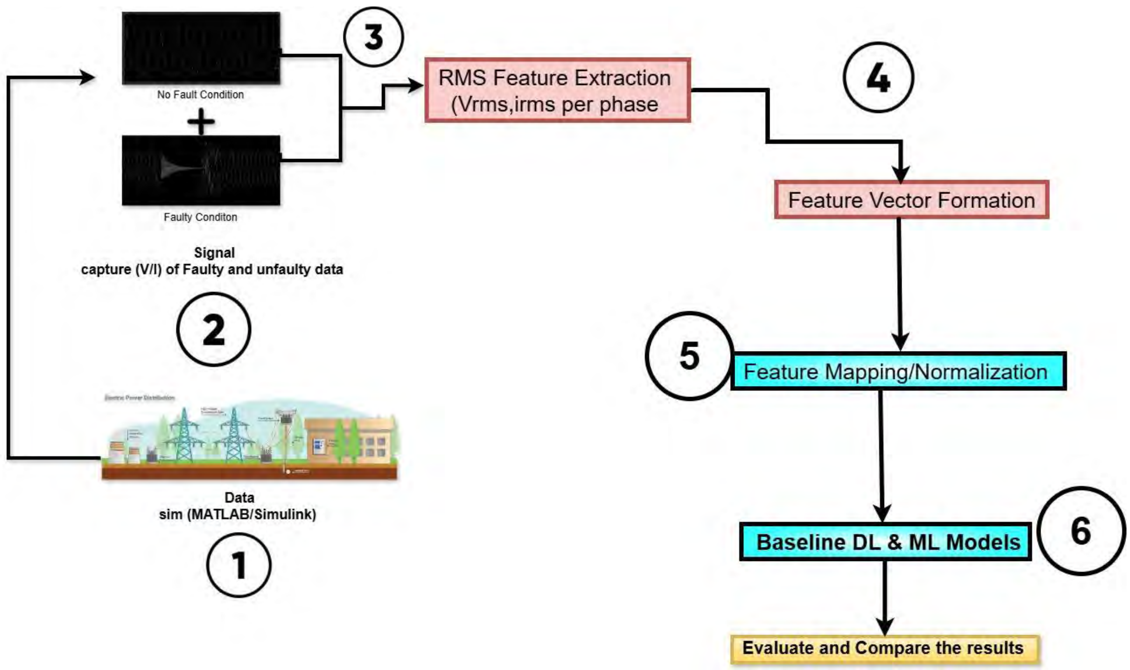

Figure 3.4 : Feature Extraction for baseline Machine learning and Deep Learning Approach

While RMS features provide noise-tolerant steady-state representations, they fail to preserve high-frequency transient components introduced by faults. This limitation becomes critical under noisy operating conditions, thereby justifying the integration of the Discrete Wavelet Transform into the proposed hybrid **DWT-CNN-BiLSTM framework**. **Figure 3.4** illustrates the **RMS-based feature-extraction framework** adopted in this thesis for baseline machine learning and deep learning model training. Firstly, a MATLAB/Simulink power system model is used to generate three-phase voltage and current signals under both healthy and faulty operating conditions, and to record them for analysis. Based on these raw signals, **Root Mean Square (RMS)** characteristics are determined for each phase: phase voltages (Vrms) and phase currents (Irms), which are practical indicators of the energy content and steady-state characteristics of the system under various fault conditions. The resulting RMS values are then arranged into a feature vector with each sample represented by a small group of scalar descriptors that reflect the electrical phases. This step of data dimensionality reduction assists in maintaining the critical data concerning faults by eliminating minor repetitive data. The resulting feature vectors are then subject to feature mapping and normalization to ensure they have the same scale and improve numerical stability during model training. Normalization helps achieve faster convergence and discourages features with higher magnitudes from dominating the learning process. Normalized RMS-based features are then fed to baseline machine learning and deep learning models to classify the faults and assess the performance. This framework, based on RMS, is used as a benchmark system, which makes it possible to directly compare it with more sophisticated time-frequency-based systems, and points out such a trade-off between simplicity of computation and the potential to capture the dynamics of transient faults in power system diagnostics.

3.2 Artificial Neural Networks (ANN)

Scientists have developed artificial neural networks (ANNs) to emulate the brain's neural networks. The architecture of the artificial neural network is dictated by the input and output data, hence providing a nonlinear statistical data by illustrating the complex relationships between inputs and outputs.

Artificial Neural Networks contain neuron layers which are interconnected. In this approach, there are two different types of learning algorithms, namely, a feedforward algorithm and a backpropagation algorithm. Feedforward method utilizes hidden nodes to pass on the input node information to the output nodes. The propagation technique generates a series of output states from the input. Moreover, weights and biases are reduced to achieve the desired outcome, and error values are assigned randomly [64]. Transfer functions are fundamental elements of artificial neural networks [64] that characterize the nonlinear connection between input and output.

The input, hidden, and output layers are the three essential components of a multi-layer neural network shown in **figure 3.6**. The input layer may link to several hidden levels. The hidden layer, composed of perceptron neurons, is connected to the output layer.

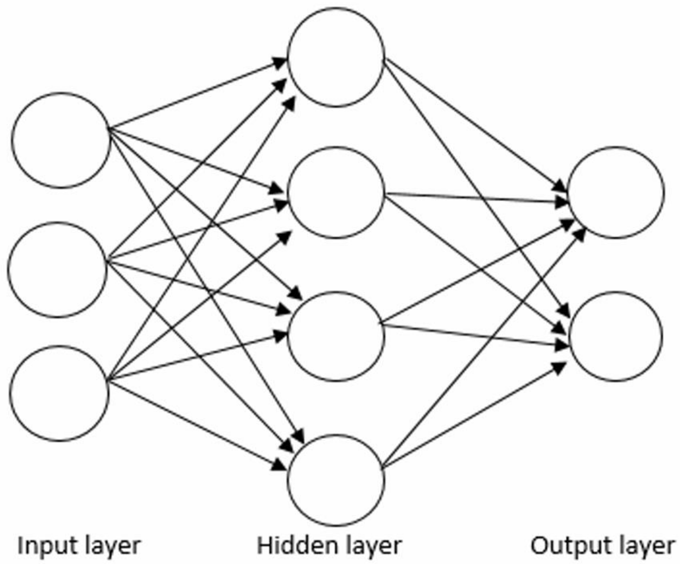

Figure 3.5 : Multi-layer Neural Network [65]

The above **Figure 3.5** illustrates the layers of the Artificial Neural Network.

3.2.1 Back Propagation Algorithm (BPNN)

The adaptability of artificial neural networks (ANNs) to complex systems renders them advantageous for defect detection and classification [66]. Some of the properties that make ANNs better suited for complex and nonlinear tasks are as follows: -

a) A neural network (NN) may modify its structure to accommodate the modifications to the power system that result from any electrical system malfunction.

b) ANN can acquire experience and make judgements because of machine learning.

c) They can multitask effortlessly due to their overwhelming numbers.

Despite the numerous benefits of the ANN, there are a few drawbacks. The learning process parameters, the quantity of neurons, the quantity of hidden layers, and the type of network employed are all critical factors to consider [67]. The use of line current and voltage readings after a problem has occurred for defect classification and identification is one limitation. Significant variations in line current and voltage are observed in fault transmission lines both before and after the incident. Therefore, the fault classification procedure necessitates the identification of the defect type by utilizing pre- and post-fault value patterns. The fundamental construction of the BPNN and the network utilized in this article are illustrated in **Figures 3.6** and **3.7**, respectively.

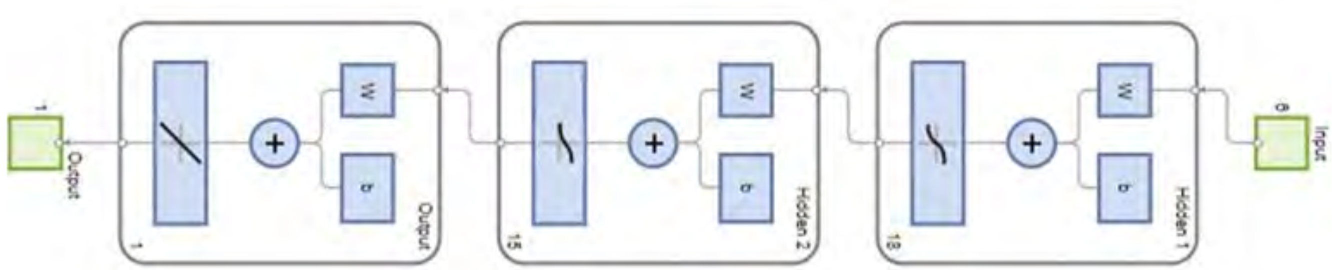

Figure 3.6: ANN structure for Fault Analysis [65]

The error rate may be reduced by appropriately adjusting the weights in BPNN [67]. The weights are determined through random selection. The outcomes are updated after each epoch, and the procedure is iterated upon. The following are a few of the numerous benefits of BPNNs: -

- ✓ Backpropagation may be successful for individuals who lack considerable network knowledge due to its ease of implementation and minimal learning time [67-79].
- ✓ We can observe the primary flow diagram of the artificial neural network defect detection process in **Figure 3.6.** No more than the sum of the counts of the concealed layers and the individual neuron counts may be employed as refining input parameters. Levenberg-Marquardt backpropagation enables the continuous modification of weights and bias during the training process. There are numerous methods available for assessing learning errors, such as mean absolute error (MAE), root mean square error (RMSE), and mean square error (MSE).

The below **Figure 3.7** shows the road map to train and validate the ANN based fault detection and classification of power system Model.

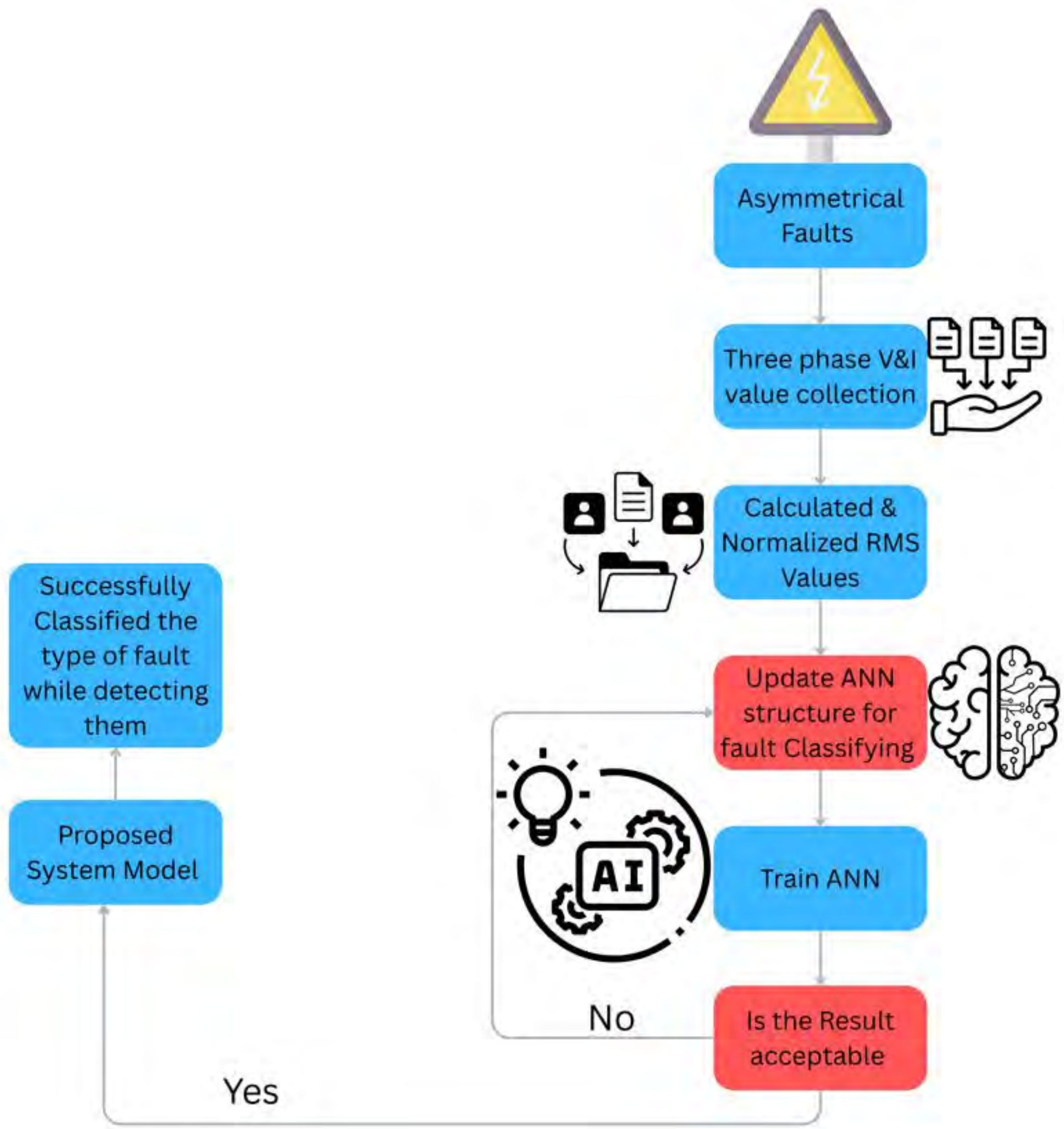

Figure 3.7: Flow Chart for ANN-Based Fault Model

3.3 Adaptive Neuro-Fuzzy Inference System (ANFIS)

ANFIS is a hybrid learning algorithm that integrates artificial neural networks and fuzzy logic. In an adaptive network with multiple layers, each node performs a specific function based on the data set used. ANFIS distinguishes between input characteristics to determine the output, and it is well-suited for complex problems due to its ability to learn from experience, generalize, and draw logical conclusions.

It is particularly effective for identifying, classifying, and localizing transmission line issues [80]. Each node in a multilayer feedforward (adaptive) network processes incoming signals according to its own parameters, as shown in **Figure 3.8.** Node selection depends on the input-output function required by the adaptive network, and node function equations may vary. Connections in an adaptive network indicate only the direction of signal transmission and do not include weights [81]. The membership function parameters in the Fuzzy Inference System (FIS) of ANFIS are adjusted using methods such as backpropagation and least-squares. While some fuzzy systems offer basic inference options, ANFIS provides more advanced capabilities and supports only Sugeno-type inference [24].

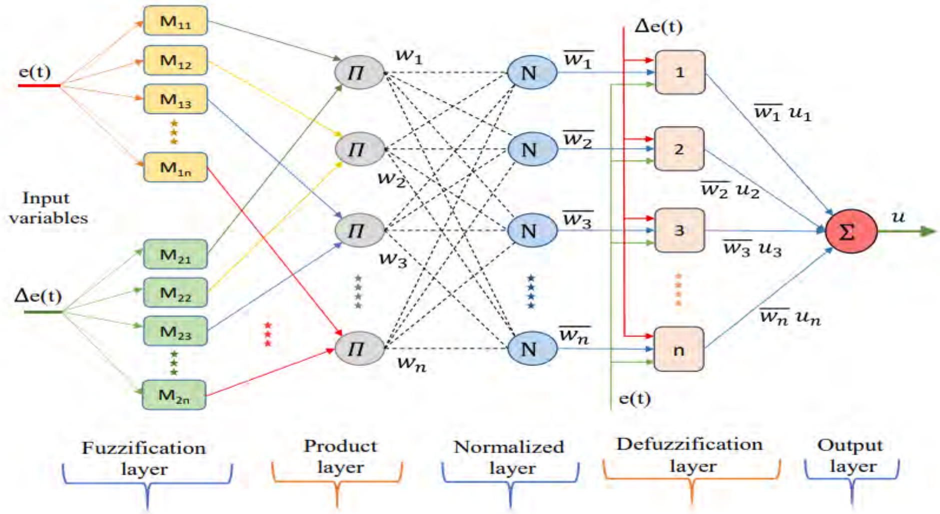

Figure 3.8: Schematic Diagram of Adaptive Neuro-Fuzzy Inference System (ANFIS) Architecture [81]

The Sugeno fuzzy model is employed by the ANFIS approach to generate fuzzy if-then logic [82].

$$R_n = if\ M^1{}_i(e) and\ M^2{}_i(\Delta e), then\ f = p_n\, e(t) + q_n\, \Delta e(t) + r_n \qquad (\mathbf{3.1})$$

as the letter n represents the entire number of laws. It is important to remember that M1i and M2i represent membership functions that are very approximate. The three linear components of every nth rule are rn, qn, and Pn.

The first ANFIS layer is a straightforward fuzzification, and the input variable stores the membership functions' degrees. Usually, each layer node functions as an adaptive function, as per [83].

$$M_{1i} = 1 / [1 + ((x - c_i) / a_i)^{bi}] \qquad (\mathbf{3.2})$$

indicating that the collection of parameters is represented by (ai, bi, ci). Be aware that layer 2 is the location of product inference, and the discharge intensity (Φ) of each node in this layer is regulated by a specific fuzzy rule. The layer's outputs are portrayed in the following manner:

$$w_i = M^1{}_i(e) \times M^2{}_i(\Delta e) \tag{3.3}$$

Upon completion of the second layer's computation of the discharge intensity, the third layer applies it to the new context by employing a normalisation layer.

$$\bar{w_i} = w_i \,/\, \Sigma_i(w_i) \tag{3.4}$$

Layer 4 receives the normalised data from Layer 3. It is important to note that the node functions designated as [84]in this matching layer represent each adaptive mode (defuzzification):

$$\bar{w}_i u = \bar{w}_i \,(p_i\, e + q_i\, \Delta e + r_i) \tag{3.5}$$

The control signal u is selected, and the set of consequence parameters is (p, q, r). If the output component of the rules is to be collected, it is essential to note that the final layer must determine the sum of all incoming signals [85].

$$\Sigma_i(\bar{w_i} u) = (\Sigma_i\, w_i u) \,/\, (\Sigma_i\, w_i) \tag{3.6}$$

The ANFIS methods flow diagram is illustrated in Figure 3.9. The ANFIS model is implemented through the following procedures:

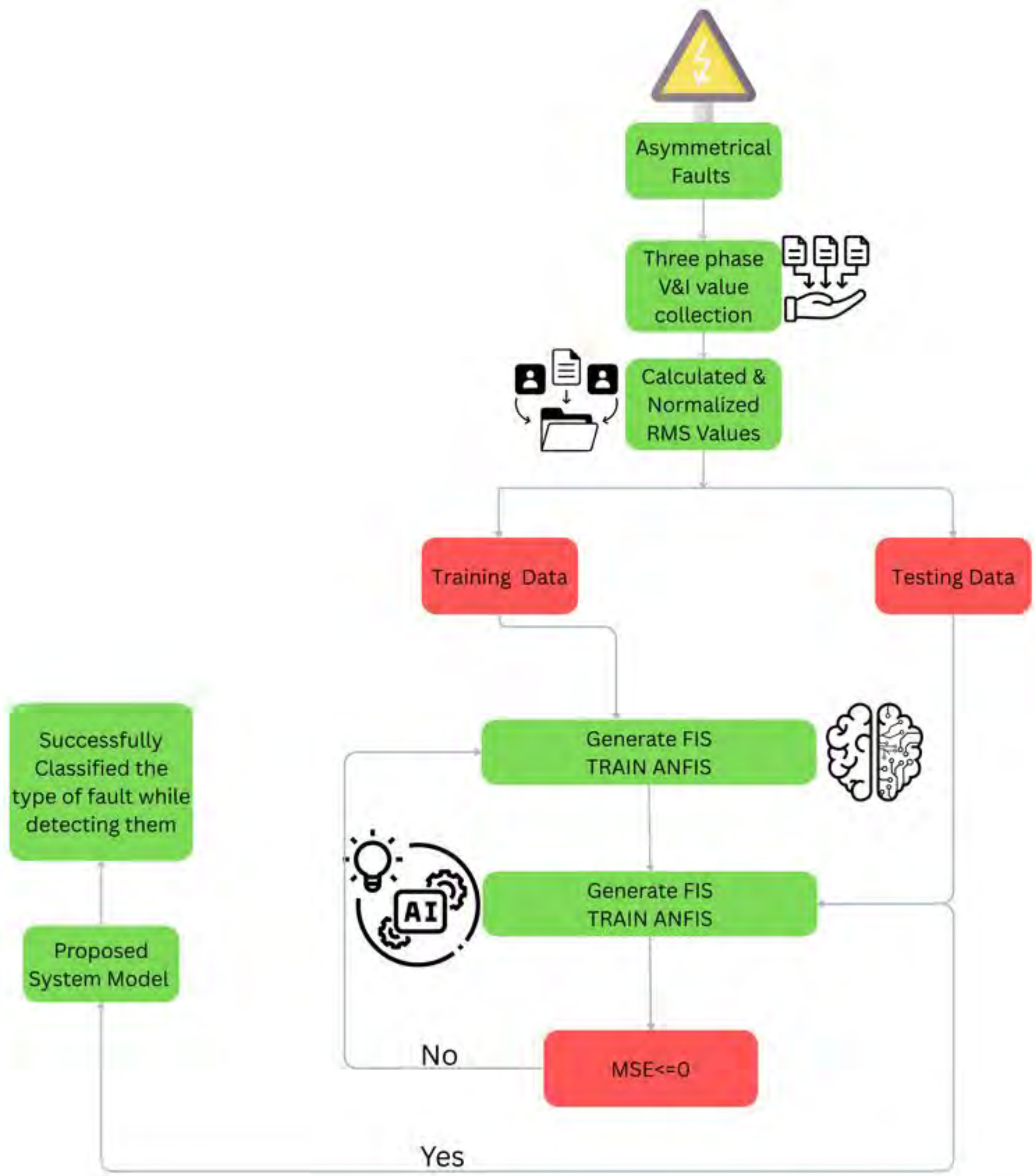

Figure 3.9: Flow Chart for ANFIS-Based Fault Model.

The above figure shows the road map to train and validate the ANFIS based fault detection and classification of power system Model.

3.4 Machine Learning Techniques

Accurate classification of the faults is essential after identifying a system failure. This classification facilitates the creation of accurate and effective repair methods by pinpointing the kind of problem. These targeted procedures enhance the system's overall performance and dependability by ensuring the effective use of resources, including staff, materials, and time. Precise fault classification enables the execution of prompt remedial measures and supports the formulation of predictive maintenance programs. By comprehending the attributes and root causes of various failures, system operators may enact preventive strategies to reduce errors. This proactive method is used to minimize unanticipated downtimes and prolong the longevity of the system's components.

The fault-detection techniques are improved based on the data obtained on fault classification and thus enhancing efficiency and robustness of the system. The introduction of fault identification and classification into the maintenance system results in a more reliable and stable power grid, therefore, promoting economic development and stability in the operations. This would prove very helpful to any power system since they are likely to experience disruptions and must undergo a lot of maintenance so that they can diagnose and categorize issues.

The accuracy and efficiency of fault classification in power systems can be greatly enhanced with the help of advanced machine learning techniques which have been shown to be highly accurate and flexible towards modern electrical infrastructure. The methods to be employed in this research will be numerous including, decision, K-Nearest neighbors, logistic regression, random forests, Naive Bayes, and gradient boosting. These methods have different advantages when it comes to the examination of complex data. The suggested techniques are shown in **Figure 3.10** that presents the fault detection and classification mechanism in based on a SIMULINK model.

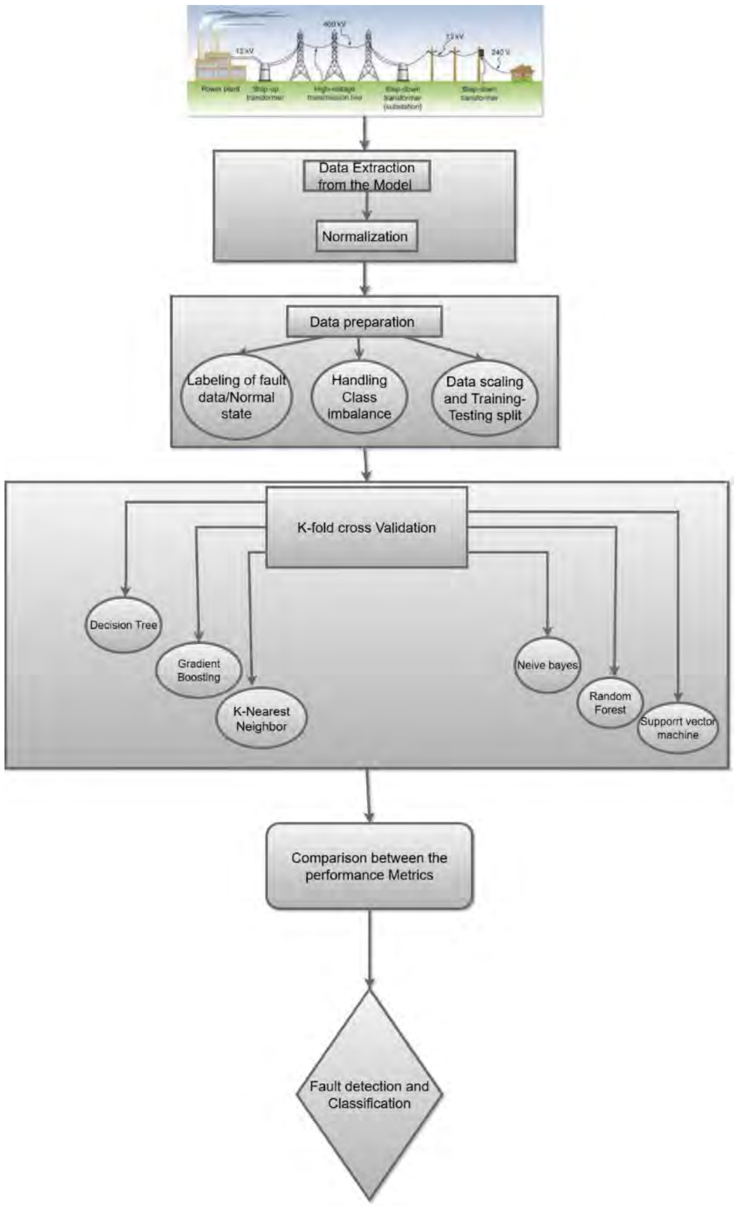

Figure 3.10: Machine Learning Process for Power System Fault Categorization.

The above **Figure 3.10** Illustrates the Machine Learning Algorithms used in this study and their process of data cleaning. Several machine learning classifiers were used to conduct fault classification in power transmission systems using voltage and current measurements as input features. The types of faults (e.g., AB, ABC, ABG) were considered as categorical output and transformed to number values with the help of the LabelEncoder method. The dataset was split into training and testing sets of all models in an 80:20 ratio and K-fold validation in order to have a fair assessment of the generalization performance. The Python-based machine learning libraries (mainly based on the Scikit-learn framework) were used to perform model training, hyperparameter tuning and evaluation.

The Support Vector Machine (SVM), Decision Tree (DT) and K-Nearest Neighbors (KNN) classifiers were initially explored because of their usefulness in the classification problems. The SVM model had various kernel functions of which the Radial Basis Function (RBF) kernel gave the best representation of the non-linear relationships once hyperparameters were optimized using the grid search CV and 3-fold cross-validation. Decision Tree classifier was chosen due to its level of interpretability, and some of the important parameters like the depth of the tree and the minimum sample split are optimized to prevent overfitting. KNN classifier was based on the distance similarity and the number of neighbors, distance measure and weighting rate were optimized to obtain the maximum classification accuracy. These models were compared in terms of accuracy, precision, recall and F1-score and error measures such as MAE, MSE and RMSE.

To enhance the robustness of fault classification, ensemble learning methods, i.e. Random Forest (RF) and Gradient Boosting (GB), were also used. Random Forest is a combination of decision trees which trained on various subsets of data and thus led to better predictive stability as well as less variance. Gradient Boosting sequentially built a series of weak learners by reducing the forecasting errors by a gradient-based maximization strategy. In both models, the hyperparameters of the number of estimators, tree depth, and learning rate were optimized using GridSearchCV. Their performance was measured by the conventional classification and regression measures, as well as confusion matrices and visualization software to understand the fault-wise classification behavior.

Lastly, the baseline probabilistic models, namely the Logistic Regression (LR) and the Naive Bayes (NB) classifier were used. Multi-class fault classification was implemented by the extension of the Logistic Regression to proper regularization and selection of solvers, whereas Naive Bayes was based on the assumption of the conditional independence of the features. Though rather simple, these models offered some significant comparative information on the performance of the fault classification. Accuracy, precision, recall, F1-score, MAE, MSE, and RMSE were the evaluation metrics that were consistently applied to all the classifiers and allowed to make a wholesome comparative analysis of their performance to detect and classify transmission line faults.

3.5 Deep Learning Techniques

The adoption of deep learning methods, which use deep neural networks, has grown as access to high-performance computing. Deep learning can process large numbers of features in unstructured data, enhancing flexibility and effectiveness. These algorithms use multiple layers, each extracting features progressively and passing them to the next. Later layers combine lower-level features from earlier layers to build a comprehensive representation [86-88].

Modern power systems are becoming more complex and larger as renewable energy sources are integrated into them. This growth is required to address the increase in energy demand and to provide a choice of sufficient supply. Nonetheless, faults cannot be avoided because of unknowledge conditions [89]. The effects of these missteps are relative to their nature, location, and time. Early and regular detection, tracing and identification of defects are required. They are aimed at efficient system protection, maintenance policies, and performance of the power system in general [90].

Many studies have explored various deep learning architectures for automated learning and precise identification of deep fault characteristics, which are often unlabeled and difficult to detect with traditional methods. The literature documents several approaches to address this challenge. Belagoune et al. [91] shows that combining SAE and LSTM architectures can identify anomalies without supervision. Li et al. [91] used SAE-LSTM and Wavelet Packet Decomposition (WPD) to evaluate rotating machine anomaly detection. Tovar et al. [92] developed a hybrid CNN-LSTM model for solar power prediction using real-world data from Temixco. In this model, the CNN extracts and selects local features, while the LSTM handles temporal features. The hybrid CNN-LSTM model in [92] outperforms standalone CNN and LSTM models. Ahmadipour et al. [93] introduced a new method for identifying solar system islands by applying wavelet packet transform (WPT) with a probabilistic neural network (PNN). This study will focus on the highly accurate Long Short-Term Memory (LSTM) networks and also examine CNNs and RNNs. We will then evaluate the performance of a combined model that uses each of these architectures.

3.5.1 Convolutional Neural Network

Recent machine learning methods, including 1D convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have achieved strong results in activity detection and classification. These algorithms reduce or eliminate the need for manual feature engineering by learning directly from raw data. CNNs can process various input types, including higher-dimensional, 1D, and 2D data, due to their flexible architectures. Input data typically uses 1-N channels. This study uses 1D input data, which is well-suited for time series analysis. CNNs are used to extract high-level features from datasets [94-95].

Each CNN neuron's output depends on its inputs, weights, and biases from the previous layer. The following equation allows for layer-by-layer adjustment of these parameters. Weights and biases for each layer can also be modified independently using equations 3.7 and 3.8.

$$\Delta w_{\mathrm{i}}(t + 1) = -(\alpha r / n)\, w_{\mathrm{i}} - (\alpha / n)\,(\partial C / \partial w_{\mathrm{i}}) + m\, \Delta w_{\mathrm{i}}(t) \qquad \textbf{(3.7)}$$

$$\Delta b_{\mathrm{i}}(t + 1) = -(\alpha / n)\,(\partial C / \partial b_{\mathrm{i}}) + m\, \Delta b_{\mathrm{i}}(t) \qquad (\mathbf{3.8})$$

In this situation, we represent the weight of a neuron while bi signifies its bias. Interactions between the learning rate (r) and the regularization parameter (α) are noted. Momentum is denoted by the symbol m, whereas the total quantity of training samples is indicated by sign n. The updating phase is indicated by t, whilst the cost function is given by C. During the training process, these characteristics are regularly modified and enhanced to ensure optimum performance. The primary components of a deep convolutional neural network (CNN) are the convolutional and pooling layers. The network layers are aptly designated as convolutional and pooling layers, as seen in **Figure 3.11.**

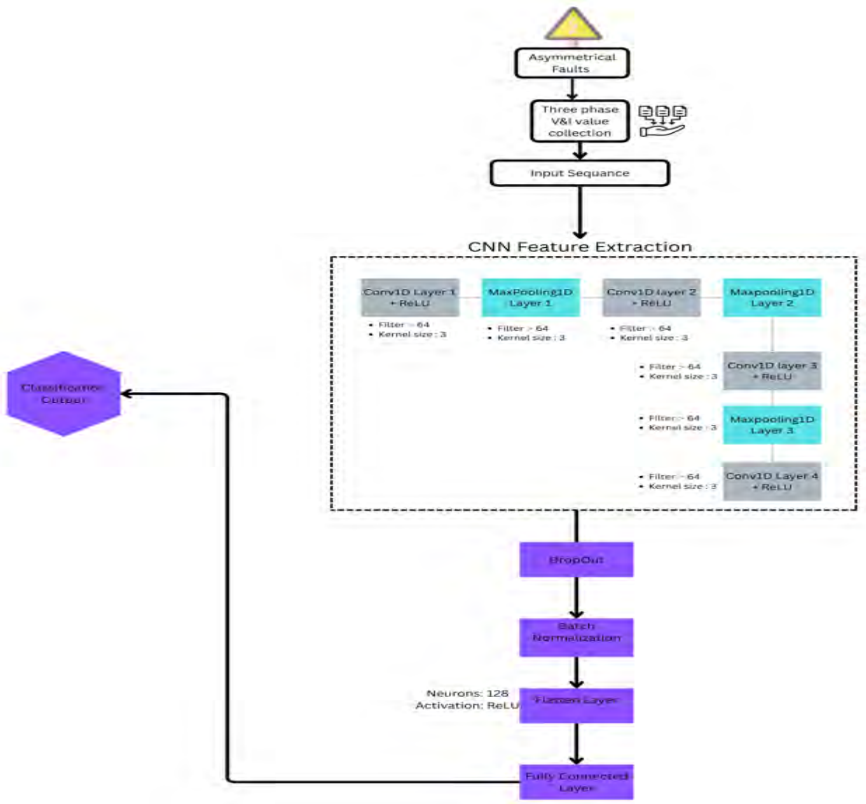

Figure 3.11: Layer Details of Proposed 1D-CNN.

The convolution layer combined multiple filters that were applied to the input to produce a unique feature vector. The mathematical description of convolution for one-dimensional data is provided by Equation 3.9.

$$y_i(k) = \Sigma_n{}^{=0\,n-1} x_i(n)h(k - n) \qquad \textbf{(3.9)}$$

The filter has a dimension of h, the input vector Xi has a dimension of N, and the output vector yi at point K has a dimension of n. The output dimensions of the convolutional layer are reduced when the pooling layer uses down-sampling. This simplification may alleviate the computational load and mitigate the risks of overfitting. The number of filter maps is a crucial hyperparameter in the development of convolutional neural networks. Based on the challenge's complexity, you may explore other values, including 8, 16, 32, 64, 128, and 256. Another essential hyperparameter to assess is the kernel size of a 1D convolutional neural network (3, 5, 7, etc.). The kernel size determines the quantity of time steps assessed for each "reading" of the input sequence. A convolutional method is then used to project the feature map onto it. A broader and more inclusive representation of the input may emerge from a more permissive data processing strategy, as shown by an increased kernel size. One-dimensional convolutional neural networks (1D CNNs) are favoured over two-dimensional variants for handling one-dimensional input because of their unique benefits.

3.5.2 LSTM

Recent advances in deep learning have positioned recurrent neural networks (RNNs) as the optimal model for classifying sequential data. Furthermore, the RNN may perform correlation analyses to identify patterns in its current and historical data. However, despite their ability to learn from sequences of any length, RNNs are impeded by issues such as gradient explosion and vanishing gradients. LSTM, a variation of RNN, effectively addresses these difficulties.

Long short-term memory (LSTM) models are distinguished from other recurrent neural networks by the fundamental concept of the cell state. The primary objective of LSTM is to identify long-term dependencies within a network. The long short-term memory (LSTM) modifies its cell state at each time step to generate a temporal feature vector (ht), known as its temporal memory, using the input Xt. The input gate, output gate, and forget gate are the three essential components of the LSTM model, as seen in **Figure 3.12**. The sigmoid activation function (σ) is used by the forget gate (ft) to regulate the amount of information eliminated from the candidate memory cell state (c∏ t) and to determine whether to retain memory from the previous time step. The output component is denoted by a value between 0 and 1.

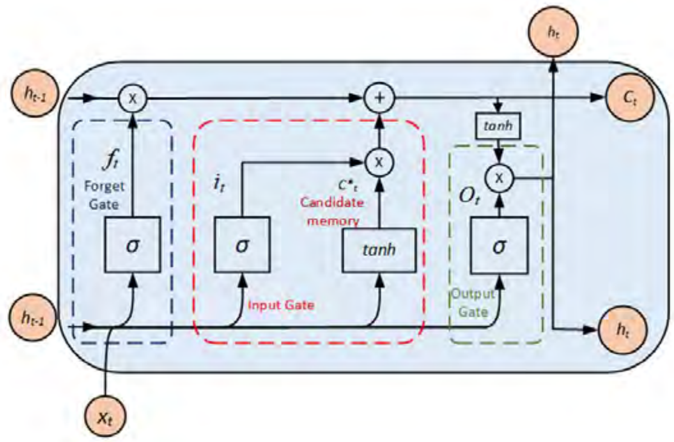

Figure 3.12 : Architecture of Single LSTM Cell [97]

The "update gate" determines whether to incorporate new information at each time-step and to what extent, as demonstrated by (it). Memory is refreshed at each stage using the function (c∏ t). The "output gate" (ot) controls the amount of data from a single time step that is passed to the next time step, along with the current time step's data [95-96].

LSTM models were developed using Python and Keras on Google Colaboratory, which provides GPU support. We evaluated the proposed structural method for identifying and classifying power system issues through tests on the Model system. To assess classifier performance, we evaluated the trained LSTM models using test data. The LSTM model shown in **Figure 3.13** was assessed using F1-score, Accuracy, Recall, and Precision.

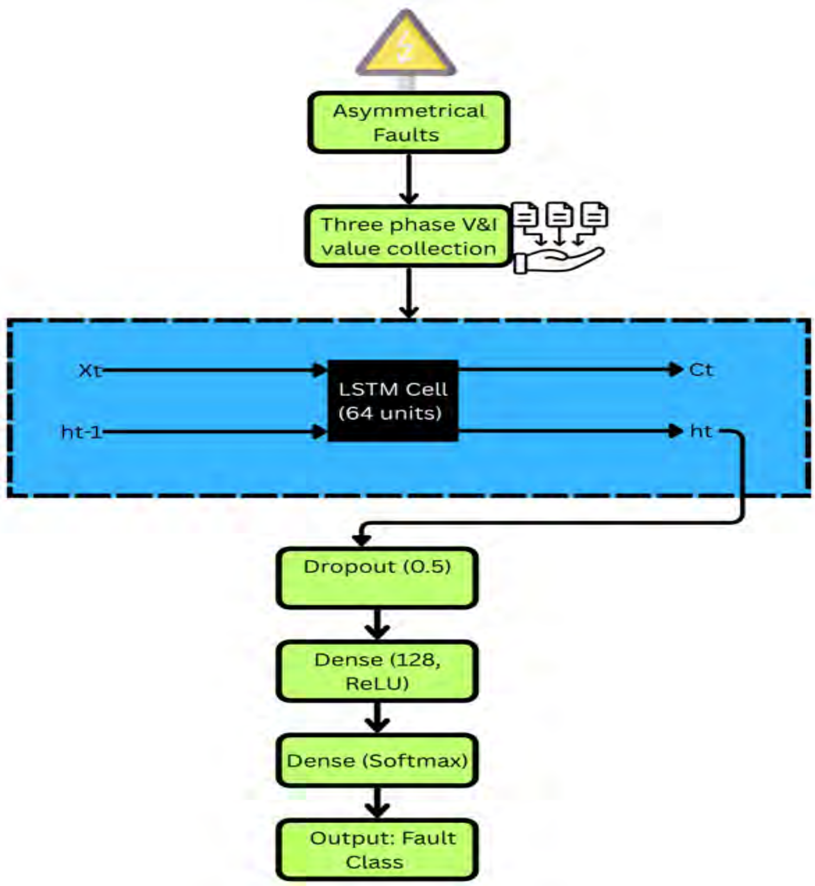

Figure 3.13: Block Diagram of Proposed LSTM.

3.5.3 Hybrid Method of CNN+LSTM

CNN layers were used to extract features from preprocessed voltage and current time-series data across all lines in the test network. One-dimensional CNNs are well-suited for time-series analysis, as they automatically identify latent features that may not be immediately visible in the temporal data. The LSTM network then processes the CNN-encoded features, learning relationships between input and output sequences through its gating mechanisms and iterative training.

The model combines 1D CNNs and LSTMs to classify power system defects using multivariate time-series data. Data is loaded from CSV files, with six features representing phase voltages and currents. Fault categories, which are non-numeric (e.g., AB, ABCG), are converted to numerical values using a Label Encoder. Features are scaled with the Standard Scaler to improve training performance. The architecture begins with a Conv1D layer (64 filters, kernel size 3, ReLU activation) to detect short-term patterns, followed by a MaxPooling1D layer to reduce signal size. A 64-unit LSTM layer captures long-term dependencies. Dropout (rate 0.5) is applied to prevent overfitting. A dense layer with 128 neurons, ReLU activation, and L2 regularization (weight decay = 0.01) maintains model simplicity. The final Dense layer with a softmax activation outputs defect-class probabilities.

To address class imbalance, class weights are calculated and applied during training. The model uses sparse categorical cross-entropy loss and the Adam optimizer. Early stopping monitors validation loss and halts training after 50 epochs without improvement to prevent overfitting. Model performance is evaluated using F1-score, recall, accuracy, precision, and error metrics such as MSE, RMSE, and MAE. Reliability and interpretability are assessed through confusion matrices and accuracy charts. The integration of feature extraction, temporal learning, and overfitting prevention enhances the accuracy of fault type prediction.

The below **figure 3.14** shows the framework of hybrid deep learning approach CNN-LSTM which in general extract the features using CNN and finalize the data by performing sequence learning and thus the model can predict better than the baseline approach.

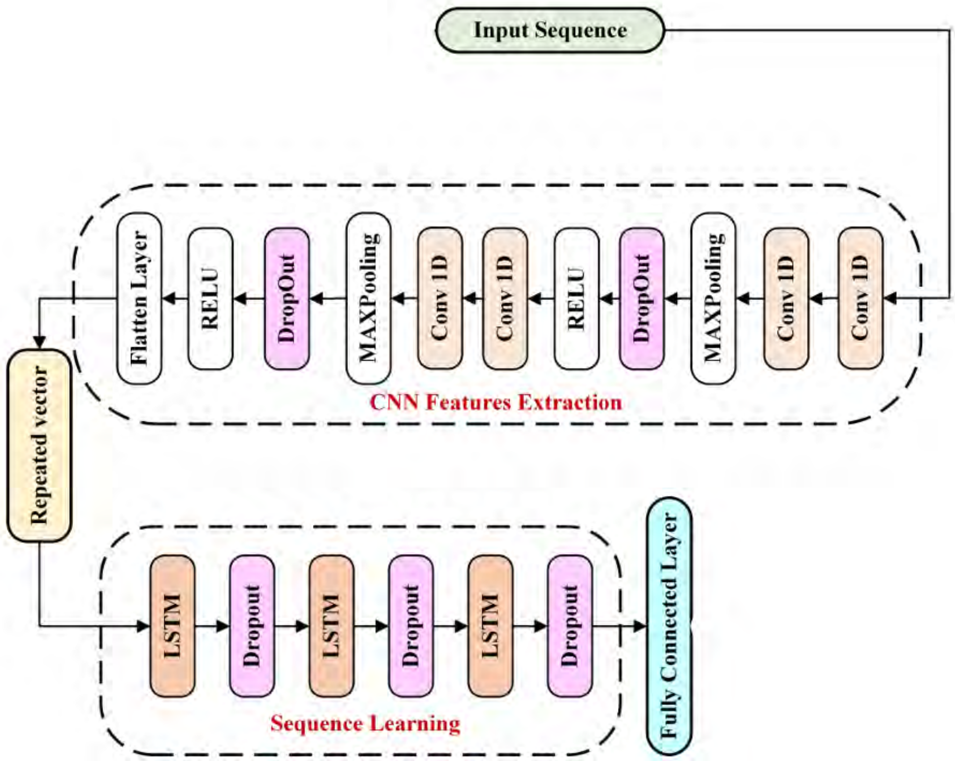

Figure 3.14: Framework of Hybrid Deep CNN-LSTM.

3.5.4 CNN-BiLSTM Approach

This study recommends a hybrid Discrete Wavelet Transform (DWT), Convolutional Neural Network (CNN), and Bidirectional Long Short-Term Memory (BiLSTM) method for accurate identification and categorization of transmission line failures. The approach combines advanced deep learning algorithms with signal processing to leverage frequency-domain feature extraction and sequential learning. The main operational stages are shown in **Figure 3.15.**

Input and output files were Signal_processing.csv. To ensure compatibility with machine learning frameworks, the LabelEncoder function was used to convert category labels to numerical values. The dataset was split into 80 percent for training and 20 percent for testing, with 20 percent of the training data reserved for validation. Features were standardized to maintain consistent scaling, as models are sensitive to input distributions. The Synthetic Minority Oversampling Technique (SMOTE) addressed class imbalance in the fault data, improving classification performance in unbalanced scenarios [97]. A random state of 42 was set for consistency.

Before classification, the Discrete Wavelet Transform (DWT) was applied to decompose the nonstationary electrical signals into multi-resolution components, which we will find transient and steady-state properties are most useful for diagnosing faults. Earlier studies have confirmed the usefulness of the DWT for identifying power system disturbances and fault signatures [85,86]. The deep learning model receives its input features from the extracted coefficients, ensuring that fault-related transients are well preserved for classification. Low-level attributes can be efficiently extracted from incoming data by the initial layers of a deep learning architecture, which typically consist of multiple convolutional layers. The convolutional layers preserve the precise spatial locations of the input sequence's features. This implies that the creation of distinctive feature maps requires only minor adjustments to the input feature coordinates.

The DWT features extracted were fed into a hybrid CNN-BiLSTM. CNN layers learned local-specific temporal and spatial features by applying pooling and convolution. The second layer was a convolutional layer with 64 filters, kernel size 3, ReLU activation, padding (same), L2 regularization (0.01), and max pooling and dropout (0.2). A second convolutional block used 128 filters with the same parameters, followed by pooling and dropout (0.3). These convolutional layers improved the extraction of fault signatures but also reduced overfitting [94-95]. Deep learning models often include a dropout layer to mitigate overfitting. Certain neurones in this layer are inadvertently disabled during the model's training process. To address overfitting, a dropout layer was incorporated into the LSTM layers and after each CNN feature-extraction layer.

The convolutional features were then passed to a BiLSTM layer with 128 units and a dropout rate of 0.3. Unlike conventional LSTMs, BiLSTMs learn both forward and backward dependencies in sequential data, making them well-suited for capturing temporal dependencies in fault waveforms [97,98]. The BiLSTM output was fed into a fully connected dense layer with 128 neurons, ReLU activation, L2 regularization (0.01), and a dropout rate of 0.4 to improve generalizability. A softmax output layer generated the probability distribution for the defect categories. The combined model was trained using the Adam optimizer with a learning rate of 0.001 and sparse categorical cross-entropy loss. Training was conducted for 50 epochs with a batch size of 32. Early stopping was applied after five epochs to restore the initial model weights. Regularization included dropout rates of 0.2, 0.3, and 0.4, as well as an L2 weight penalty of 0.01, to reduce overfitting. CNN-LSTM remains the primary method for power system defect classification, consistent with the configurations described [96-100]. Optimization methods are widely used in this context.

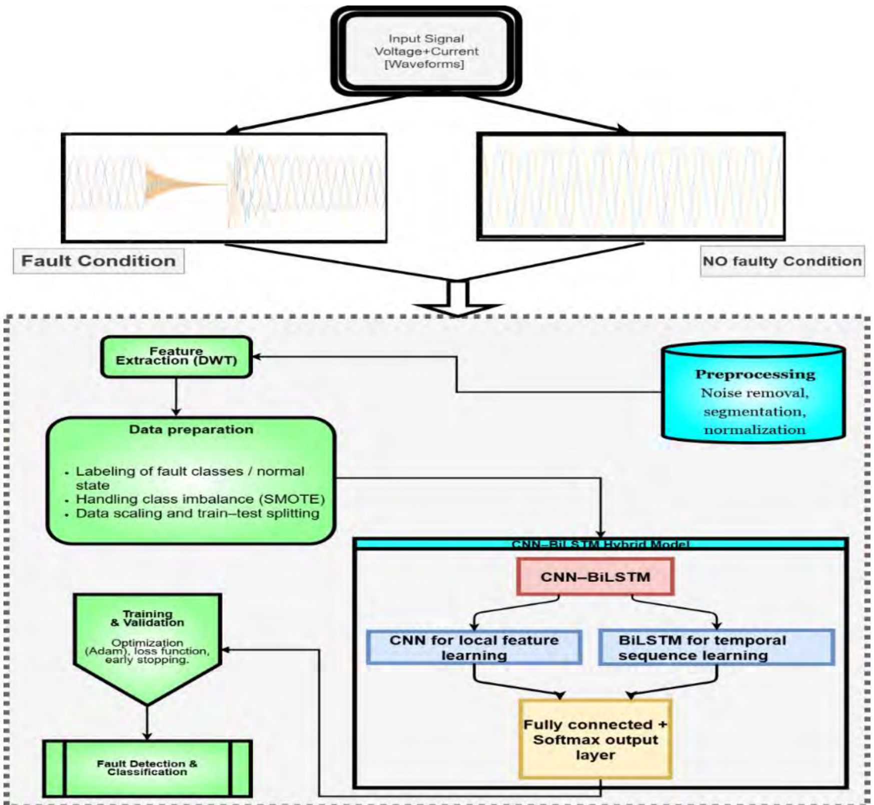

Figure 3.15: Proposed Framework of Hybrid DWT-CNN-LSTM.

Table 3.2 illustrates the summary of Methodology and Techniques Used for Fault Detection and Classification techniques in power system for this thesis study.

Table 3.2: Summary of Methodology and Techniques Used for Fault Detection and Classification

Method/Technique	**Description & Key Features**
System Studied	MATLAB/Simulink system with 2 buses, 2 transmission lines, 1 load, and 3-phase generator; used for simulation of faults.
Artificial Neural Networks (ANN)	ANN mimics biological neural networks, using feedforward and backpropagation learning. Layers: input, hidden, output.

Adaptive Neuro-Fuzzy Inference System (ANFIS)	Hybrid ANN + fuzzy logic; Sugeno fuzzy rules; uses backpropagation & least squares for membership function tuning.
Machine Learning Techniques	General workflow for fault classification: preprocessing, training, testing, evaluation (accuracy, precision, recall, F1-score).
Support Vector Machine (SVM)	Uses RBF, linear, polynomial kernels; GridSearchCV for tuning C & γ; evaluated with confusion matrix.
Decision Tree (DT)	Interpretable, rule-based classifier; hyperparameters: max depth, min samples split/leaf.
K-Nearest Neighbors (KNN)	Distance-based classification; Manhattan distance; tuned neighbors = 9.
Random Forest (RF)	Ensemble of decision trees; hyperparameters: estimators, depth, split criteria.
Logistic Regression (LR)	Multi-class classification; tuned with C, solver, and penalty.
Gradient Boosting	Iterative ensemble learning with weighted weak learners; tuned learning rate & depth.
Naïve Bayes	GaussianNB; assumes conditional independence; optimized with var_smoothing.
Deep Learning Techniques	Includes CNN, LSTM, and hybrids for extracting temporal & spatial features.
Convolutional Neural Network (CNN)	1D CNN for time-series; convolution + pooling layers; kernel size and filters tuned.
Long Short-Term Memory (LSTM)	Sequential learning; forget, input & output gates; trained on time-series fault data.
Hybrid CNN+LSTM	Combines CNN feature extraction with LSTM temporal learning; uses dropout, Adam optimizer, early stopping.
CNN-BiLSTM	Enhanced hybrid with CNN feature extraction and BiLSTM sequence learning; prevents overfitting using dropout & pooling.

Table 3.3 below describes the hyper-parameter values used for Fault Detection and Classification.

Table 3.3: Hyper-Parameter Values Used for Fault Detection and Classification

Model	Best / Used Hyper-parameters
Decision Tree	max_depth=5, min_samples_split=2, min_samples_leaf=2
Gradient Boosting	n_estimators=50, max_depth=3, learning_rate=0.05, subsample=1.0
K-Nearest Neighbors	n_neighbors=9, weights='uniform', algorithm='ball_tree', p=1
Logistic Regression	C=1000, penalty='l2', solver='lbfgs', multi_class='ovr', max_iter=500
Naïve Bayes	GaussianNB (defaults)
Random Forest	n_estimators=50, max_depth=3, min_samples_split=2, min_samples_leaf=1, max_features='sqrt'
SVM	C=10, gamma='scale', kernel='poly'
ANN (feedforwardnet)	hiddenLayerSize=10, trainFcn='trainlm', performFcn='mse', single hidden layer, 80/20 split, 4 input features, one-hot outputs
ANFIS (admission)	genfis2 (Sugeno), radius=0.5, epochs=50, hybrid learning, Gaussian MFs, inputs normalized [0,1], 80/20 split, decision=round
ANFIS (fault classification, no wavelet)	genfis2 (Sugeno), radius=0.5, epochs=50, hybrid learning, Gaussian MFs, inputs normalized [0,1], multi-ANFIS (one per output), 80/20 split, decision=round
CNN	Conv1D: 64 filters, kernel=3, ReLU → MaxPool(2) → Dense(128, ReLU, L2=0.01) → Dropout(0.5) → Softmax; Optimizer=Adam; Loss=sparse_categorical_crossentropy; Epochs=50; Batch=32; EarlyStopping(patience=10); Class weights for imbalance
LSTM	LSTM(64 units, dropout=0.3, recurrent_dropout=0.2, L2=1e-2) → Dense(64, ReLU, L2=1e-2) → Dropout(0.3) → Softmax; Optimizer=Adam(lr=1e-3); Loss=sparse_categorical_crossentropy; Epochs=60; Batch=32; EarlyStopping(patience=10); ReduceLROnPlateau; Class weights applied

CNN+LSTM	Conv1D(64,3,ReLU) → BN → MaxPool(2) → Dropout(0.3) → Conv1D(128,3,ReLU) → BN → MaxPool(2) → Dropout(0.3) → LSTM(128, dropout=0.3) → Dense(128, ReLU, L2=0.001) → Dropout(0.4) → Softmax; Optimizer=Adam; Loss=Focal Loss(γ=2, α=0.25); Epochs=80; Batch=32; EarlyStopping+ReduceLR; Class weights (balanced + ABCG boosted ×1.5)
DWT-CNN-BiLSTM	Reshape → Conv1D(64,3,ReLU,L2=0.01)+MaxPool(2)+Dropout(0.2) → Conv1D(128,3,ReLU,L2=0.01)+MaxPool(2)+Dropout(0.3) → BiLSTM(128, dropout=0.3) → Dense(128, ReLU, L2=0.01)+Dropout(0.4) → Softmax; Optimizer=Adam; Loss=sparse_categorical_crossentropy; Epochs=50; Batch=32; EarlyStopping(patience=5); Input scaled with StandardScaler; SMOTE applied for imbalance

Chapter 4: Results and Discussion

This chapter presents experimental results for fault-type classification and fault detection on power system transmission lines, where faults are most common. We evaluate various model families, including ANN, ANFIS, traditional machine-learning classifiers (Decision Tree, Random Forest, Gradient Boosting, k-Nearest Neighbours (KNN), Logistic Regression, Naïve Bayes, and SVM), deep learning architectures such as CNN, LSTM, and hybrid models (CNN+LSTM, DWT-BiLSTM, DWT-CNN, DWT-ANN, and DWT-LSTM).The performance of the models are assessed by using standard error metrics (MAE, MSE, RMSE), correctness measures (Accuracy, Precision, Recall, F1-score) and supplemented by confusion matrices for class-wise analysis. All models are compared within a consistent evaluation pipeline following dataset preprocessing and training.

The discussion is divided into two parts. First, we evaluate models for multiclass classification, where the choice of network architecture and feature extraction significantly affects class separability, particularly for complex multi-phase faults. Second, we address the binary detection problem (fault vs. no-fault), where most techniques achieve near-perfect performance and robustness, making interpretability the primary interest. Where applicable, we compare trade-offs in predictive power and interpretability and point to instances of systematic confusion brought to light by the matrices.

4.1 Comparative Result and Performance Analysis for Fault Classification

In this section, we compare fault classification methods across three evaluation stages to provide a clear, in-depth appraisal. In the first place, we report the model errors (MAE, MSE, and RMSE) to give an idea of the extent of the model's inaccuracy. Second, we introduce the classification measures (Accuracy, Precision, Recall, and F1-score) to compare the ability of each model to detect and identify the correct fault type, balance between false alarms and missed faults, and guarantee stable performance levels by the model across classes. Finally, we introduce confusion matrices to provide a more detailed view of correct and incorrect class-by-class predictions, making it easy to identify where misclassifications occur and the type of fault most difficult to detect. All three steps offer a clear, objective, and inclusive comparison of each model's performance.

4.1.1 Comparative Performance Evaluation of Error Metrics for Fault Classification

This section presents several methods that aim to distinguish between different types of fault in power transmission lines based on diverse machine learning, deep learning models and combined deep learning and signal processing methods. The main objective of the study would be to compare and analyze methods according to the models' error performance (MAE, MSE and RMSE).

Table 4.1 below compares several error metric approaches for evaluating the effectiveness of classification methods in power systems. The techniques are assessed using Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Accuracy.

Table 4.1: Error Metrics Evaluation of the Effectiveness of a Variety of Classification Methodologies

Technique	**MAE**	**MSE**	**RMSE**	**ACCURACY**
ANFIS	0.1010	0.1010	0.3146	**89.31%**
ANN	0.0810	0.0810	0.2599	**91.68%**
Deep Learning Approach				

CNN	0.0963	0.0963	0.3104	**90.37%**
LSTM	0.0840	0.0840	0.2899	**91.60%**
CNN+LSTM	0.0840	0.0840	0.2899	**91.60%**
DWT-CNN-BiLSTM	0.0660	0.0868	0.2946	**93.75%**
DWT-CNN	0.0688	0.0688	0.2622	**93.12%**
DWT-ANN	0.0681	0.0681	0.2609	**93.19%**
DWT-LSTM	0.1257	0.2576	0.5076	**90.21%**
Machine Learning Approach				
Decision Tree	0.0937	0.0946	0.3076	**90.67%**
Gradient Boosting	0.1060	0.1060	0.3256	**89.40%**
K-Nearest Neighbor	0.1254	0.1254	0.3541	**87.46%**
Logistic Regression	0.0968	0.1126	0.3356	**90.63%**
Naïve Bayes	0.3128	0.5301	0.7281	**79.41%**
Random Forest	0.0928	0.0928	0.3047	**90.72%**
Support Vector Machine	0.0928	0.0928	0.3047	**90.72%**

4.1.1.1 Error Metrics Evaluation of Hybrid Approaches

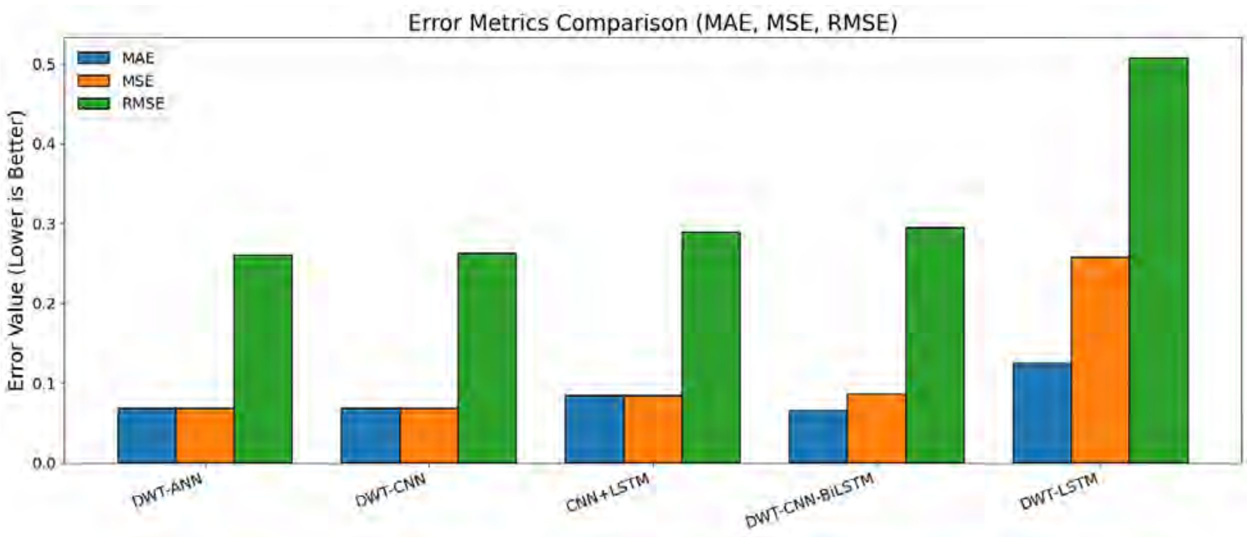

Figure 4.1: - Error Metrics Evaluation of Hybrid Approaches

Figure 4.1 above shows the error evaluation metrics (MAE, MSE, RMSE) for five models; the smaller the bar, the better the performance (lower prediction error). The three bars for each model are MAE (average absolute error), MSE (mean square error), and RMSE (root mean square error), which indicate the average error in the original scale. Since all three metrics are shown on the same chart, we can easily identify the model that is most accurate on average (low MAE) but also the model that does not have massive spikes in error (low MSE/RMSE).

Overall, the lowest error values across the three metrics are obtained with the DWT-based hybrids (DWT-CNN, DWT-ANN and DWT-CNN), which yield the most consistent and dependable predictions in the given comparison. Their MAE and MSE bars are lowest, and they also have the lowest RMSE (around 0.26), indicating that they maintain both the average and the magnitude of error at low levels. The proposed DWT-CNN-BiLSTM presents the lowest MAE (one of the best), but with a slightly higher MSE and RMSE, compared with DWT-ANN/DWT-CNN, and is close to the CNN+LSTM baseline, i.e., it also performs well; however, its squared error is slightly more sensitive to large errors that occur.

DWT-LSTM performs the worst, with the highest MAE, MSE, and RMSE values, particularly an RMSE near 0.51. This indicates it produces the largest average errors and the greatest error variation, making it the least reliable of the models compared.

Although the proposed DWT-CNN-BiLSTM model achieved the highest classification rate of 93.75% (see Table 4.1), its error rates were relatively high. This is due to the difference between categorical classification and numerical prediction. While the model effectively separates fault classes, its regression-based outputs are sensitive to transient signal components and wavelet decomposition outliers. As a result, a few high-deviation samples can increase the RMSE without significantly affecting classification accuracy.

In summary, DWT-ANN and DWT-CNN have the lowest error values and are the most effective. CNN+LSTM and DWT-CNN-BiLSTM show moderate performance, while DWT-LSTM has the highest error values and is the least effective.

4.1.1.2 Error Metrics Evaluation of Baseline Model and Proposed approach

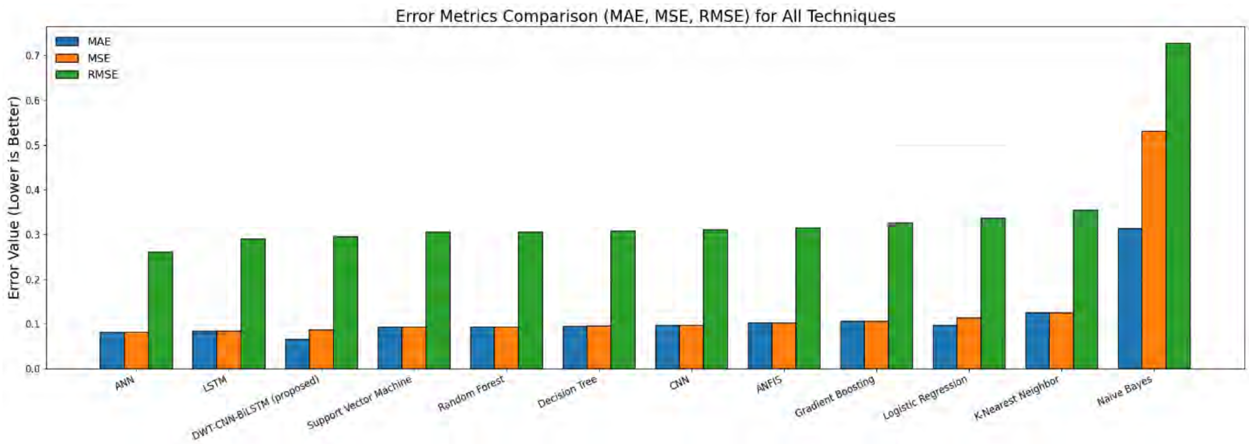

Figure 4.2: Error metrics Evaluation of Baseline Model and Proposed approach

Figure 4.2 compares the error measures MAE, MSE, and RMSE for both the Baseline and Proposed models. Lower bars indicate better performance, meaning predictions are closer to actual values. MAE measures average absolute error, MSE penalizes larger deviations more heavily, and RMSE reflects the average error in the original units. Most models perform similarly, but Naive Bayes shows the highest MAE, MSE, and RMSE, indicating the largest and most unstable prediction errors.

The **DWT-CNN-BiLSTM** achieved the lowest MAE (0.0660), hence it is better than the other models at minimizing error. Its predictions, on average, deviate least from the ground truth, indicating stable performance. The hybrid models have a significantly lower average error than other strong competitors, such as ANN (0.0810 MAE), LSTM (0.0840 MAE), and tree-based models such as Random Forest/SVM (approximately 0.0928 MAE). This indicates that the integrated architecture is more stable in its predictions, rather than being sporadically out of place.

Though the proposed model is not the one with the smallest RMSE (e.g., ANN with an RMSE of 0.2599), its benefit lies in its lower overall average error (MAE) whilst maintaining MSE/RMSE within a range of strong baselines. This means that the proposed method minimizes the expected prediction error but can still produce large errors on a relatively small scale. Conversely, algorithms such as KNN and, particularly, Naive Bayes have significantly higher error rates, lower accuracy, and are more likely to yield greater prediction error. In general, the suggested **DWT-CNN-BiLSTM** is the most consistent in minimizing errors, and the decrease in MAE is most evident relative to the other methods.

4.1.1.3 Error Metrics Evaluation of All Approaches

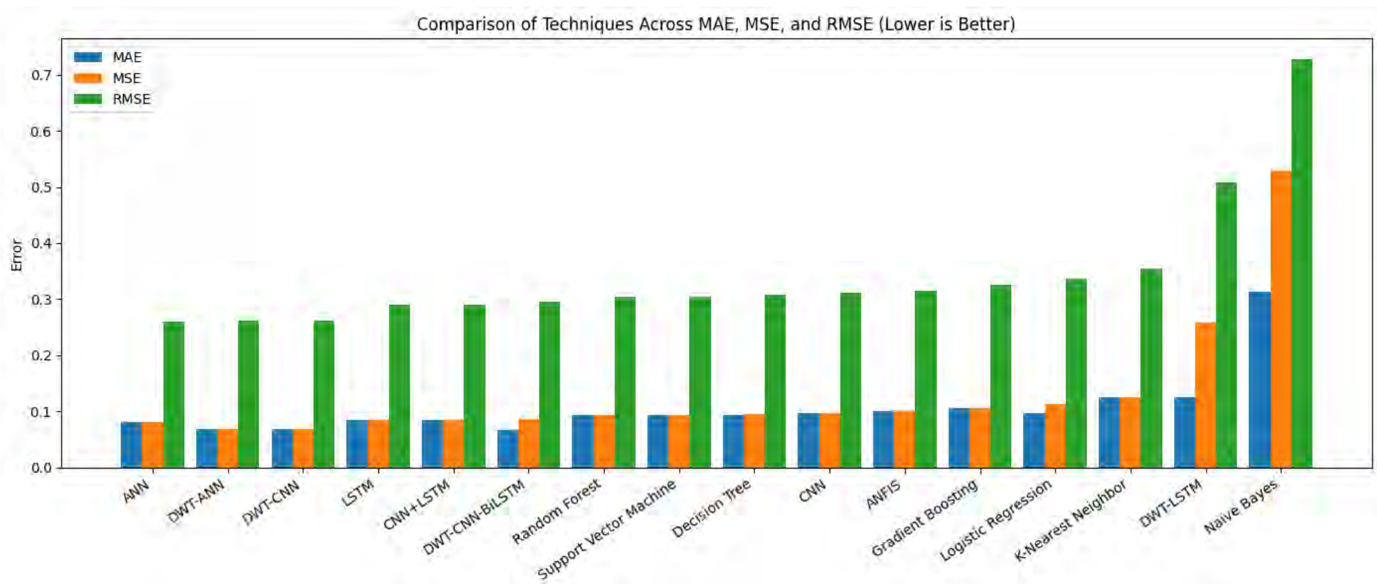

Figure 4.3: Overall Comparison of All Techniques

Figure 4.3 shows significant performance differences among soft-computing, deep learning, and traditional machine learning models, yet even the best and worst ones can be easily distinguished using RMSE (lower is better). The best performer overall is ANN (MAE = 0.0810, MSE = 0.0810, RMSE = 0.2599), indicating that the average error is minimal and the overall error is lower than all listed methods. Just behind, the performance of the deep learning versions using the wavelet-based models also performs well; that is, the DWT-ANN (RMSE = 0.2609) and the DWT-CNN (RMSE = 0.2622) are also doing very well, indicating that wavelet preprocessing is useful in improving predictive accuracy as it adds cleaner informative features to the deep learning models. Around the middle of the range, a few models are in the RMSE range 0.29-0.33, which includes LSTM / CNN+LSTM (0.2899), DWT-CNN-BiLSTM (0.2946), Random Forest and SVM (0.3047), Decision Tree (0.3076), and CNN (0.3104) and the others are indicating fair but not the best performance results than ANN and DWT-enhanced models. The least performances are recorded by the DWT-LSTM (RMSE = 0.5076) that provides unstable result and with high error spikes and by the worst overall approach, the Naive Bayes (MAE = 0.3128, MSE = 0.5301, RMSE = 0.7281) which performs much worse in comparison to all others because of its strong independence assumptions that are unlikely to be similar to the structure of the datasets. Conclusively, it is recommended that ANN is the best and most precise model; DWT-enhanced models are good, and Naive Bayes should not be used, as it consistently generates the most errors.

4.1.2 Comparative Result and Performance of Model Metric Evaluation for Fault Classification

This section presents a clear comparative evaluation of fault classification models based on key performance measurement criteria. The analysis begins by examining **model performance metrics (Accuracy, Precision, Recall, and F1-score)** to assess how effectively each approach identifies fault classes, balances false alarms and missed detections, and maintains consistency across different faults.

Table 4.2 demonstrates the evaluation of fault classification models based on **model performance metrics (Accuracy, Precision, Recall, and F1-score)**

Table 4.2: Model Performance Metric

Technique	***F-1 score***	***Recall***	***Precision***	***Accuracy***
ANN	***0.91021***	***0.91065***	***0.91070***	**91.68%**
ANFIS	***0.89015***	***0.89118***	***0.89086***	***89.309%***
Deep Learning Approach				
CNN	0.9005	0.9007	0.9008	**90.37%**
LSTM	0.8788	0.9091	0.8636	**91.07%**
CNN+LSTM	0.8800	0.9091	0.8650	**91.32%**
DWT-CNN-BiLSTM	0.9333	0.9356	0.9421	**93.75%**
DWT-ANN	0.9277	0.9307	0.9376	**93.19%**
DWT-CNN	0.9231	0.9287	0.9430	**93.12%**
DWT-LSTM	0.8825	0.8977	0.9085	**90.21%**
Machine Learning Approach				
Decision Tree	0.9635	0.9990	0.9466	**90.67%**
Gradient Boosting	0.8889	0.8896	0.8890	**89.40%**
K-Nearest Neighbor	0.8705	0.8707	0.8707	**87.46%**

Logistic Regression	0.8759	0.9078	0.8610	**90.63%**
Naïve Bayes	0.7707	0.8137	0.8419	**79.41%**
Random Forest	0.9640	0.9995	0.9471	**90.72%**
Support Vector Machine	0.9640	0.9995	0.9471	**90.72%**

Table 4.2 illustrates different models' ability to classify faults including Hybrid Models, single Models of Deep Learning and Machine Learning Approaches

4.1.2.1 Model Performance Metric Evaluation of Hybrid Approaches

In this section, we have analyzed performance metrics—namely Accuracy, Precision, Recall, and F1-score—of various Hybrid Deep Learning models to evaluate their effectiveness in accurately identifying fault classes, balancing false alarms and missed detections, and ensuring consistency across different fault types.

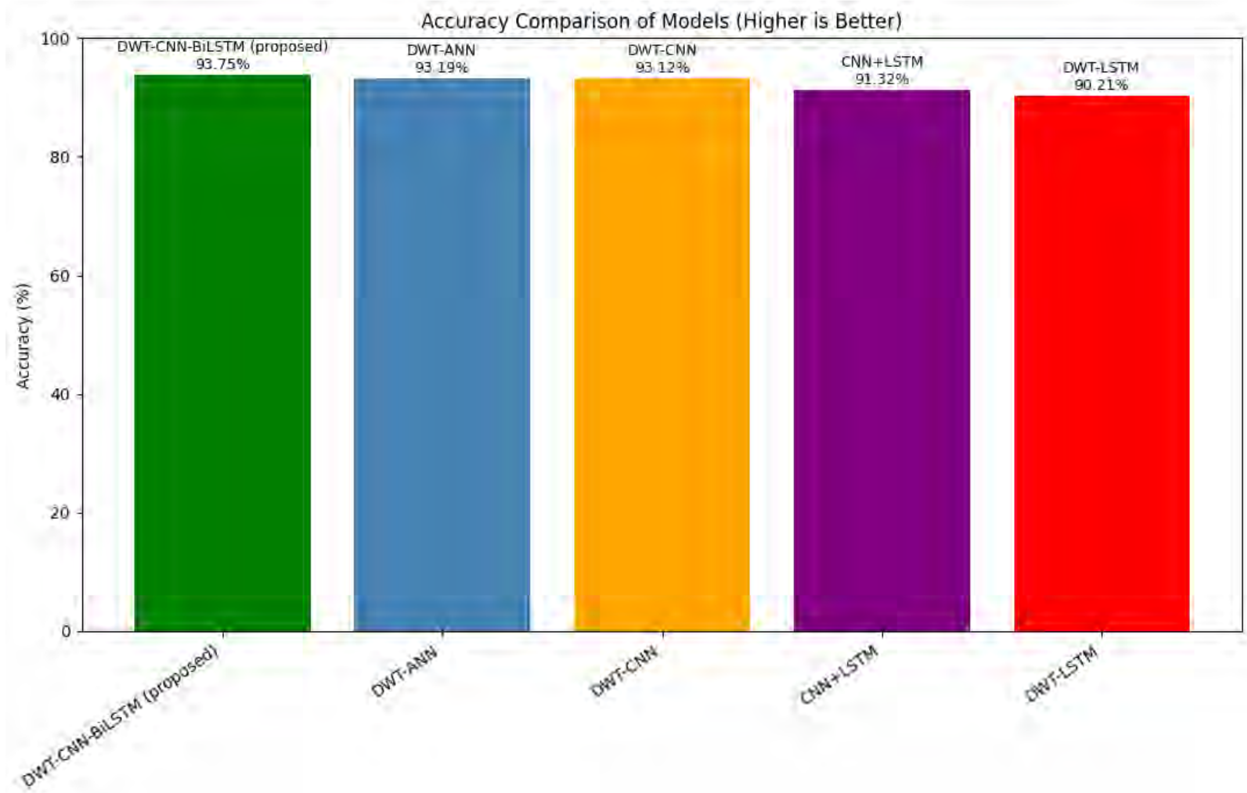

Figure 4.4: Accuracy Comparison of Hybrid Approach

Figure 4.4 demonstrates that the proposed **DWT-CNN-BiLSTM** achieves the best results at 93.75%. This means it provides the best fault classification among the reviewed hybrid models. The following are the best performers: DWT-ANN (93.19%) and DWT- CNN (93.12%) after the proposed Model. The close outcomes indicate that DWT-based preprocessing consistently improves classification accuracy by extracting more discriminative, cleaner features before learning. The hybrid CNN+LSTM attains 91.32%. performing reasonably well but remaining clearly below the top DWT-based methods, it is evident that a combination of spatial and temporal learning is not as effective as the use of the wavelet feature enhancement. The worst accuracy is recorded by DWT-LSTM, at 90.21% among all the hybrid approaches, indicating weaker generalization and a greater likelihood of misclassification than with the other methods. All in all, the findings prove the hypothesis that DWT-CNN-BiLSTM achieves the highest classification accuracy, whereas DWT-LSTM is the most ineffective model in this comparison.

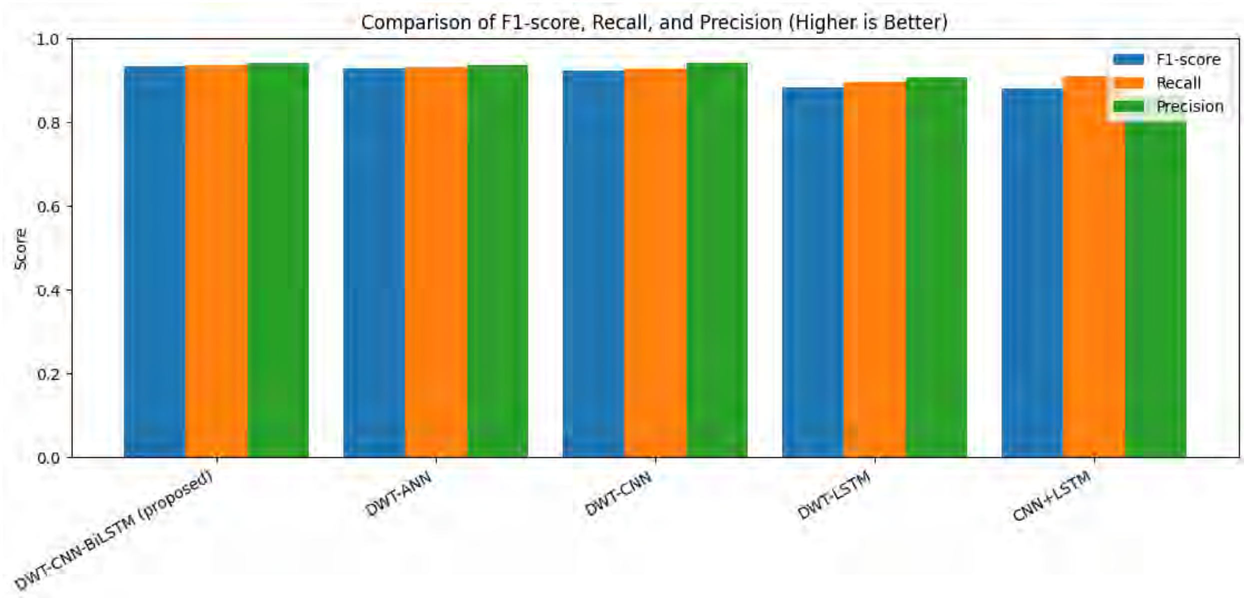

Figure 4.5: Model Performance Metric Evaluation Comparison of Hybrid Approach

The F1-score, recall, and precision comparisons in **Figure 4.5** show that the proposed DWT-based approach, particularly the **DWT-CNN-BiLSTM**, consistently outperforms the other models providing the best overall balance: with the highest F1-score (0.9333) and the highest recall (0.9356), the model is considered the most valuable to use in the correctly identified fault classes with a low number of falsely overlooked fault cases. Its precision (0.9421) is also high; indicating accurate fault predictions with minimal false alarms. The combination is the reason why it is the strongest and most stable model across the three metrics.

DWT-CNN and DWT-ANN also show good performance and are close to the proposed method. DWT-CNN has the best precision (0.9430), i.e., the fewest false positives, and is the most conservative and accurate in its fault predictions. Its recall (0.9287) and F1-score (0.9231) are slightly lower than DWT-CNN-BiLSTM. The performance of DWT-ANN is quite balanced (F1= 0.9277, recall= 0.9307, precision= 0.9376), offering no better scores than the other two, but it is a good alternative for its simple architecture.

The CNN+LSTM achieves lower overall performance (F1 = -0.8800, precision = -0.8650, recall = -0.9091) than all DWT-enhanced models. The recall is good, that is, it detects a significant number of faults, but the accuracy is the lowest, which leads to a high number of false alarms and low-class separation. DWT-LSTM performs better than CNN+LSTM on precision (0.9085), although it recalls the fewest real faults (0.8977) in the set; hence, DWT-LSTM's overall F1 score is lower (0.8825). Overall, the inclusion of DWT feature extraction leads to a significant improvement in fault classification quality: DWT-CNN-BiLSTM provides the best general performance, DWT-CNN reduces false alarms, and the least powerful representatives of this category are CNN+LSTM and DWT-LSTM.

4.1.2.2 Performance Metrics Comparison of Baseline Models and the Proposed Model

In this section, we evaluate the performance metrics—Accuracy, Precision, Recall, and F1-score—of several Machine Learning models and compare it with the proposed **DWT-CNN-BiLSTM** approach. This assessment focuses on classification accuracy, the balance between false positives and missed detections, and consistency across different fault types.

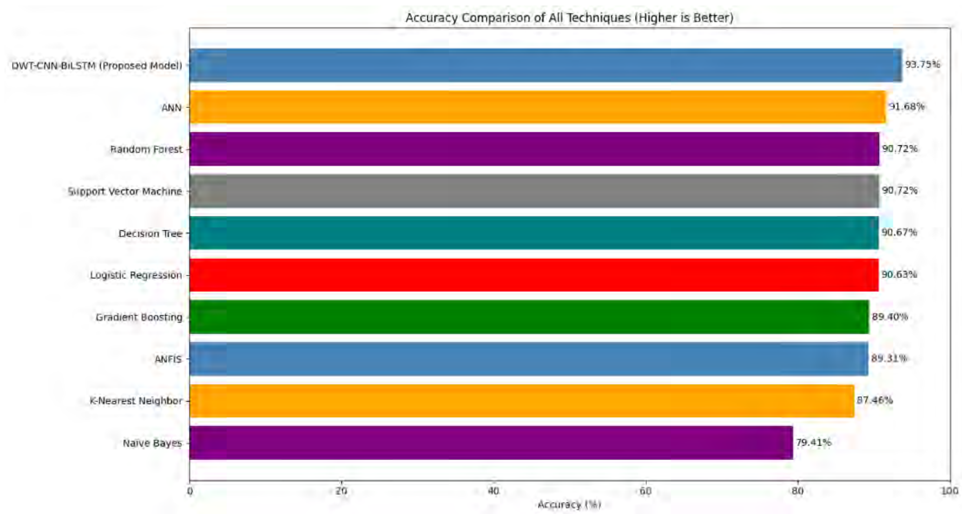

Figure 4.6: Accuray Comparison of Baseline Vs Proposed Approach

The horizontal bar chart in **Figure 4.6** shows how the various techniques tested ranked in terms of accuracy. Higher bars indicate better performance. The proposed **DWT-CNN-BiLSTM** achieves the highest accuracy (93.75%), indicating that it is the most effective model at identifying all faults. This validates the use of wavelet-based (DWT) feature extraction, which enhances accuracy by providing cleaner, more informative features for learning. The standalone **ANN** also achieves a high result of 91.68%, yet it is still lower than the best DWT methods, suggesting that preprocessing still has its benefits.

A mid-performing cluster is observed around 90–91%, including Random Forest (90.72%), Support Vector Machine (90.72%), Decision Tree (90.67%), and Logistic Regression (90.63%). These findings indicate that the established machine-learning models achieve competitive performance but fail to outperform the proposed models. Gradient Boosting (89.40%) and ANFIS (89.31%) achieve slightly lower accuracy, indicating that they generalize less well than the best-performing methods. K-nearest neighbor (87.46 %) scores worse, which may be due to sensitivity to scaling of features and rough edges in the data. Lastly, Naive Bayes is the least accurate, with an accuracy of 79.41%, indicating that its strong independence assumptions do not reflect the fault data and lead to greater misclassification. In general, the figure indicates that the suggested DWT -CNN -BiLSTM model is the most precise approach; Naive Bayes is the least powerful, and the other methods represent an intermediate performance scope.

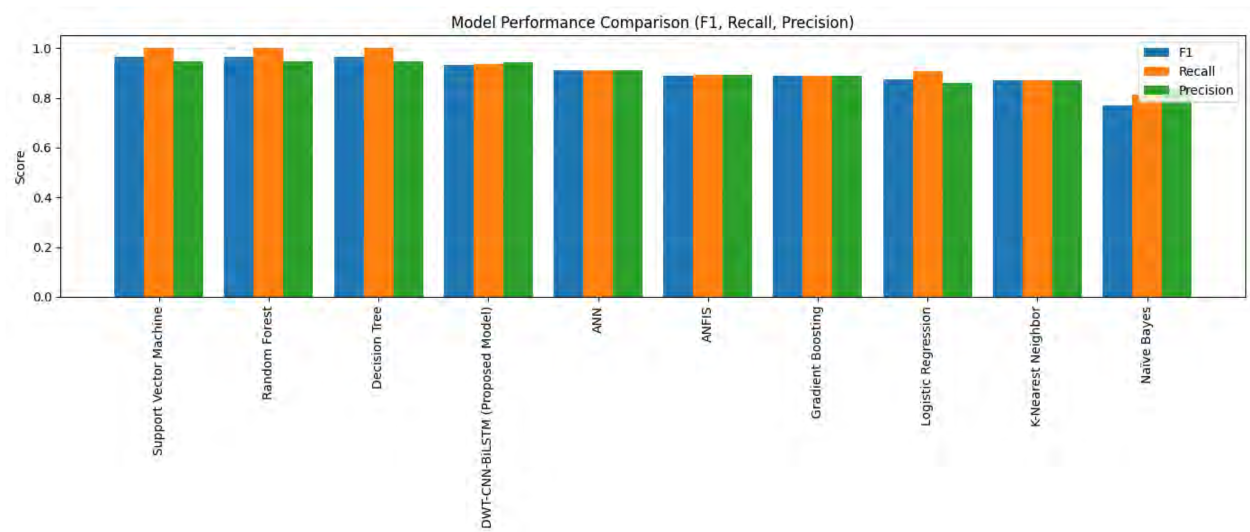

Figure 4.7: Model Performance Comparison of Baseline Vs Proposed

Figure 4.7 indicates that the proposed DWT-CNN-BiLSTM model achieves steady, high results, with an F1 score of 0.933, recall of 0.936, and precision of 0.942. The impressive discovery is the balance between precision and recall, as both measures are high and similar, indicating that the model is not based on the other. The proposed model is clearly better than more traditional soft-computing methods such as ANNs and ANFIS. It is significantly improved in F1 and precision scores, i.e., it is better in overall correctness and the reliability of positive predictions.

Compared with traditional machine learning baselines, the proposed model also outperforms Gradient Boosting, K-Nearest Neighbors (KNN), Logistic Regression, and Naive Bayes. Such models have lower F1 scores and, in some cases, lower precision or recall. Naive Bayes, for example, does not perform as well on average, and KNN and Gradient Boosting do not show any improvement over the proposed model on the three metrics. Logistic Regression has low recall and accuracy, which may lead to increased false positives. The model that is presented maintains a more favorable precision-recall balance and is therefore more stable and reliable.

Nonetheless, as shown in the chart, Random Forest and SVM perform best in this comparison, with F1 very high and recall close to perfection, while the Decision Tree is also slightly better than the offered model. In general, it can be concluded that the suggested DWT-CNN-BiLSTM is among the most effective and more robust than most single models, including the simpler ANN/ANFIS and many classical ML techniques. Simultaneously, both RF/SVM (and DT) continue to dominate the numbers in this dataset and evaluation environment, with the fact that the proposed models are highly balanced in their performance, as opposed to being the absolute leader in this metric.

4.1.2.3 Performance Metrics Comparison of All Approaches

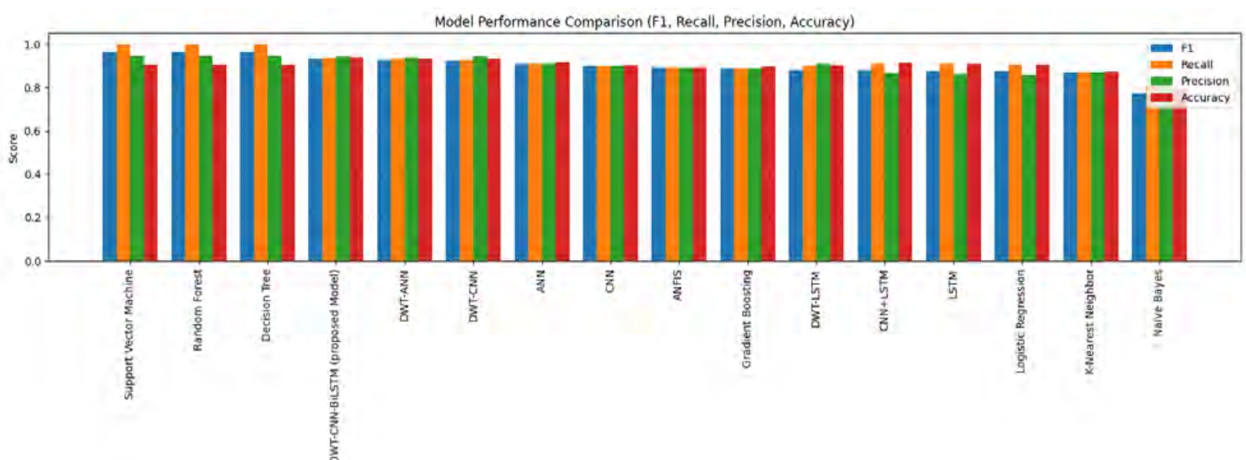

Figure 4.8: Model Performance Metric Evaluation Comparison of All Approaches

Figure 4.8 above compares various methods based on F1-score, recall, precision, and accuracy, which collectively illustrate the performance of each model and its balanced predictions. Overall, the most accurate model is the proposed DWT-CNN-BiLSTM with 93.75, and the good and balanced values of F1 (0.9333), recall (0.9356), and precision (0.9421). This suggests that the proposed approach is not only more likely to classify correctly than the others but also maintains a good trade-off between the number of cases detected as positive (high recall) and the number of false alarms (high precision). Other hybrids are also DWT-based and achieve good results, with DWT-ANN (93.19) and DWT-CNN (93.12) confirming that DWT-based hybrids outperform the simple CNN/LSTM/CNN+LSTM hybrids, which still attain a high accuracy of about 90-91.

Among machine learning methods, Random Forest and SVM achieved the highest F1-score (0.9640) and recall (0.9995), indicating strong overall F1 performance and minimally missed positive cases. Decision Tree is similar, with a recall of 0.9990. However, their accuracy is 90.7%, which is lower than that of the proposed DWT-CNN-BiLSTM. Naive Bayes performs the worst across all metrics (F1 = 0.7707, recall = 0.8137, accuracy = 79.41%), making it the least suitable option. The DWT-CNN-BiLSTM is the most appropriate model when accuracy and balanced precision-recall are priorities, whereas Random Forest and SVM are preferable when maximizing recall and F1-score are the main objectives.

4.1.3 Confusion Metrics of Fault classification

This section examines Confusion metrics for fault classification in power transmission lines by relying on a wide variety of machine learning, deep learning models and signal processing methods. The key aim of this section is to analyze and contrast several methods by looking at their confusion metric.

4.1.3.1 Confusion Metrics Comparison of Hybrid Approach

In this section, we have analyzed the performance metrics—specifically the Confusion metrics—of various individual hybrid Deep Learning models in comparison with the proposed DWT-CNN-BiLSTM approach to evaluate their effectiveness in accurately classifying fault categories, balancing false positives and missed detections, and ensuring consistency across different fault types.

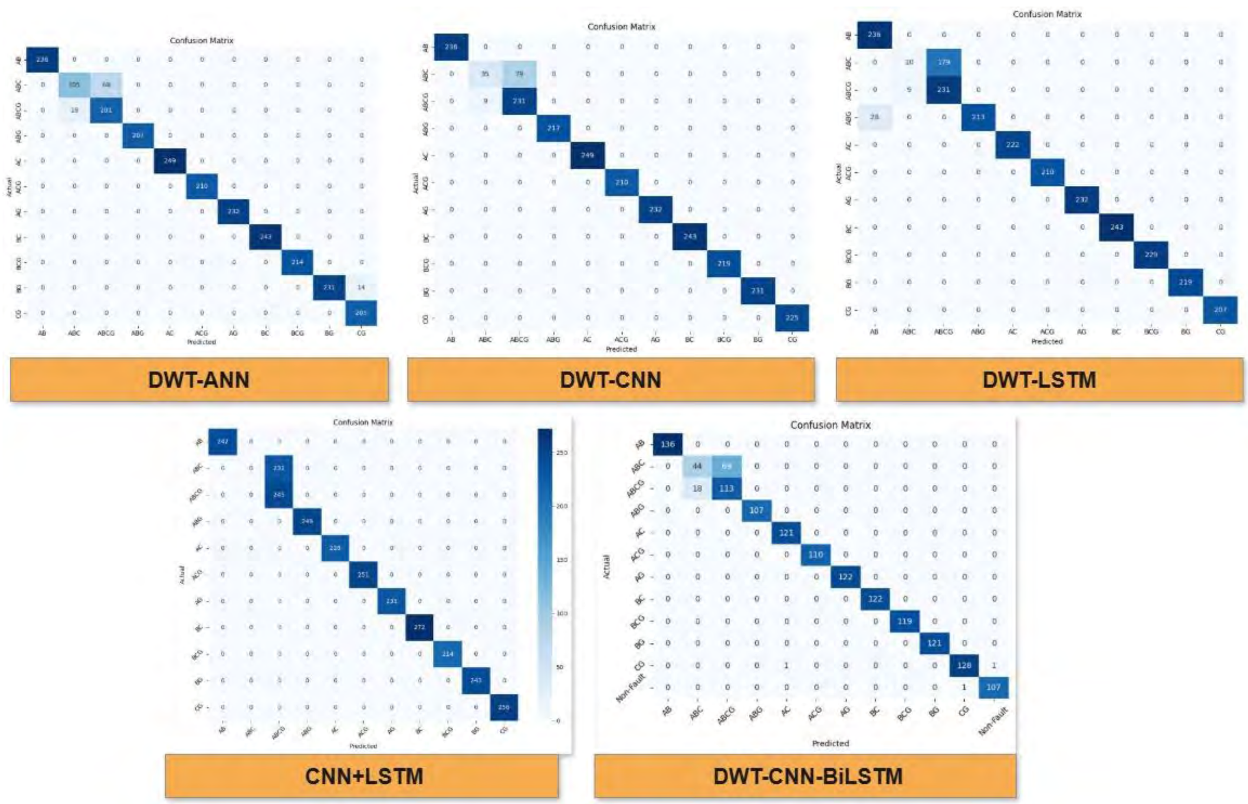

Figure 4.9: Confusion Matrix of Proposed Hybrid Approaches

Across the five confusion matrices from Figure 4.9, the proposed DWT-CNN-BiLSTM shows the cleanest overall pattern: most samples fall on the main diagonal (correct classifications), while the off-diagonal cells (errors) are sparse and generally very small. This indicates that the proposed hybrid is better at separating the classes consistently, which matches the table results where it achieves the highest accuracy (93.75%) and a strong balance of precision (0.9421) and recall (0.9356). In practice, that means it is not only getting more predictions right overall, but it is also keeping both false negatives and false positives under control.

- **DWT-ANN**
  - Strong diagonal dominance overall, meaning most classes are correctly identified.
  - Noticeable confusion appears among the early, closely related fault classes (e.g., ABC / ABCG / ABG-type categories), where a portion of samples leak into neighboring classes.
  - It also shows a small but visible mix-up in the last classes (e.g., BG being predicted as CG), indicating difficulty in separating a couple of similar end categories.
  - Overall: good performance, but with repeated errors in a few “look-alike” class pairs.
- **DWT-CNN**
  - Cleaner diagonal than DWT-ANN in many classes, showing stronger feature discrimination.
  - Very low off-diagonal counts in the mid-to-late classes (better separation there).
  - Remaining errors are mostly concentrated in the early fault categories, again suggesting these classes share similar patterns.
  - Overall: one of the best baselines among the non-proposed methods, but still not as consistently error-free as the proposed hybrid.

- **DWT-LSTM**
  - Displays the most visible off-diagonal activity among the DWT variants, especially near the top-left portion of the matrix.
  - Indicates higher confusion between similar classes and less stable boundaries.
  - Compared to DWT-ANN and DWT-CNN, it misses more samples from their correct class and spreads mistakes across more cells.
  - Overall: weakest of the DWT-based single hybrids, consistent with its lower reported metrics.
- **Hybrid CNN+LSTM**
  - Good diagonal concentration across most classes, meaning the hybrid improves over simpler single learners.
  - However, there are still a few confusion spots, especially in classes that are structurally similar (again often in the early categories).
  - Generally stable in the mid and later classes, but not as consistently "tight" as the proposed approach.
  - Overall: strong hybrid baseline but still leaves more misclassification than the proposed DWT-based hybrid.
- **Proposed: Hybrid DWT-CNN-BiLSTM**
  - Shows the **cleanest and strongest diagonal dominance** across the matrix.

- Off-diagonal errors are minimal and mostly limited to the hardest, most similar class pairs.
- Indicates the most reliable class separation and the lowest overall confusion, which matches the table where it achieved the **highest accuracy (93.75%)** along with strong precision and recall.
- Overall: best-performing approach in terms of balanced classification and reduced confusion.

Overall comparison (big picture)

- **Best overall: DWT-CNN-BiLSTM (Proposed)** most correct predictions (strongest diagonal), least confusion (fewest off-diagonal errors).
- **Next strongest: DWT-CNN** and **DWT-ANN** — generally accurate, but they still show recurring confusion in a few similar-class pairs.
- **Solid baseline hybrid: CNN+LSTM** — improved diagonal clarity compared to single deep models, but still not as clean as the DWT-enhanced proposed method.
- **Worst among these shown: DWT-LSTM** — more widespread off-diagonal errors, indicating greater difficulty distinguishing similar classes.

4.1.3.2 Confusion Metrics Comparison of Baseline Models and the Proposed Model

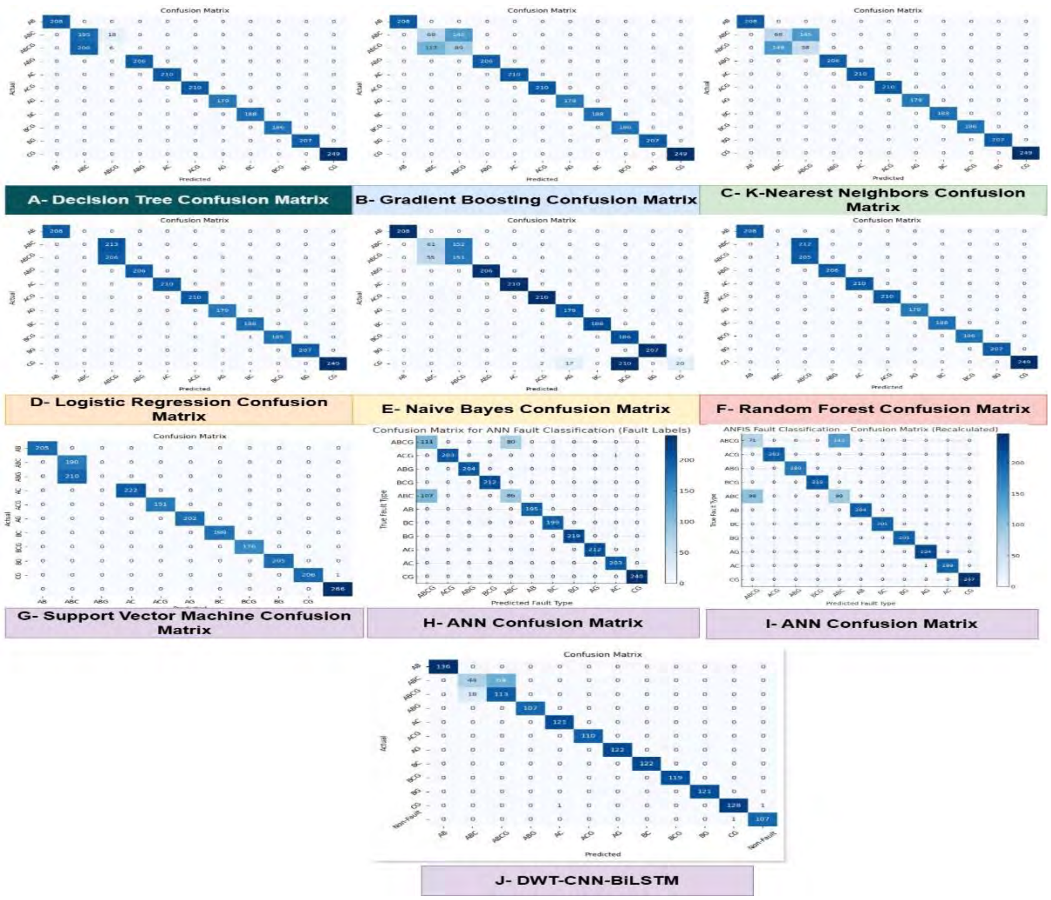

Figure 4.10: Confusion Matrix of Baseline Models and the Proposed Model

The above **Figure 4.10** shows the classification Matrix for single Models and the proposed approach and their further explanation is being given below:

Explanation of Confusion Matrices for Machine Learning Approaches

A. Decision Tree

- Most classes (ACG, ABG, BCG, CG) are classified correctly with strong diagonal values.

- Some confusion appears between **ABCG and ABC**, where a few ABCG cases are misclassified.
- Overall, Decision Tree provides good interpretability but risks **overfitting**, which causes occasional misclassification.

B. Gradient Boosting

- Strong diagonal dominance indicates high accuracy.
- Misclassifications mainly occur between **ABCG** ↔ **ABC** (multi-phase faults).
- Gradient Boosting improves stability compared to a single tree but still struggles in **overlapping fault categories**.

C. K-Nearest Neighbors (KNN)

- Performs very well, with nearly perfect classification across most fault types.
- Very small misclassifications observed in **ABCG vs ABC**.
- Shows that KNN is effective when **fault feature clusters are well-separated**.

D. Logistic Regression

- Performs fairly well, most predictions are correct.
- Misclassifications increase for **complex multi-phase faults** due to the model's **linear decision boundaries**.
- While reliable, Logistic Regression is less capable of handling **non-linear separations** in the dataset.

E. Naïve Bayes

- The weakest among all models.
- Significant misclassifications are seen in **ABCG, ABC, and AB** classes.
- This is due to Naïve Bayes assuming **independent features**, which does not hold for fault datasets where signals are highly correlated.

F. Random Forest

- Very strong performance, one of the **best models** here.
- Almost perfect diagonal dominance with **minimal misclassifications**.
- Combining multiple trees reduces variance and improves reliability, making it robust for fault classification.

G. Support Vector Machine (SVM)

- Among the **top performers**, with nearly flawless diagonal accuracy.
- Handles **non-linear separability** very well using kernels, reducing errors in complex fault types.
- Very small errors still appear in multi-phase conditions, but overall accuracy is excellent.

Overall Comparison of the machine learning approaches

- **Best performers:** Random Forest, SVM, KNN (strong diagonal accuracy, minimal misclassification).

- **Moderate performers:** Decision Tree, Gradient Boosting, Logistic Regression (accurate but some overlap in complex faults).
- **Weakest performer:** Naïve Bayes (high misclassification rates, poor handling of feature correlations).

Key Observations – ANN:

- Most fault types such as ACG (203/203), ABG (204/204), BCG (212/212), BG (219/219), AG (212/212), and CG (240/240) are classified with near-perfect accuracy.
- The main confusion occurs between ABCG and ABC:
    - ✓ 111 ABCG samples were classified correctly, but 80 were misclassified as ABC.
    - ✓ Similarly, 107 ABC faults were misclassified as ABCG.
- Overall, ANN shows high accuracy across nearly all fault categories, with only minor overlap in closely related classes.

Key Observations – ANFIS:

- ANFIS performs well for many fault types, including ACG (203), BCG (210), BG (201), AG (224), and CG (247).
- Misclassification between ABCG and ABC is much higher than in ANN:
    - ✓ Only 71 ABCG were correctly classified, while 143 were misclassified as ABC.
    - ✓ For ABC, 99 were predicted as ABCG and 90 were misclassified as ABCG.
- This indicates ANFIS has more difficulty distinguishing between complex multi-phase faults compared to ANN.

Proposed: Hybrid DWT-CNN-BiLSTM

- Shows the cleanest and strongest diagonal dominance across the matrix.
- Off-diagonal errors are minimal and mostly limited to the hardest, most similar class pairs.
- Indicates the most reliable class separation and the lowest overall confusion, which matches the table where it achieved the highest accuracy (93.75%) along with strong precision and recall.
- Overall: best-performing approach in terms of balanced classification and reduced confusion

Best overall (most reliable, lowest confusion): Proposed Hybrid DWT-CNN-BiLSTM

- ✓ Cleanest diagonal dominance and minimal off-diagonal errors, meaning the most consistent class separation (especially for difficult, similar fault pairs like ABC ↔ ABCG).
- ✓ Matches the metrics table where it achieves the highest accuracy (93.75%) with strong precision and recall.

Best traditional Machine Learning performers (strongest ML baselines): Random Forest, SVM, and KNN

- ✓ Confusion matrices show very strong diagonal dominance with only tiny misclassifications.
- ✓ RF and SVM are particularly robust for complex/nonlinear patterns; KNN performs extremely well when fault clusters are well separated.

Moderate / acceptable performers (good but with noticeable overlap in complex faults): Decision Tree, Gradient Boosting, Logistic Regression, and ANN

- ✓ Generally high correctness, but more visible errors in overlapping multi-phase faults (again mainly **ABC ↔ ABCG**).
- ✓ Decision Tree can misclassify due to overfitting, Gradient Boosting improves stability but still overlaps in hard classes, Logistic Regression is limited by linear boundaries, and ANN has minor confusion mainly in similar fault types.

Weakest performers (highest confusion, least reliable): Naïve Bayes and ANFIS

- ✓ **Naïve Bayes** is the weakest overall due to significant misclassification (independence assumption fails with correlated fault features).
- ✓ **ANFIS** shows heavier confusion than ANN, especially for **ABC/ABCG multi-phase faults**, indicating weaker separation of complex categories.

4.2 Comparative Result and Performance Analysis for Fault Detection:

In this section, we compare fault detection methods across three evaluation stages for a clear, thorough assessment. First, we report model output errors **(MAE, MSE, and RMSE)** to quantify accuracy, with RMSE highlighting the magnitude of typical errors and major deviations. Second, we present classification metrics—**Accuracy, Precision, Recall, and F1-score**—to evaluate each model's ability to identify fault types, balance false alarms and missed faults, and maintain consistent performance across classes. Finally, we use **confusion matrices** to detail correct and incorrect predictions by class, making it easier to identify misclassifications and the most challenging fault types. Together, these steps provide an objective and comprehensive comparison of each model's performance.

4.2.1 Comparative Performance Evaluation of Error Metrics for Fault Detection:

This section examines several techniques that help detect faults in power transmission lines by relying on a wide variety of machine learning, deep learning models and signal processing methods. The key aim of the study is to analyze and contrast several methods by looking at their accuracy, as well as MAE, MSE, and RMSE.

Table 4.3 below compares several error metric approaches for evaluating the effectiveness of classification methods in power systems. The techniques are assessed using Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Accuracy.

Table 4.3: Error metrics Performance Comparison of different techniques for Fault Detection

Technique	**MAE**	**MSE**	**RMSE**	**ACCURACY**
ANFIS	0.013058	0.0057875	0.076076	**99.35%**
ANN	0.013671	0.0051743	0.071932	**99.43%**
Deep Learning Approach				
CNN	0.0048	0.0048	0.0696	**99.52%**
LSTM	0.0048	0.0048	0.0696	**99.52%**

CNN+LSTM	0.0048	0.0048	0.0696	**99.52%**
DWT-CNN-BiLSTM	**0.0014**	**0.0014**	**0.0373**	**99.86%**
DWT-ANN	**0.0021**	**0.0021**	**0.0456**	**99.79%**
DWT-CNN	**0.0027**	**0.0027**	**0.0364**	**99.83%**
DWT-LSTM	**0.0035**	**0.0035**	**0.0589**	**99.65%**
Machine Learning Approach				
Decision Tree	0.0032	0.0032	0.0569	**99.68%**
Gradient Boosting	0.0016	0.0016	0.0402	**99.84%**
K-Nearest Neighbor	0.0053	0.0053	0.0725	**99.47%**
Logistic Regression	0.0048	0.0048	0.0696	**99.52%**
Naïve Bayes	0.0081	0.0081	0.0899	**99.19%**
Random Forest	0.0016	0.0016	0.0402	**99.84%**
Support Vector Machine	0.0048	0.0048	0.0696	**99.52%**

4.2.1.1 Model Performance Metric Evaluation of Hybrid Approaches for Fault Detection

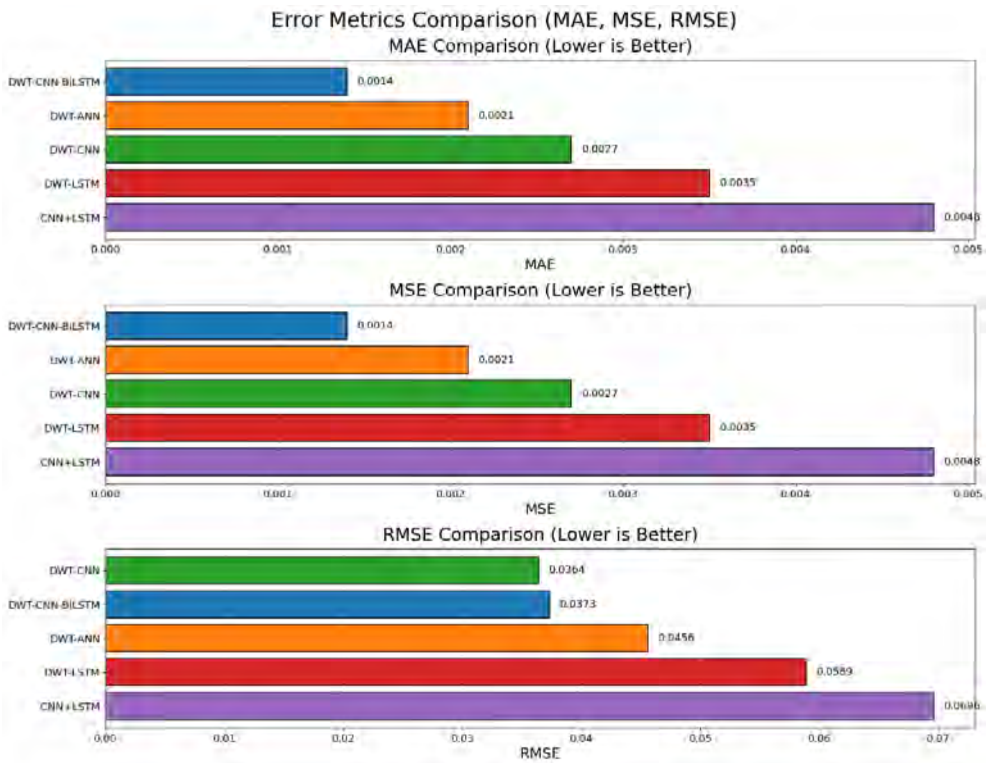

Figure 4.11: Performance Metric Evaluation of Hybrid Approaches for Fault Detection

Figure 4.11 compares the error performance of five models using MAE, MSE, and RMSE. In each panel, the lower bars indicate better performance, as indicated by smaller prediction errors. The figure consists of three horizontal bar charts: the top shows MAE (mean absolute error), the middle shows MSE (mean squared error), and the bottom shows RMSE (root mean squared error). Consistent model colors across panels help track each technique across all metrics.

Based on the findings, the DWT-CNN-BiLSTM is overall the best in terms of MAE and MSE since it has the lowest MAE (0.0014) and the lowest MSE (0.0014), and thus results in the lowest average error, as well as the growth of the square error is kept within a relatively small range. The best result on the RMSE panel is DWT-CNN (0.0364), which is slightly narrower than the proposed DWT-CNN-BiLSTM (0.0373). The difference is minimal, demonstrating that both approaches are excellent at controlling the usual error value. DWT-ANN is positioned in the middle between all three measures, whereas the CNN+LSTM base is much higher in MAE/MSE and RMSE, and thus it reduces errors less effectively. The least suitable in this case is DWT-LSTM, which has the highest errors among the panels (particularly RMSE), i.e., its results are less related to the actual values and less predictive than those of other DWT-based hybrids.

4.2.1.2 Error metrics Evaluation of Baseline Models and the Proposed Model

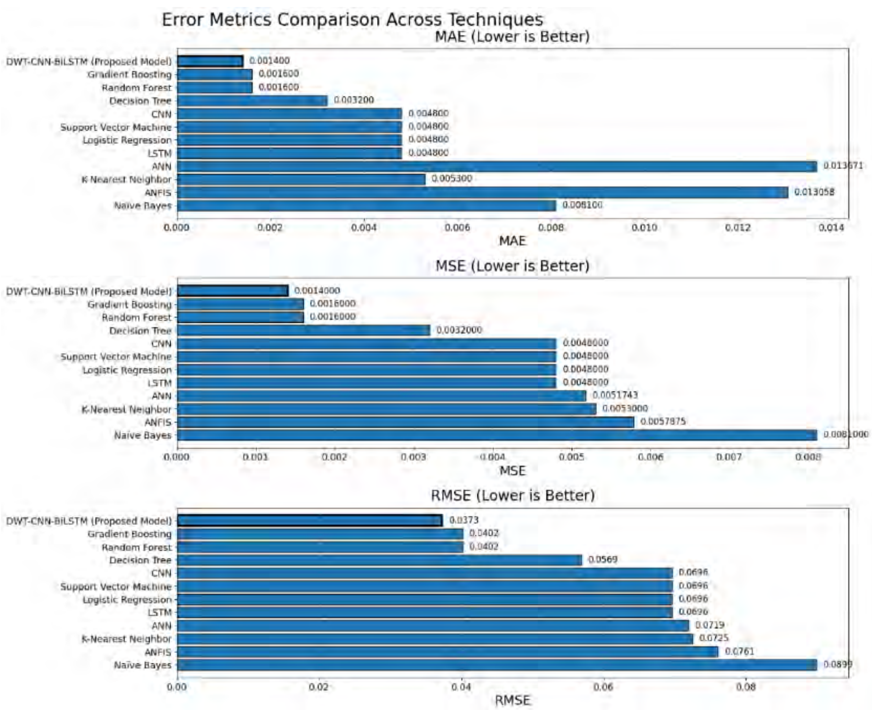

Figure 4.12: Error Metrics Evaluation of Baseline Models and the Proposed Model

Figure 4.12 compares all techniques more clearly across three error-metric panels: MAE, MSE, and RMSE. Each method in each panel is represented by a horizontal bar, with shorter bars indicating lower error (better performance). The suggested **DWT-CNN-BiLSTM** bar has also been highlighted (with a thicker outline), making it easy to recognize among the panels.

The proposed **DWT-CNN-BiLSTM** has the lowest MAE among the MAE panel; that is, it has the least average deviation between its predictions and the actual values, making the most consistent predictions on average. The nearest ones are Gradient Boosting and Random Forest, which also yield very low MAE values. On the other hand, ANN/ANFIS and Naive Bayes exhibit larger MAEs, indicating greater average errors.

The proposed model is once again among the best in the MSE panel, and this is significant because the MSE increases sharply as a model commits more errors. Other models, such as Gradient Boosting/Random Forest, are also suitable in this case, with Naive Bayes having the highest MSE, indicating the highest spikes in error. Lastly, the RMSE panel (which displays the magnitude of common errors) shows the best-performing group in the list, namely the proposed DWT-CNN-BiLSTM, and the best baselines with the lowest RMSE, i.e., their predictions are closer to the actual values.

Overall, the figure shows that the proposed **DWT-CNN-BiLSTM** offers the most consistent error reduction, which can be observed in the form of the smallest MAE (the highest average accuracy) and highly competitive MSE/RMSE (the ability to control the larger errors), whereas Naive Bayes is always the weakest, as evidenced by the largest errors in all of the metrics.

4.2.1.3 Error metrics Evaluation of All approaches

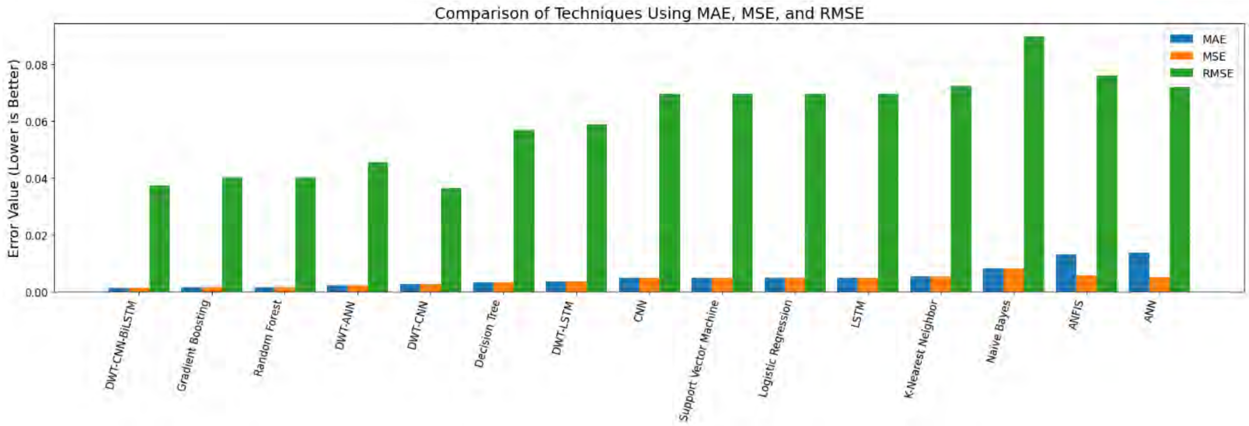

Figure 4.13: Comparison of All Approaches

Figure 4.13 presents MAE, MSE, and RMSE for all techniques, with lower values indicating better performance. The proposed **DWT-CNN-BiLSTM** achieves the lowest error values (MAE = 0.0014, MSE = 0.0014, RMSE = 0.0373), demonstrating strong accuracy and stability. Gradient Boosting and Random Forests are closely matched (MAE/MSE = 0.0016, RMSE = 0.0402), representing the most competitive conventional machine learning baselines.

DWT-based variants generally outperform non-DWT models. DWT-ANN (MAE/MSE = 0.0021, RMSE = 0.0456) and DWT-LSTM (MAE/MSE = 0.0035, RMSE = 0.0589) show clear error reductions compared to their non-DWT counterparts. DWT-CNN achieves the lowest RMSE (0.0364), indicating fewer large error spikes, although its MAE/MSE (0.0027) is higher than that of the proposed model. DWT-CNN-BiLSTM remains the most consistently accurate overall.

The mid-performing group—CNN, LSTM, Logistic Regression, and SVM—shows similar errors (MAE/MSE = 0.0048, RMSE = 0.0696) and is less accurate than the DWT-based hybrids and top ensembles. KNN (MAE/MSE = 0.0053, RMSE = 0.0725) performs slightly worse. Naive Bayes demonstrates the poorest results (MAE/MSE = 0.0081, RMSE = 0.0899), with the highest average errors. Overall, DWT-based hybrids, particularly the proposed DWT-CNN-BiLSTM, achieve the lowest errors, followed by Gradient Boosting and Random Forest. Naive Bayes and ANN/ANFIS are the least accurate.

4.2.2 Comparative Result and Performance of Model Performance Metric Evaluation for Fault Detection

This section provides a concise comparative assessment of fault detection models, based on critical performance measurement criteria. The assessment commences with an examination of model performance metrics (**accuracy, precision, recall, and F1-score**) to evaluate the efficacy of each method in detecting faults, mitigating false alarms and ignored detections, and ensuring consistency across varying fault types.

Table 4.4 demonstrates the evaluation of fault detection models based on **model performance metrics (Accuracy, Precision, Recall, and F1-score)**

Table 4.4: Model Performance Metric for Fault Detection

Technique	***F-1 score***	***Recall***	***Precision***	***Accuracy***
ANN	***0.9969***	***0.9943***	***0.9996***	***99.43%***
ANFIS	***0.99647***	***0.99341***	***0.99956***	***99.35%***
Deep Learning Approach				
CNN	0.9973	0.9947	0.9990	**99.52%**
LSTM	0.9973	0.9947	0.9990	**99.52%**

CNN+LSTM	0.9973	0.9947	0.9990	**99.52%**
DWT-CNN-BiLSTM	**0.9992**	**0.9992**	**0.9992**	**99.86%**
DWT-ANN	**0.9989**	**0.9985**	**0.9992**	**99.79%**
DWT-CNN	**0.9986**	**1.0000**	**0.9982**	**99.83%**
DWT-LSTM	**0.9981**	**0.9970**	**0.9992**	**99.65%**
Machine Learning Approach				
Decision Tree	0.9982	0.9996	0.9969	**99.68%**
Gradient Boosting	0.9991	1.0000	0.9982	**99.84%**
K-Nearest Neighbor	0.9971	0.9965	0.9978	**99.47%**
Logistic Regression	0.9973	0.9947	1.0000	**99.52%**
Naïve Bayes	0.9956	0.9912	1.0000	**99.19%**
Random Forest	0.9991	1.0000	0.9982	**99.84%**
Support Vector Machine	0.9973	0.9947	1.0000	**99.52%**

4.2.2.1 Model Performance Metric Evaluation of Hybrid Approaches

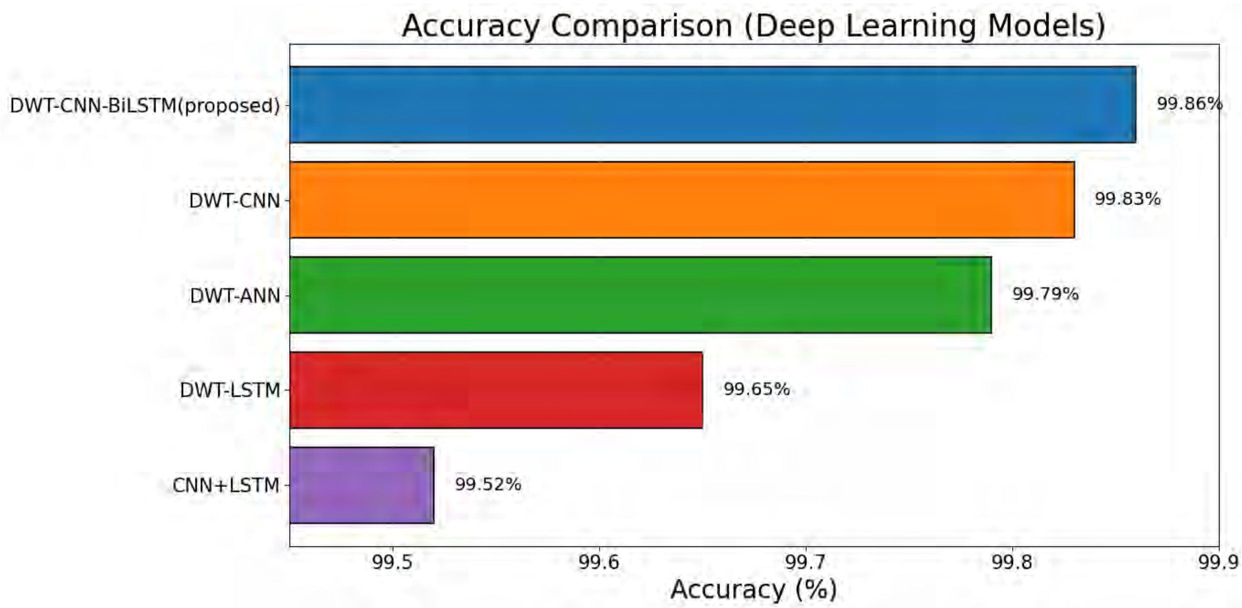

Figure 4.14: Accuracy of Hybrid Approach

Figure 4.14 compares the accuracy (%) of the deep learning models, with longer bars indicating higher accuracy. The models are ranked from best to worst based on their results, with all results very high (around 99.5%-99.9%), indicating that all approaches perform well in general. Nevertheless, the minor variations are not irrelevant, since accuracy is already close to the ceiling, and even a 0.1 percent difference can make a significant difference in terms of additional correct predictions when the data is large.

The best-performing method in this comparison is the proposed DWT-CNN-BiLSTM, with the highest accuracy (99.86%). The nearest model is DWT-CNN (99.83%), next comes DWT-ANN (99.79%). These findings demonstrate a general trend: models that integrate DWT (Discrete Wavelet Transform) with the learning architecture are more accurate, indicating that DWT facilitates more informative feature extraction and reduces noise before classification. DWT-LSTM (99.65%) achieves worse results than the other DWT-based hybrids, indicating that DWT-

CNN/BiLSTM is more effective in this context than DWT-LSTM. Lastly, CNN + LSTM (99.52) is the least accurate of the listed deep learning models, indicating that it commits the most errors.

Overall, the plot shows that the proposed DWT-CNN-BiLSTM provides the most reliable forecasts and demonstrates the advantage of DWT-based feature extraction, as all DWT-based versions are more effective than the traditional CNN+LSTM baseline.

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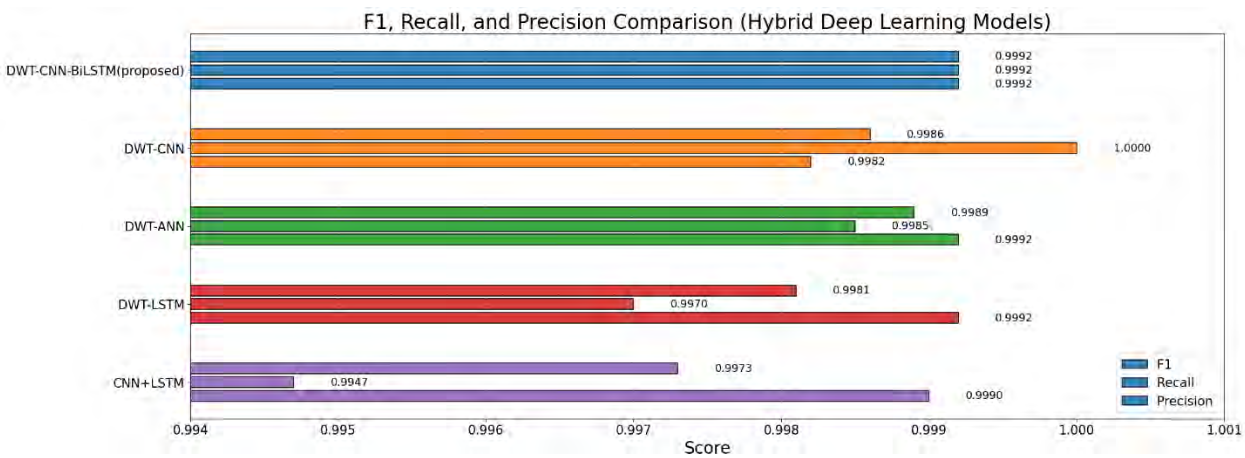

Figure 4.15: Performance Metrics of the Hybrid Approaches

Figure 4.15 compares F1-score, Recall, and Precision for the hybrid deep learning models, where values closer to 1.0 indicate better performance. Because the x-axis is zoomed (around 0.994–1.001), even small differences are meaningful: a change of a few thousandths can represent a noticeable reduction in misclassifications when evaluated on many samples. Each model has three horizontal bars—one for F1, one for Recall, and one for Precision—so you can see not only how strong the model is overall, but also whether it favors recall (catching positives) or precision (avoiding false positives).

The proposed **DWT-CNN-BiLSTM** is the most balanced and maintains its high performance consistently: F1, Recall, and Precision are about 0.9992, indicating it detects almost perfectly, and the false alarms are at the lowest possible level. **DWT-CNN** is also very robust and has the highest Recall (1.0000), and hence, it is said to capture practically all true examples; it has a lower Precision (approximately 0.9982), indicating that it is slightly less precise and will therefore have fewer false positives than the proposed model. **DWT-ANN** performs near the best models, with a precision of around 0.9992 and high F1/recall; however, it remains a bit lower than the proposed solution overall. **DWT-LSTM** exhibits the most significant imbalance among the DWT-based hybrids: its precision (~0.9992) is high, but its recall (~0.9970) is lower, resulting in a lower F1 score. Lastly, CNN+LSTM is the poorest in comparison, with the lowest recall (~0.9947), and F1 indicates it does not perform well at completely separating the fault classes without DWT feature extraction.

Overall, all the above-mentioned plots confirm two important observations: (1) DWT-based hybrids have always better performance than the CNN+LSTM baseline does, (2) the proposed **DWT-CNN-BiLSTM** provides the best all-around performance, offering the most stable balance between high recall and high precision rather than excelling in just one metric.

4.2.2.2 Model Performance Metric Evaluation of Baseline Models and the Proposed Model

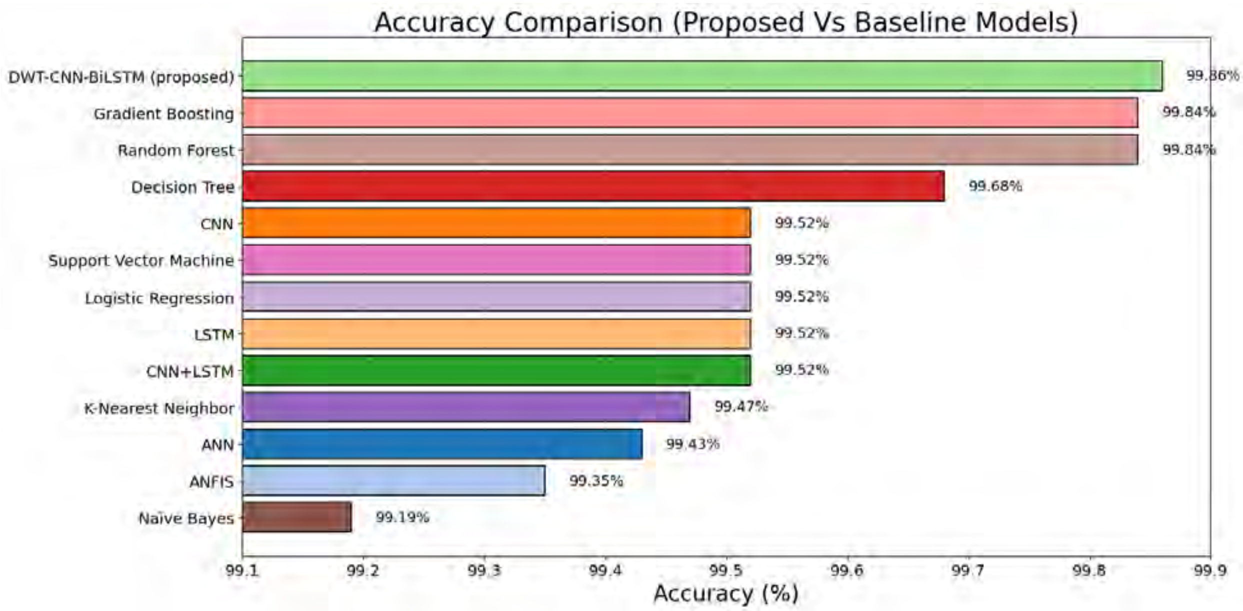

Figure 4.16: Accuracy Comparison of Proposed Vs Baseline Method

Figure 4.16 ranks all methods by accuracy (%) and directly compares the proposed **DWT-CNN-BiLSTM** to the baseline models. Because the x-axis is zoomed in to 99.1%-99.9%, even small changes in accuracy are significant. The models are already performing near the maximum, so gains of a few tenths of a percent represent meaningful improvements in correct classification.

The proposed **DWT-CNN-BiLSTM** achieves the highest accuracy at 99.86%, leading the chart. Gradient Boosting and Random Forest follow closely at 99.84% but remain slightly below the proposed model. The DWT-CNN-BiLSTM also outperforms other baselines, including Decision Tree (99.68%), deep learning models such as CNN, LSTM, and CNN+LSTM (approximately 99.52%), and similarity or linear methods like KNN (99.47%), ANN (99.35%), and ANFIS (99.43%). Naive Bayes, with 99.19%, shows the largest gap compared to the proposed approach.

The proposed method outperforms **baseline models** by integrating complementary strengths within a single pipeline. DWT transforms raw signals into informative time–frequency components, **CNN** extracts discriminative local features, and **BiLSTM** captures sequential dependencies in both directions. This hybrid approach enhances class separability and reduces misclassifications that persist in simpler models. In summary, while many baselines perform well, the **DWT-CNN-BiLSTM achieves the highest overall accuracy, even in a high-accuracy context where further improvements are challenging.**

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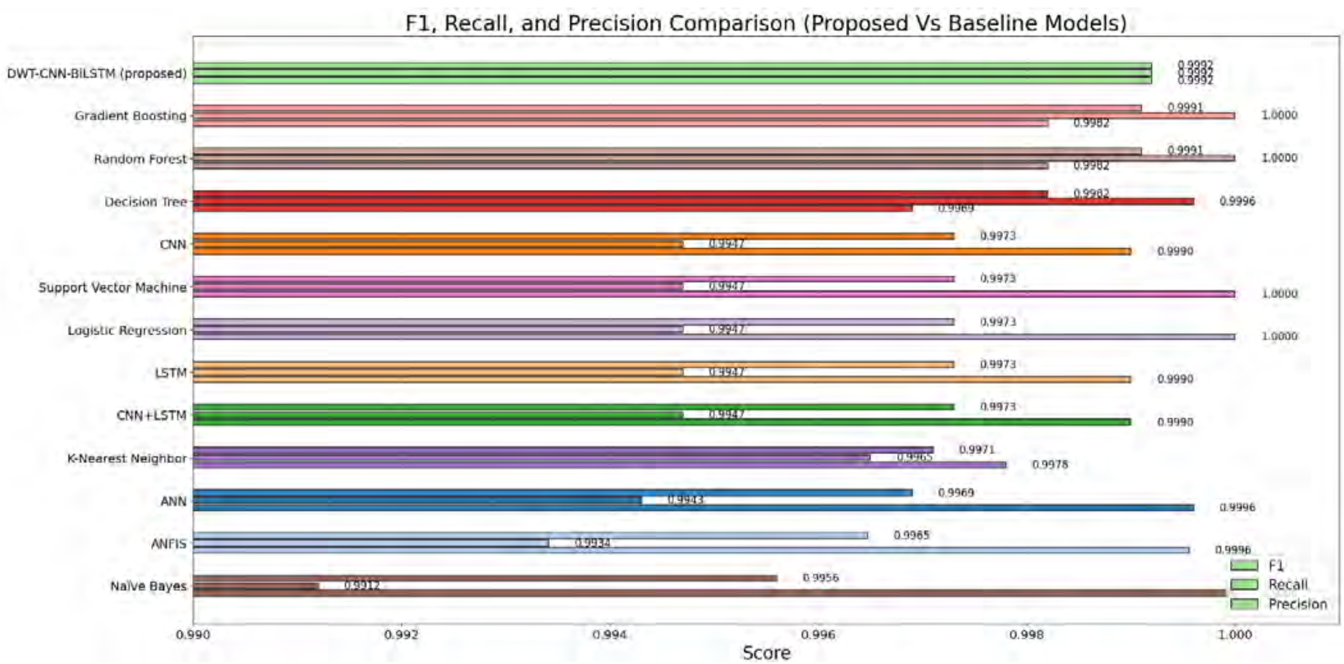

Figure 4.17: Performance Metrics of the Proposed Vs Baseline Models

Figure 4.17 compares **F1-score, Recall, and Precision** for the **proposed model versus the baseline models**. Each technique has three horizontal bars: **F1** (overall balance), **Recall** (ability to detect true cases), and **Precision** (reliability of positive predictions). Because the x-axis is zoomed tightly between **0.990 and 1.000**, the differences look small, but they are still important—at this performance level, even a change of **0.001** can represent many additional correct or incorrect classifications.

The suggested **DWT-CNN-BiLSTM** has the highest and most balanced values across all three metrics (F1: 0.9992, Recall: 0.9992, Precision: 0.9992). This is the most important strength: it demonstrates that the model achieves high recall (high detection) and very low false alarms (high precision), resulting in a close-to-perfect F1 Score. On the other hand, certain robust baselines exhibit a small degree of trade-offs. As an illustration of this, Gradient Boosting and Random Forest have a Recall = 1.0000, i.e., they will identify nearly all the true cases, though Precision = lower (0.9982), i.e., they are more prone to the false-positive tendency, which is unacceptable in this case. Decision Tree also performs well and is more robust to imbalance, with lower accuracy (approximately 0.9969) than its recall (approximately 0.9996), suggesting greater confusion in certain categories. The middle-performing group- CNN, LSTM, CNN+LSTM, SVM, and Logistic Regression tends to converge around F1 0.9973 and Recall 0.9947, which is still large, however, still significantly lower than the proposed approach. This shows that these models lose more actual cases (lower recall), which decreases F1 even when precision is high. Such methods as KNN, ANN, and ANFIS are also competitive but slightly lower and less consistent than the three measures. Naive Bayes is the weakest overall, largely because of its lowest recall (0.9912) and F1 (0.9956), indicating more false omissions and an overall imbalance.

Overall, the figure shows that the **proposed DWT-CNN-BiLSTM not only achieves near-top values but also offers the best balance between recall and precision**, which is why it produces the strongest F1-score. Even though a few baselines match or exceed it in **one** metric (e.g., recall hitting 1.0000), the proposed model maintains **consistently high performance across all three**, indicating more stable and reliable classification behavior.

4.2.2.3 Model Performance Metric Evaluation of All approaches

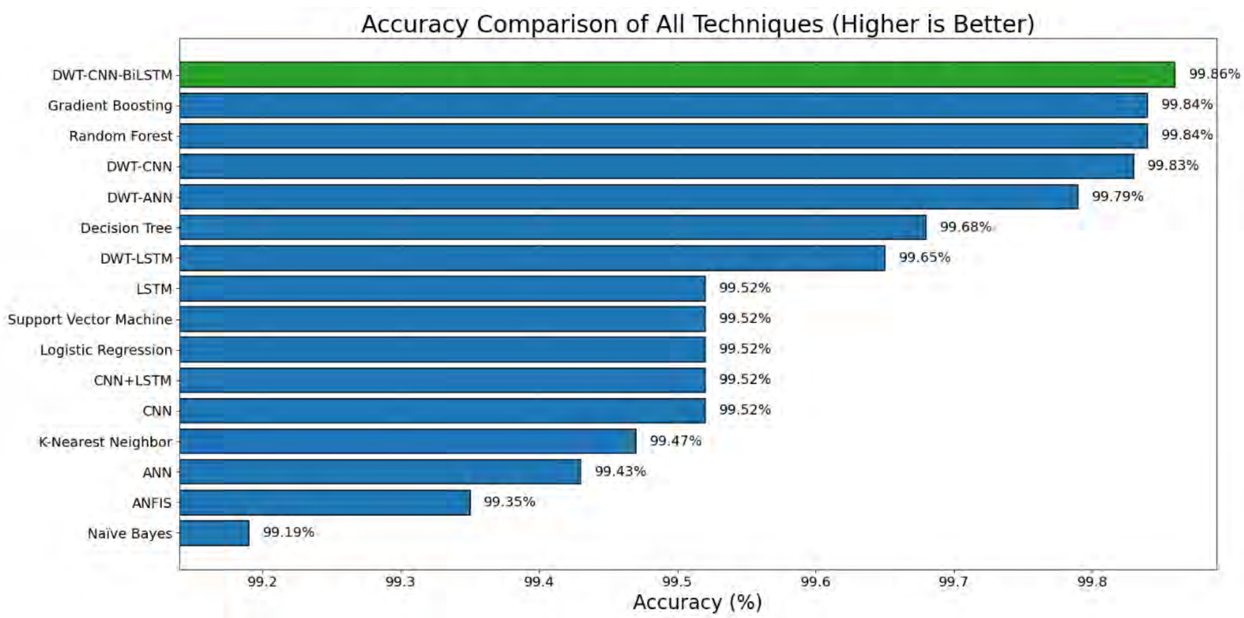

Figure 4.18: Accuracy Evaluation of All Models

From **Figure 4.18,** the **best overall model is DWT-CNN-BiLSTM**, because it achieves the **highest accuracy (99.86%)** and maintains an excellent and balanced performance across **F1 (0.9992), Recall (0.9992), and Precision (0.9992)**. The closest competitors are **Gradient Boosting** and **Random Forest** with **99.84% accuracy**, but the proposed DWT-CNN-BiLSTM still slightly surpasses them and remains highly consistent across the three core classification metrics. On the weaker side, **Naïve Bayes** performs the worst overall with the lowest accuracy (99.19%) and the lowest recall (0.9912), meaning it misses more true cases compared to the other techniques.

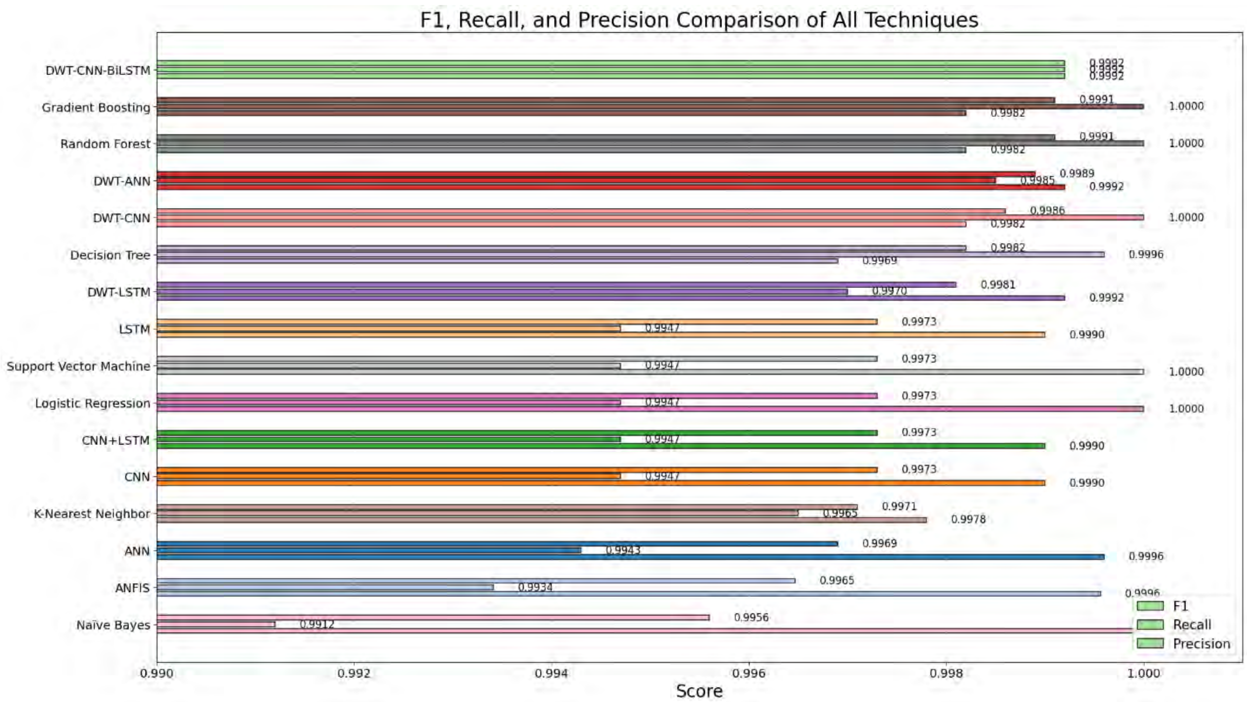

Figure 4.19: Evaluation Metrics Comparison of All Models

Figure 4.19 compares **F1-score, Recall, and Precision** for **all techniques** in one chart. Each technique has three horizontal bars: **F1** summarizes the overall balance between precision and recall, **Recall** shows how well the model captures true cases (low false negatives), and **Precision** shows how reliable the predicted positives are (low false positives). The x-axis is zoomed to **0.990-1.000**, so the differences appear small, but they are important because all models already perform at a very high level; even a change of a few thousandths can translate into many additional correct or incorrect classifications on large datasets. This figure compares **F1-score, Recall, and Precision** for **all techniques** in one chart. Each technique has three horizontal bars: **F1** summarizes the overall balance between precision and recall, **Recall** shows how well the model captures true cases (low false negatives), and **Precision** shows how reliable the predicted positives are (low false positives). The x-axis is zoomed to **0.990-1.000**, so the differences appear small, but they are important because all models already perform at a very high level; even a change of a few thousandths can translate into many additional correct or incorrect classifications on large datasets.

The **best overall pattern** is shown by **DWT-CNN-BiLSTM**, which sits at the top with very high, well-balanced values (0.9992 F1, recall, and precision). This balance suggests that the proposed method is both robust at identifying the correct class (high recall) and at avoiding false alarms (high precision) and hence achieves the highest F1 among the plotted methods. The ensemble models - Gradient Boosting and Random Forest - are the most robust competitors in this context, as they achieve Recall = 1.0000, i.e., they recognize almost every true case. Nevertheless, they are slightly less precise (approximately 0.9982) and thus more prone to producing several false positives than the suggested model, which maintains all three metrics at a high level.

A mid-tier group, such as CNN, LSTM, CNN+LSTM, SVM, and Logistic Regression, clusters around F1 0.9973 and Recall 0.9947, indicating that they perform well but miss more true cases than the best models, thereby lowering F1 even though they are very accurate. KNN, ANN, and ANFIS remain competitive, but they decline further, with ANFIS and ANN achieving much higher recall, indicating greater confusion in some classes. The lowest results are observed with Naive Bayes, which has the lowest recall (0.9912) and F1 (0.9956), indicating it misses the most true cases and is overall more balanced.

Overall, the figure shows that the numerous baselines achieve scores close to perfection, but the suggested DWT-CNN-BiLSTM has the most consistent and balanced performance across F1, recall, and precision, making it the most suitable overall in this comparison.

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method is both robust at identifying the correct class (high recall) and at avoiding false alarms (high precision), and hence achieves the highest F1 among the plotted methods. The ensemble models - Gradient Boosting and Random Forest - are the most robust competitors in this context, as they achieve Recall = 1.0000, i.e., they recognize almost every true case. Nevertheless, they are slightly less precise (approximately 0.9982) and thus prone to adding several false positives compared to the suggested model, which maintains all three metrics at a high level.

A mid-tier group, such as CNN, LSTM, CNN+LSTM, SVM, and Logistic Regression, clusters around F1 0.9973 and Recall 0.9947, indicating that they perform well but miss more true cases than the best models, thereby lowering F1 even though they are very accurate. KNN, ANN, and ANFIS are still competitive, but they decline further, with much higher recall in ANFIS and ANN, indicating greater confusion in some classes. The lowest results are observed with Naive Bayes, which has the lowest recall (0.9912) and the lowest F1 (0.9956), meaning it misses the most true cases and is more balanced overall.

Overall, the figure shows that the numerous baselines achieve scores close to perfection, but the suggested DWT-CNN-BiLSTM has the most consistent and balanced performance across F1, recall, and precision, which is why it should be considered the most suitable overall in this comparison.

4.2.3 Confusion Metrix for Fault Detection

This section examines Confusion metrics for fault detection in power transmission lines by relying on a wide variety of machine learning, deep learning models and signal processing methods. The key aim of this section is to analyze and contrast several methods by looking at their confusion metric.

4.2.3.1 Confusion Metrics of Hybrid Approaches

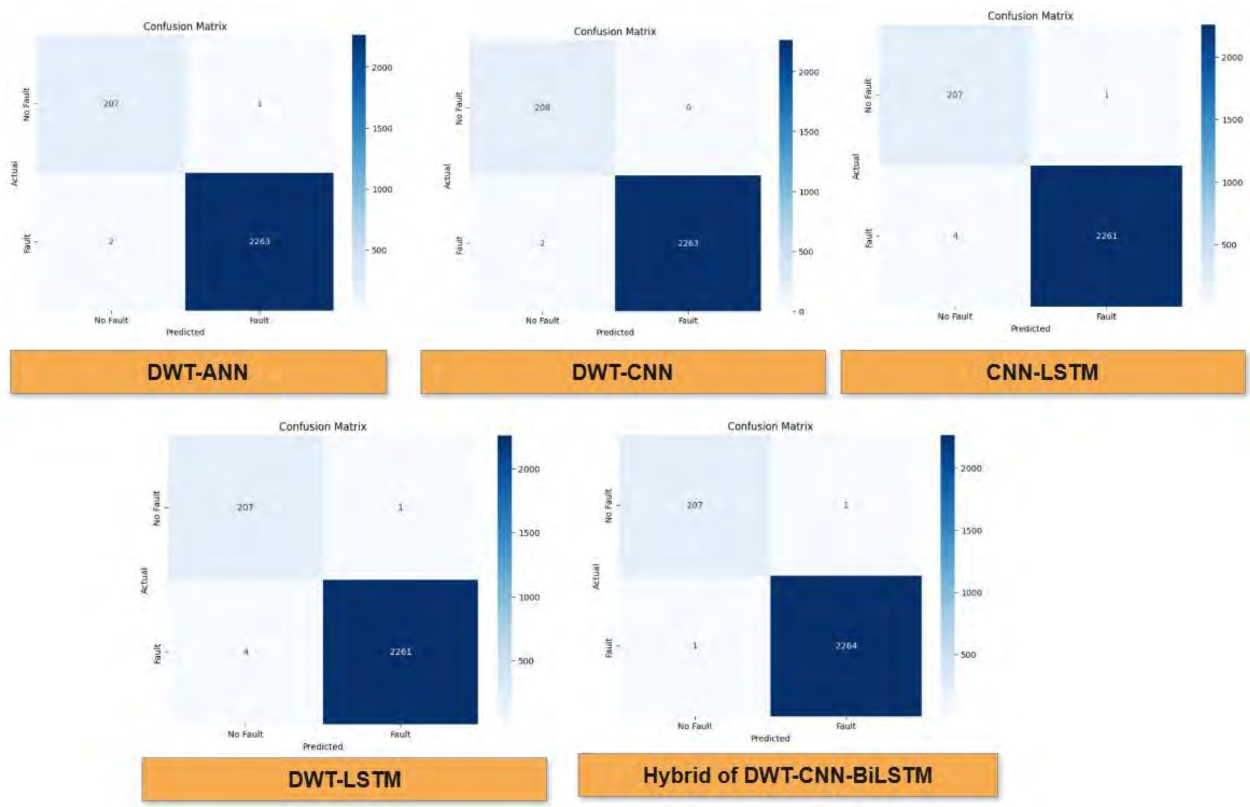

Figure 4.20: Confusion Metrics of Hybrid Approach

Based on the confusion matrices from **figure 4.20**, Hybrid DWT-CNN-BiLSTM (proposed) is the most successful hybrid method of fault detection. Its matrix indicates the most immaculate separation of No Fault and Fault, and nearly all the things are concentrated around the main diagonal. It implies that it can detect faults and non-faults correctly most of the time, and it has the smallest number of missed faults, which is the most severe need in detection issues (it is more severe to miss a real fault than a false alarm).

- **Hybrid DWT-CNN-BiLSTM (Proposed) Best overall detection**
  - The confusion matrix is the cleanest (strongest diagonal).

    - Very few mistakes, meaning it detects faults very reliably.
    - Shows the lowest confusion between "Fault" and "No Fault," so it's the most stable approach.

- **DWT-ANN — Very good detection, but slightly behind the proposed model**
    - Strong diagonal dominance (most samples correctly classified).
    - A small number of errors remain, so it misses a few more cases than the proposed model.
- **DWT-CNN — Strong performance, especially good at reducing false alarms**
    - Also shows a strong diagonal, indicating high correctness.
    - Compared to other baselines, it tends to be better at not raising unnecessary fault alarms.
    - Still not as consistently perfect as the proposed hybrid.
- **DWT-LSTM — Weakest among the DWT-based hybrids**
    - More visible off-diagonal values than DWT-ANN and DWT-CNN.
    - Indicates more confusion between fault and no-fault cases (more missed detections).
- **CNN+LSTM (baseline hybrid without DWT) — weaker than DWT-based hybrids**
    - More confusion than the DWT-enhanced models.
    - Shows that adding DWT significantly improves separation and detection quality.

- **Overall conclusion**
    - **Best detection:** Hybrid **DWT-CNN-BiLSTM (Proposed)**
    - **Strong alternatives: DWT-CNN** and **DWT-ANN**
    - **Least reliable detection: DWT-LSTM** (and the non-DWT CNN+LSTM baseline)

4.2.3.2 Confusion Metrics of Baseline Models and the Proposed Model

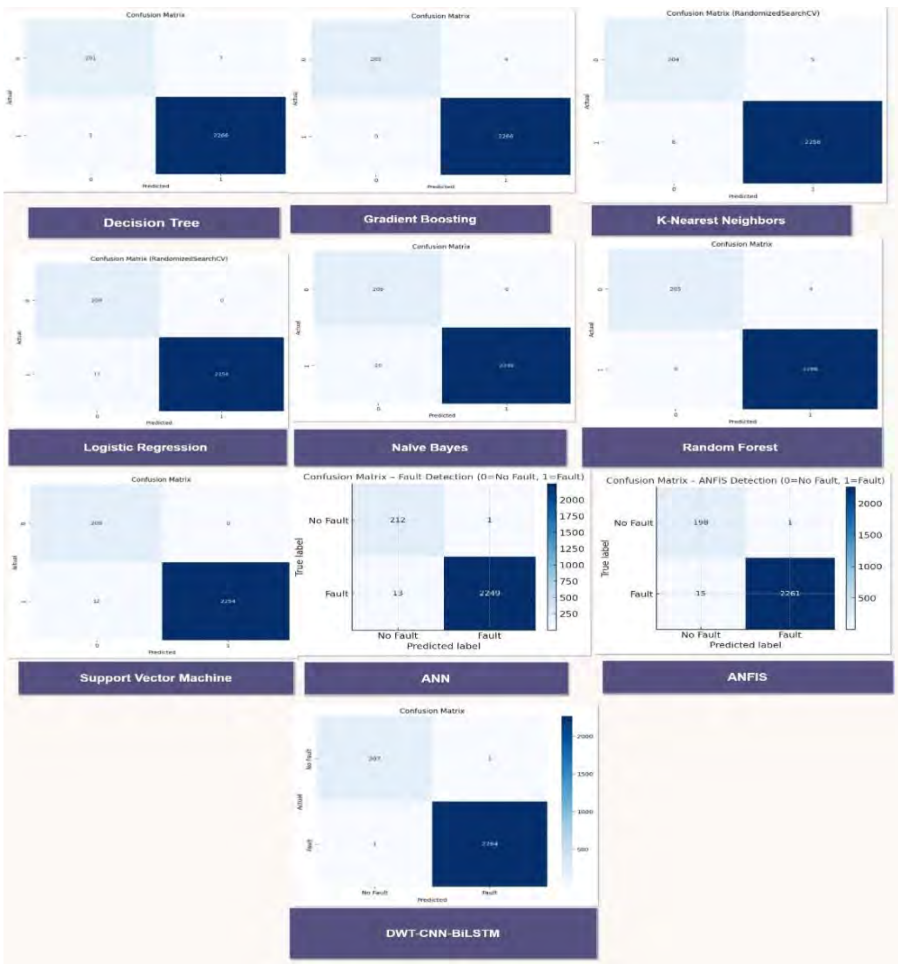

Figure 4.21: Confusion Metrics of Proposed Method Vs Baseline Methods

The confusion matrices of the seven traditional machine learning classifiers listed below are displayed in **Figure 4.21** above, which include Decision Tree, Gradient Boosting, K -Nearest Neighbors (KNN), Logistic Regression, Naive Bayes, Random Forest, and Support Vector Machine (SVM). The following matrices demonstrate the classification outcomes of two categories No-Fault (0) and Fault (1) in the fault-detection task.

- **Decision Tree:** Most of the cases were identified in the correct classification, and 201 no-fault and 2,266 fault cases were identified. Only 7 no-fault items were incorrectly identified as faults and one fault case was incorrectly identified as no-fault.
- **Gradient Boosting:** There was an increase in performance with 205 no-fault detections and 2,266 fault detections and only four no-fault samples were falsely categorized as faults.
- **K-Nearest Neighbors (KNN):** We identified 204 no-fault and 2,258 cases of fault correctly. Nevertheless, 5 no-fault and 8 fault cases were false classified.
- **Logistic Regression:** The system gave a good performance with the right detection of 209 no-fault and 2,254 fault incidents. But it falsely categorized 12 flaw events as no-fault.
- **Naïve Bayes:** The model had a fair hit with the identification of 209 no-fault cases and 2,246 fault cases. But it gave the greatest misclassifications, with 20 fault samples reported as no-fault.
- **Random Forest:** The model performed very well in its accuracy with the detection of 205 no-fault cases and 2,266 fault cases with only four cases misclassified as no-fault.
- **Support Vector Machine (SVM):** Fully identified 209 non-fault cases and 2,254 fault cases, and 12 cases of fault were misclassified as non-fault.
- **The ANN :-** determined 212 cases of no-fault and 2,249 cases of fault and 14 false identifications

- **ANFIS model** found 198 no-fault cases and 2, 261 fault cases and 16 misclassifications.
- **DWT-CNN-BiLSTM (Proposed) Best overall**
  - The matrix is almost perfectly diagonal: it makes **very few mistakes** in both directions.
  - It shows the **strongest and most reliable fault detection** while also keeping false alarms very low.

- Best **detection and best balance: DWT-CNN-BiLSTM (Proposed)**
- Strongest **single baseline for detection: KNN** (very strong detection, but can produce some false alarms)
- Weakest **for detection reliability: Naïve Bayes** (most confusion / missed faults)

Chapter 5: Thesis Conclusion

This thesis examined **reliable transmission-line fault detection and multi-class fault classification** in modern power systems, where conventional methods often struggle with dynamic conditions, noise, and system complexity. The study evaluated a wide range of approaches, including independent AI models (ANN/ANFIS), deep learning architectures (CNN, LSTM, CNN+LSTM), traditional machine learning classifiers (DT, RF, GB, LR, SVM, KNN, NB), and hybrid frameworks combining signal processing and deep learning (DWT-ANN, DWT-CNN, DWT-LSTM, DWT-CNN-BiLSTM), using a consistent evaluation environment and common metrics.

The study found that the proposed hybrid **DWT-CNN-BiLSTM** which is the first objective of the study, delivers the most stable and accurate performance. This is achieved by combining DWT for time-frequency decomposition and noise reduction, CNN for feature extraction, and BiLSTM for bidirectional temporal modeling. The hybrid model achieved 93.75% accuracy in fault classification and 99.86% in fault detection, demonstrating that integrating signal processing with deep learning offers a more robust solution than using either approach alone. In addition to high accuracy, the error-metric analysis verifies the reliability of the hybrid method. DWT-CNN-BiLSTM had the lowest MAE, MSE, and RMSE during fault detection (MAE = 0.0014, MSE = 0.0014, RMSE = 0.0373) and fault classification (MAE = 0.0012), indicating fewer misclassifications and greater reliability under challenging conditions. Although ensemble machine learning models like Gradient Boosting and Random Forest also achieved good results, the hybrid architecture was the most reliable as it combined well both the extraction of features and time learning, which is fundamental with real fault waveforms and dynamic system behavior.

Practically, the findings indicate the feasibility of hybrid deep learning architecture, which includes but is not confined **to DWT-CNN-BiLSTM**, to be used in real-time fault detection, enhanced grid stability, and informed maintenance. Future directions have also been noted in the thesis as validation against wider datasets and testing against real field measurements, optimization of the computational pipeline to be deployed to embedded or edge devices, and operation in noisy and uncertain environments. This study presents an excellent benchmark and shows that hybrid signal processing and deep learning systems are a better solution to inaccurate and robust transmission-line fault detection and multi-class fault classification in current power systems where traditional methods may fail to perform well in dynamic operating environments, noise, and more intricate systems by. To address this requirement, the study assessed a broad variety of approaches and perform a comprehensive comparative evaluation models under identical experimental conditions including: independent AI models (ANN/ANFIS), deep-learning architectures (CNN, LSTM, CNN+LSTM), traditional machine-learning classifiers (DT, RF, GB, LR, SVM, KNN, NB), and hybrid frameworks of signal-processing-informed methods and deep learning (DWT-ANN, DWT-CNN, DWT-LSTM, DWT-CNN-BiLSTM) which was second objective of the study .

The major finding of this comparative study is that the proposed hybrid DWT-CNN-BiLSTM gives the most stable and predictive cumulative performance due to the combination of: (i) DWT time-frequency decomposition to emphasize transient fault characteristics and eliminates noise, (ii) CNN learning features to extract useful patterns based on the obtained coefficients, and (iii) BiLSTM sequence modeling to learn a bidirectional temporal relationship hence, full filling the third objective of this theses. This hybrid pipeline, according to the thesis, achieves 93.75% accuracy in fault classification and 99.86% in fault detection, demonstrating that signal processing combined with deep learning provides a more resilient end-to-end solution than either family of models.

In practical terms, the results indicate the use of hybrid deep learning models, such as DWT-CNN-BiLSTM, to monitor faults in real time and enhance grid stability, operational stability, and maintenance decision-making, as they are established to detect faults in real time and classify them accurately across a variety of classes. However, the thesis also provides clear directions for future work: extending validation to broader datasets (including more operating scenarios and disturbance types), testing on real field measurements beyond simulation, and optimizing the computational pipeline for embedded/edge deployment while maintaining robustness in noisy, uncertain environments. Overall, the research provides a comprehensive benchmark and demonstrates that hybrid (signal-processing + deep learning) architectures are a superior pathway for accurate and resilient transmission-line fault detection and classification in modern power systems.

Reference

1. R. Heffron *et al*., "Industrial demand-side flexibility: A key element of a just energy transition and industrial development," *Applied Energy*, vol. 269, Art. no. 115026, 2020.
2. P. Gautam and A. K. Jhala, "Fault detection and classification of three-phase transmission line," *Int. Res. J. Eng. Technol.*, vol. 2, no. 9, pp. 2629–2633, 2015.
3. W. Elmasry and M. Wadi, "Detection of faults in electrical power grids using an enhanced anomaly-based method," *Arab. J. Sci. Eng.*, vol. 47, no. 11, pp. 14899–14914, 2022.
4. N. Ahmed *et al*., "Fault detection through discrete wavelet transform in overhead power transmission lines," *Energy Sci. Eng.*, vol. 11, no. 11, pp. 4181–4197, 2023.
5. S. Zhao, F. Blaabjerg, and H. Wang, "An overview of artificial intelligence applications for power electronics," *IEEE Trans. Power Electron.*, vol. 36, no. 4, pp. 4633–4658, 2020.
6. S. A. Aleem, N. Shahid, and I. H. Naqvi, "Methodologies in power systems fault detection and diagnosis," *Energy Syst.*, vol. 6, pp. 85–108, 2015.
7. D. Lu *et al*., "Time-domain transmission line fault location method with full consideration of distributed parameters and line asymmetry," *IEEE Trans. Power Deliv.*, vol. 35, no. 6, pp. 2651–2662, 2020.
8. A. Yadav and A. Swetapadma, "Single-ended directional fault section identification and fault location for double-circuit transmission lines using wavelet and ANN," *Int. J. Electr. Power Energy Syst.*, vol. 69, pp. 27–33, 2015.
9. Z. Jiao and R. Wu, "A new method to improve fault location accuracy in transmission lines based on fuzzy multi-sensor data fusion," *IEEE Trans. Smart Grid*, vol. 10, no. 4, pp. 4211–4220, 2018.

10. M. Moscoso, S. Hosseini, G. J. Lloyd, and K. Liu, “Operation and design of a protection relay for transformer condition monitoring,” in *Proc. 11th IET Int. Conf. Developments in Power Systems Protection (DPSP)*, Stevenage, U.K., Apr. 2012, p. 42.

11. A. Latrach, “Application of deep learning for predictive maintenance of oilfield equipment,” *arXiv preprint* arXiv:2306.11040, 2023.

12. F. Pozo, D. A. Tibaduiza, and Y. Vidal, “Sensors for structural health monitoring and condition monitoring,” *Sensors*, vol. 21, no. 5, Art. no. 1558, 2021.

13. E. E. O. Mammadov, *Predictive Maintenance of Wind Generators Based on AI Techniques*, M.Sc. thesis, Univ. Waterloo, Waterloo, ON, Canada, 2019.

14. A. Mellit and S. A. Kalogirou, “A survey on the application of artificial intelligence techniques for photovoltaic systems,” in *McEvoy's Handbook of Photovoltaics*, Academic Press, 2018, pp. 735–761.

15. M. T. Hoq, *Distance Protection of Transmission Lines with High Levels of Series Compensation: A Study on Frequency and Time Domain Communication Independent Distance Protection for Series Compensated Lines*, Ph.D. dissertation, KTH Royal Inst. Technol., Stockholm, Sweden, 2023.

16. M. J. B. Reddy and D. K. Mohanta, “Performance evaluation of an adaptive-network-based fuzzy inference system approach for location of faults on transmission lines using Monte Carlo simulation,” *IEEE Trans. Fuzzy Syst.*, vol. 16, no. 4, pp. 909–919, 2008.

17. E. E. Ngu and K. Ramar, “A combined impedance and traveling wave based fault location method for multi-terminal transmission lines,” *Int. J. Electr. Power Energy Syst.*, vol. 33, no. 10, pp. 1767–1775, 2011.

18. A. Mukherjee, P. K. Kundu, and A. Das, “Transmission line faults in power system and the different algorithms for identification, classification and localization: A brief review of methods,” *J. Inst. Eng. India Ser. B*, pp. 1–23, 2021.

19. A. Abdullah, “Ultrafast transmission line fault detection using a DWT-based ANN,” *IEEE Trans. Ind. Appl.*, vol. 54, no. 2, pp. 1182–1193, 2017.

20. M. S. Alvarez-Alvarado *et al*., “Power system reliability and maintenance evolution: A critical review and future perspectives,” *IEEE Access*, vol. 10, pp. 51922–51950, 2022.

21. P. Poór, D. Ženíšek, and J. Basl, “Historical overview of maintenance management strategies: Development from breakdown maintenance to predictive maintenance in accordance with four industrial revolutions,” in *Proc. Int. Conf. Ind. Eng. Oper. Manage. (IEOM)*, Pilsen, Czech Republic, Jul. 2019, pp. 23–26.

22. O. Motaghare, A. S. Pillai, and K. I. Ramachandran, “Predictive maintenance architecture,” in *Proc. 2018 IEEE Int. Conf. Comput. Intell. Comput. Res. (ICCIC)*, Dec. 2018, pp. 1–4.

23. M. S. Alvarez-Alvarado *et al*., “Power system reliability and maintenance evolution: A critical review and future perspectives,” *IEEE Access*, vol. 10, pp. 51922–51950, 2022.

24. M. Molęda, B. Małysiak-Mrozek, W. Ding, V. Sunderam, and D. Mrozek, “From corrective to predictive maintenance—A review of maintenance approaches for the power industry,” *Sensors*, vol. 23, no. 13, Art. no. 5970, 2023.

25. L. Bertling, *Reliability-Centred Maintenance for Electric Power Distribution Systems*, Ph.D. dissertation, Elektrotekniska System, 2002.

26. B. Yssaad, M. Khiat, and A. Chaker, “Reliability centered maintenance optimization for power distribution systems,” *Int. J. Electr. Power Energy Syst.*, vol. 55, pp. 108–115, 2014.

27. H. N. Teixeira, I. Lopes, and A. C. Braga, “Condition-based maintenance implementation: A literature review,” *Procedia Manuf.*, vol. 51, pp. 228–235, 2020.

28. M. X. Zhao, J. Su, and S. G. Liu, “Risk assessment based maintenance management for distribution network,” *J. Int. Council Electr. Eng.*, vol. 2, no. 1, pp. 84–89, 2012.

29. L. B. Gordon and T. R. Martinez, “A complete electrical risk assessment method for all electrical hazards and its application,” in *Proc. 2018 IEEE IAS Electr. Safety Workshop (ESW)*, Mar. 2018, pp. 1–8.

30. R. P. Y. Mehairjan, “Risk-based maintenance for electricity network organizations,” in *Risk-Based Maintenance for Electricity Network Organizations*. Cham, Switzerland: Springer, 2017, pp. 9–30.

31. H. Manninen, J. Kilter, and M. Landsberg, “A holistic risk-based maintenance methodology for transmission overhead lines using tower specific health indices and value of loss load,” *Int. J. Electr. Power Energy Syst.*, vol. 137, Art. no. 107767, 2022.

32. J. O. Gidiagba *et al*., “Review on the evolution and impact of IoT-driven predictive maintenance: Assessing advancements, their role in enhancing system longevity, and sustainable operations in both mechanical and electrical realms,” *Comput. Sci. IT Res. J.*, vol. 5, no. 1, pp. 166–189, 2024.

33. T. Goswami and U. B. Roy, “Predictive model for classification of power system faults using machine learning,” in *Proc. TENCON 2019—IEEE Region 10 Conf. (TENCON)*, Oct. 2019, pp. 1881–1885.

34. S. B. Righetto *et al*., “Predictive maintenance 4.0: Concept, architecture and electrical power systems applications,” in *Proc. CIRED 2021—26th Int. Conf. Exhib. Electr. Distrib.*, vol. 2021, Sep. 2021, pp. 1722–1726.

35. S. B. Righetto, M. A. I. Martins, E. G. Carvalho, L. T. Hattori, and S. De Francisci, “Predictive maintenance 4.0 applied in electrical power systems,” in *Proc. 2021 IEEE PES Innov. Smart Grid Technol. Conf. (ISGT)*, Feb. 2021, pp. 1–5.

36. P. R. N. da Silva, M. M. L. Negrão, P. V. Junior, and M. A. Sanz-Bobi, “A new methodology of fault location for predictive maintenance of transmission lines,” *Int. J. Electr. Power Energy Syst.*, vol. 42, no. 1, pp. 568–574, 2012.

37. S. Babu, E. Shayesteh, and P. Hilber, “Analysing correlated events in power system using fault statistics,” in *Proc. 2016 Int. Conf. Probabilistic Methods Appl. Power Syst. (PMAPS)*, Oct. 2016, pp. 1–6.

38. A. J. Patil, A. Singh, and R. K. Jarial, “Some aspects of design and condition monitoring of electric power transmission towers,” *IJISSET J.*, vol. 5, no. 10, 2019.

39. A. Firos *et al*., “Fault detection in power transmission lines using AI model,” in *Proc. 2023 IEEE Int. Conf. Integr. Circuits Commun. Syst. (ICICACS)*, Feb. 2023, pp. 1–6.

40. K. Janarthanam *et al*., “Electrical faults-detection and classification using machine learning,” in *Proc. 2022 Int. Conf. Electron. Renew. Syst. (ICEARS)*, Mar. 2022, pp. 1289–1295.

41. G. A. Fonseca, D. D. Ferreira, F. B. Costa, and A. R. Almeida, “Fault classification in transmission lines using random forest and notch filter,” *J. Control, Autom. Electr. Syst.*, vol. 33, no. 2, pp. 598–609, 2022.

42. O. W. Chuan, N. F. Ab Aziz, Z. M. Yasin, N. A. Salim, and N. A. Wahab, “Fault classification in smart distribution network using support vector machine,” *Indonesian J. Electr. Eng. Comput. Sci.*, vol. 18, no. 3, pp. 1148–1155, 2020.

43. N. Sapountzoglou, J. Lago, and B. Raison, “Fault diagnosis in low voltage smart distribution grids using gradient boosting trees,” *Electr. Power Syst. Res.*, vol. 182, Art. no. 106254, 2020.

44. S. K. Singh, D. N. Vishwakarma, and R. K. Saket, “An intelligent scheme for categorising fault events in compensated power network using k-nearest neighbour technique,” *Int. J. Power Energy Convers.*, vol. 11, no. 4, pp. 352–368, 2020.

45. B. Patel, “A new FDOST entropy based intelligent digital relaying for detection, classification and localization of faults on the hybrid transmission line,” *Electr. Power Syst. Res.*, vol. 157, pp. 39–47, 2018.

46. E. E. Aker, M. L. Othman, I. Aris, N. I. A. Wahab, H. Hizam, and O. Emmanuel, “Transmission line fault identification and classification with integrated FACTS device using multiresolution analysis and naïve Bayes classifier,” *Int. J. Power Electron. Drive Syst.*, vol. 11, no. 2, p. 907, 2020.

47. P. R. N. da Silva, H. A. Gabbar, P. V. Junior, and C. T. da Costa Junior, “A new methodology for multiple incipient fault diagnosis in transmission lines using QTA and Naïve Bayes classifier,” *Int. J. Electr. Power Energy Syst.*, vol. 103, pp. 326–346, 2018.

48. S. Kanwal and S. Jiriwibhakorn, “Advanced fault detection, classification, and localization in transmission lines: A comparative study of ANFIS, neural networks, and hybrid methods,” *IEEE Access*, 2024.

49. J. Rajashekar and A. Yadav, “Transmission lines fault detection and classification using deep learning neural network,” in *Proc. 2022 2nd Int. Conf. Adv. Electr., Comput., Commun. Sustain. Technol. (ICAECT)*, Apr. 2022, pp. 1–6.

50. S. K. Shukla, E. Koley, and S. Ghosh, “Grey wolf optimization-tuned convolutional neural network for transmission line protection with immunity against symmetrical and asymmetrical power swing,” *Neural Comput. Appl.*, vol. 32, no. 22, pp. 17059–17076, 2020.

51. A. S. Alhanaf, H. H. Balik, and M. Farsadi, “Intelligent fault detection and classification schemes for smart grids based on deep neural networks,” *Energies*, vol. 16, no. 22, Art. no. 7680, 2023.

52. M. Y. Arafat, M. J. Hossain, and L. Li, “Advanced deep learning based predictive maintenance of DC microgrids: Correlative analysis,” *Energies*, vol. 18, no. 6, Art. no. 1535, 2025.

53. K. Sundaram, S. Akash, S. Dhanush, R. S. Dheenadayalan, and N. Jagannathan, “A deep learning approach to smart grid stability prediction with LSTM network,” in *Proc. 2024 2nd Int. Conf. Advancement in Computation & Computer Technologies (InCACCT)*, 2024, pp. 265–270.

54. M. Devi, A. K. Rai, A. R. Reddy, G. Neelima, S. Obaid, and S. Chidambaranathan, “Deep learning techniques for overcoming interoperability challenges in smart grid systems,” in *Proc. 2024 Int. Conf. IoT, Commun. Autom. Technol. (ICICAT)*, 2024, pp. 1254–1259.

55. H. Kaplan, K. Tehrani, and M. Jamshidi, “Fault diagnosis of smart grids based on deep learning approach,” in *Proc. 2021 World Automation Congress (WAC)*, 2021, pp. 164–169.

56. K. M. Udofia and C. Nnekwukalu, “Fault detection, classification and location on 132 kV transmission line based on DWT and ANFIS,” *Surge (VS)*, vol. 7, no. 6, 2020.

57. H. R. Goyal, M. Almusawi, S. Otero-Potosi, N. Varshney, V. Sharma, and A. K. Rao, "Predictive maintenance in smart grids with long short-term memory networks (LSTM)," in *Proc. 2024 Int. Conf. Commun., Comput. Sci. Eng. (IC3SE)*, 2024, pp. 1370–1375.

58. T. Anwar *et al*., "Robust fault detection and classification in power transmission lines via ensemble machine learning models," *Sci. Rep.*, vol. 15, no. 1, Art. no. 2549, 2025.

59. M. A. I. Rafi, M. R. Sohan, M. H. Nadid, T. S. Rafa, and A. Jawad, "Enhancing power transmission line fault detection with a hybrid ANN–SVM machine learning model: A comparative study," in *Proc. 2024 Int. Conf. Adv. Comput., Commun., Electr., Smart Syst. (iCACCESS)*, Mar. 2024, pp. 1–6.

60. D. P. Mishra and P. Ray, "Fault detection, location and classification of a transmission line," *Neural Comput. Appl.*, vol. 30, pp. 1377–1424, 2018.

61. J. Hosseinzadeh, F. Masoodzadeh, and E. Roshandel, "Fault detection and classification in smart grids using augmented K-NN algorithm," *SN Appl. Sci.*, vol. 1, no. 12, Art. no. 1627, 2019.

62. M. Alrifaey *et al*., "Hybrid deep learning model for fault detection and classification of grid-connected photovoltaic system," *IEEE Access*, vol. 10, pp. 13852–13869, 2022.

63. R. S. Jawad and H. Abid, "HVDC fault detection and classification with artificial neural network based on ACO-DWT method," *Energies*, vol. 16, no. 3, Art. no. 1064, 2023.

64. N. Narasimhulu, D. V. Ashok Kumar, and M. Vijaya Kumar, "Detection and classification of high impedance fault in power distribution system using hybrid technique," *J. Circuits Syst. Comput.*, vol. 29, no. 8, Art. no. 2050118, 2020.

65. A. S. Alhanaf, M. Farsadi, and H. H. Balik, “Fault detection and classification in ring power system with DG penetration using hybrid CNN-LSTM,” *IEEE Access*, vol. 12, pp. 59953–59975, 2024.
66. C. F. Mbey, V. J. Foba Kakeu, A. T. Boum, and F. G. Y. Souhe, “Fault detection and classification using deep learning method and neuro-fuzzy algorithm in a smart distribution grid,” *J. Eng.*, vol. 2023, no. 11, Art. no. e12324, 2023.
67. W. Gao and R.-J. Wai, “A novel fault identification method for photovoltaic array via convolutional neural network and residual gated recurrent unit,” *IEEE Access*, vol. 8, pp. 159493–159510, 2020.
68. S. Kanwal and S. Jiriwibhakorn, “Advanced fault detection, classification, and localization in transmission lines: A comparative study of ANFIS, neural networks, and hybrid methods,” *IEEE Access*, 2024.
69. U. Ahmad, S. Salisu, Y. Jibril, and M. D. Almustapa, “Identification and classification of high impedance fault on a medium voltage distribution line using radial base function neural network (RBFNN),” *Savannah J. Sci. Eng. Technol.*, vol. 2, no. 3, pp. 75–81, 2024.
70. W. J. Zhang, Q. Ge, and C. Y. Huang, “The research of photovoltaic array intelligent fault diagnosis based on the BP neural network,” *Adv. Mater. Res.*, vol. 936, pp. 2201–2206, 2014.
71. M. Ben Rahmoune, A. Hafaifa, and M. Guemana, “Fault diagnosis in gas turbine based on neural networks: Vibrations speed application,” in *Advances in Acoustics and Vibration: Proc. ICAV 2016*, Hammamet, Tunisia, Mar. 2016, pp. 1–11. (Springer, 2017).

72. C. Guo, Q. Jiang, X. Cao, and Y. Cao, "Recent developments on applications of neural networks to power systems operation and control: An overview," in *Proc. Int. Symp. Neural Networks*, Aug. 2004, pp. 188–193. (Springer, Berlin, Heidelberg).

73. S. S. Tayarani-Bathaie, Z. S. Vanini, and K. Khorasani, "Dynamic neural network-based fault diagnosis of gas turbine engines," *Neurocomputing*, vol. 125, pp. 153–165, 2014.

74. R. Mohammadi, E. Naderi, K. Khorasani, and S. Hashtrudi-Zad, "Fault diagnosis of gas turbine engines by using dynamic neural networks," in *Proc. ASME Turbo Expo: Power for Land, Sea, and Air*, vol. 43987, Oct. 2010, pp. 365–376.

75. S. O. T. Ogaji, Y. G. Li, S. Sampath, and R. Singh, "Gas path fault diagnosis of a turbofan engine from transient data using artificial neural networks," in *Proc. ASME Turbo Expo: Power for Land, Sea, and Air*, vol. 36843, Jan. 2003, pp. 405–414.

76. I. Loboda, "Neural networks for gas turbine diagnosis," in *Artificial Neural Networks—Models and Applications*, 2016.

77. S. Rahman Fahim, S. K. Sarker, S. M. Muyeen, M. R. I. Sheikh, and S. K. Das, "Microgrid fault detection and classification: Machine learning based approach, comparison, and reviews," *Energies*, vol. 13, no. 13, Art. no. 3460, 2020.

78. F. Jia, Y. Lei, J. Lin, X. Zhou, and N. Lu, "Deep neural networks: A promising tool for fault characteristic mining and intelligent diagnosis of rotating machinery with massive data," *Mech. Syst. Signal Process.*, vol. 72, pp. 303–315, 2016.

79. D. F. Amare, T. B. Aklilu, and S. I. Gilani, "Gas path fault diagnostics using a hybrid intelligent method for industrial gas turbine engines," *J. Braz. Soc. Mech. Sci. Eng.*, vol. 40, no. 12, Art. no. 578, 2018.

80. S. Esmaeilbeigi and H. K. Karegar, “Intelligent fault detection and location scheme for low voltage microgrids based on recurrent and radial basis function neural networks,” in *Proc. 2020 28th Iranian Conf. Electr. Eng. (ICEE)*, Aug. 2020, pp. 1–6.

81. J. S. Jang, “ANFIS: Adaptive-network-based fuzzy inference system,” *IEEE Trans. Syst., Man, Cybern.*, vol. 23, no. 3, pp. 665–685, 1993.

82. A. F. Bendary, A. Y. Abdelaziz, M. M. Ismail, K. Mahmoud, M. Lehtonen, and M. M. Darwish, “Proposed ANFIS based approach for fault tracking, detection, clearing and rearrangement for photovoltaic system,” *Sensors*, vol. 21, no. 7, Art. no. 2269, 2021.

83. M. Sugeno and K. Tanaka, “Successive identification of a fuzzy model and its applications to prediction of a complex system,” *Fuzzy Sets Syst.*, vol. 42, no. 3, pp. 315–334, 1991.

84. M. Elsisi, M. Q. Tran, K. Mahmoud, M. Lehtonen, and M. M. Darwish, “Robust design of ANFIS-based blade pitch controller for wind energy conversion systems against wind speed fluctuations,” *IEEE Access*, vol. 9, pp. 37894–37904, 2021.

85. X. G. Magagula, Y. Hamam, J. A. Jordaan, and A. A. Yusuff, “Fault detection and classification method using DWT and SVM in a power distribution network,” in *Proc. 2017 IEEE PES PowerAfrica*, Jun. 2017, pp. 1–6.

86. S. H. Asman, N. F. Ab Aziz, U. A. Ungku Amirulddin, and M. Z. A. Ab Kadir, “Decision tree method for fault causes classification based on RMS–DWT analysis in 275 kV transmission lines network,” *Appl. Sci.*, vol. 11, no. 9, Art. no. 4031, 2021.

87. T. Goswami and U. B. Roy, “Predictive model for classification of power system faults using machine learning,” in *Proc. TENCON 2019—IEEE Region 10 Conf. (TENCON)*, Oct. 2019, pp. 1881–1885.

88. S. S. Bafjaish, “Comparative analysis of Naive Bayesian techniques in health-related for classification task,” *J. Soft Comput. Data Mining*, vol. 1, no. 2, pp. 1–10, 2020.

89. A. Mathew, P. Amudha, and S. Sivakumari, “Deep learning techniques: An overview,” in *Adv. Mach. Learn. Technol. Appl. (AMLTA 2020 Proc.)*, pp. 599–608, 2021.

90. H. Fathabadi, “Ultra high benefits system for electric energy saving and management of lighting energy in buildings,” *Energy Convers. Manage.*, vol. 80, pp. 543–549, 2014.

91. S. Belagoune, N. Bali, A. Bakdi, B. Baadji, and K. Atif, “Deep learning through LSTM classification and regression for transmission line fault detection, diagnosis and location in large-scale multi-machine power systems,” *Measurement*, vol. 177, Art. no. 109330, 2021.

92. Z. Li, J. Li, Y. Wang, and K. Wang, “A deep learning approach for anomaly detection based on SAE and LSTM in mechanical equipment,” *Int. J. Adv. Manuf. Technol.*, vol. 103, pp. 499–510, 2019.

93. M. Tovar, M. Robles, and F. Rashid, “PV power prediction using CNN–LSTM hybrid neural network model: Case study Temixco-Morelos, México,” *Energies*, vol. 13, no. 24, Art. no. 6512, 2020.

94. M. Ahmadipour, H. Hizam, M. L. Othman, and M. A. Mohd Radzi, “An anti-islanding protection technique using a wavelet packet transform and a probabilistic neural network,” *Energies*, vol. 11, no. 10, Art. no. 2701, 2018.

95. W. Rawat and Z. Wang, “Deep convolutional neural networks for image classification: A comprehensive review,” *Neural Comput.*, vol. 29, no. 9, pp. 2352–2449, 2017.

96. A. Krizhevsky, I. Sutskever, and G. E. Hinton, “ImageNet classification with deep convolutional neural networks,” *Commun. ACM*, vol. 60, no. 6, pp. 84–90, 2017.

97. A. Agga, A. Abbou, M. Labbadi, Y. El Houm, and I. H. O. Ali, “CNN–LSTM: An efficient hybrid deep learning architecture for predicting short-term photovoltaic power production,” *Electr. Power Syst. Res.*, vol. 208, Art. no. 107908, 2022.

98. M. Bakkar, S. Bogarra, F. Córcoles, and J. Iglesias, “Overcurrent protection based on ANNs for smart distribution networks with grid-connected VSIs,” *IET Gener., Transm. Distrib.*, vol. 15, no. 7, pp. 1159–1174, 2021.

99. R. F. Pujiantara, M. Pujiantara, A. Priyadi, and D. A. Asfani, “Protection coordination using zone selective interlocking method and neural network in IEEE 9 bus plan,” in *Proc. 2018 Int. Conf. Inf. Commun. Technol. (ICOIACT)*, Mar. 2018, pp. 196–201.

100. A. S. Alhanaf, M. Farsadi, and H. H. Balik, “Fault detection and classification in ring power system with DG penetration using hybrid CNN–LSTM,” *IEEE Access*, vol. 12, pp. 59953–59975, 2024.