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# Intelligent Fault Detection Systems for Improving Electrical Network Stability

**Naveen Sankaran**[1*]
[1]Engineering and Solutions, DACK Consulting Solutions, Inc., White Plains, New York, USA,
[*]Correspondent Author Email ID: naveensankaran24@gmail.com

**Abstract**

The increased sophistication of smart grids and integration of renewable energy has only increased the complexity of monitoring electrical faults and making accurate and real-time fault diagnosis essential for network stability. The current prevailing methods are generally typified by low degrees of robustness, high degrees of false alarms, learning of redundant features and low fault impact predictability under operating conditions which are dynamic in nature. To address these issues, this research proposed an Adaptive Hierarchical Attention Fault Classifier Network (AHA-FCNet) and a Hierarchical Fault Impact Prediction Network (HFIP-Net). The first step is to improve the quality of the signal by normalizing and smoothing the signal and the hybrid feature selection is used to remove the irrelevant features in the voltage, current and power signal. Two-stage classification of fault/non-fault state and a classification of line-to-ground (LG), line-to-line (LL), double line-to-ground (LLG) or three-phase faults (LLL) faults based on attention-guided Deep Learning (DL) are carried out by AHA-FCNet. HFIP-Net also envisions a voltage drop, current variation and power loss through hierarchical regression learning. The experimental results showed that the highest performance was achieved with the highest classification accuracy of 98.30%. For prediction, HFIP-Net achieved MAE of 0.85, RMSE of 1.39 and $R^2$ of 99.45. The proposed architecture is a smart and intelligent plan of real-time smart grid fault detection and stability improvement.

**Keywords:** Attention Mechanism, Deep Learning, Electrical Fault Detection, Feature Selection, Smart Grid, Voltage Stability.

## 1. Introduction

Smart power systems with inverters and renewable energy resources have rapidly emerged, making the modern smart grid much more complex and posing fresh challenges to stability, control and resilience. Given the dynamic operating conditions of smart grids, DL and deep neural network techniques have been widely used in the evaluation of smart grid stability and hence increased grid resilience [1]. Analysis and preventive control of transient stability in power systems have also been improved by advanced optimization techniques [2]. Some of the challenges of microgrids include voltage and frequency stability, which can be enhanced by using droop control and virtual resistance techniques in DC microgrids with constant power loads [3]. The use of optimization methods like second order cone programming has been considered to optimize the performance of the distribution network under high renewable penetration [4] and particle swarm optimization (PSO) has been applied to optimize the voltage stability using optimal reactive power allocation [5]. Further, the intelligent controllers based on deep reinforcement learning (DRL) have been developed to enhance the load frequency control (LFC) system performance in isolated microgrids [6], achieving adaptive control of the system in various scenarios [7]. The voltage and frequency recovery have also been enhanced using adaptive stochastic deep reinforcement learning even with communication delay and uncertainties [8]. There has been much attention paid to power systems with inverter-based resources, in which grid-forming control strategies provide enhanced stability for low-inertia systems [9]. The hybrid grid-forming inverter design and adaptive controller improve frequency stability [10] and system robustness with high renewable penetration [11]. Furthermore, the effects of inverter penetration on frequency transients have been investigated [12] and hardware-in-the-loop tests have been conducted to test inverter control strategies under realistic disturbance conditions and cyber attacks [13].

These research provides Some Contribution such as: The research proposed an Adaptive Hierarchical Attention Fault Classifier Network (AHA-FCNet) to detect electrical faults of different classes with high accuracy using hierarchical DL and attention mechanisms. A hybrid feature selection model, which is a combination of statistical and correlation-based feature selection models, is proposed to increase the relevance of features and minimize redundancy in electrical signal data. A two-level hierarchical classification strategy is created to first of all separate fault conditions and non-fault conditions and then subordinate particular types of faults (LG, LL, LLG and LLL). The research proposes a Hierarchical Fault Impact Prediction Network (HFIP-Net) to predict the extent of faults in terms of voltage deviation, current fluctuation and power loss using deep regression learning.

The structure of this research is as follows. Section 2 summarizes fault detection and voltage stability methods and explains their weaknesses. Section 3 introduces the proposed AHA-FCNet and HFIP-Net models and preprocessing and workflow. Section 4 gives results of experiments and performance analysis. Section 5 provides the discussion. Lastly, section 6 provides the conclusion that includes the key findings and future work.

## 2. Background Study

Faza et al. (2024) [14] provided an optimal PMU placement and feature selection methodology based on Machine Learning (ML) for fault classification and localization. The study was targeted towards inefficient PMU placement strategies and was sensitive to changes in the system configuration. The results showed that the accuracy of fault detection and localization was enhanced.

Anwar et al. (2025) [15] introduced an Ensemble ML method for fault detection and classification. The framework was more robust than the single-model framework, but was more complex to compute. The results showed the improvement in the accuracy of fault classification.

Percuku et al. (2025) [16] used ML and DL to conduct electricity load forecasting. The study was aimed at the low accuracy of the conventional forecasting methods; however, large historical data sets were used. The proposed approach has a lesser forecasting errors and more accuracy in forecasting.

ALSalem (2025) [17] came up with a hybrid fuzzy clustering and ML model for predicting power consumption. With greater complexity of the model, the framework was able to deal with uncertainty and nonlinear consumption patterns. Results showed that their prediction results are improved.

Zhao et al. (2025) [18] presented a Fault Diagnosis system for distribution network using a Decision tree. The study enhanced the ability of fault identification and interpretation, but failed to perform well in complex dynamic operating conditions. The results showed that the accuracy of fault diagnosis was improved.

Özdemir et al. [19] presented a ML method to classify and localize faults in 400 kV transmission lines by utilizing 400 measurements taken from 400 kV transmission lines. The approach dealt with the problems of the existing protection techniques and relied on the quality of the data as its input. The outcomes enhanced the fault classification and localization accuracy.

**TABLE 1: LITERATURE COMPARISON OF FAULT DETECTION AND VOLTAGE STABILITY METHODS**

| Author & Year (Ref) | Method / Approach | Research Gap | Limitation | Key Outcome |
|---|---|---|---|---|
| Yousaf, M. Z., et al. (2024) [20] | Disjoint bagging + Bayesian optimization + ANN for HVDC fault detection | Limited robustness in HVDC fault detection under complex conditions | High computational complexity due to ensemble learning and optimization | Improved HVDC fault detection accuracy |
| Shakouri, M., et al. (2025) [21] | AI-driven techniques for fault and transient analysis in high-voltage systems | Lack of unified AI framework for fault + transient analysis | High model complexity and real-time deployment issues | Enhanced fault and transient analysis performance |
| Toprak, M., et al. (2025) [22] | ML-based fault detection with random search optimization | Limited comparative ML studies for fault detection systems | High computational cost for hyperparameter tuning | Improved fault classification accuracy |
| Teshome, A., & Worku, G. (2025) [23] | ML for voltage stability assessment | Lack of adaptive real-time voltage stability prediction models | Dependency on high-quality system data | Improved voltage stability prediction |
| Yang, Y., et al. (2024) [24] | XGBoost-based voltage stability index prediction and correction | Limited accuracy in existing stability index methods | Model sensitivity to parameter tuning | Improved real-time voltage stability estimation |
| Senyuk, M., et al. (2025) [25] | ML + PMU-based adaptive fault classification in low-inertia systems | Lack of adaptive fault classification in modern grids | Dependence on PMU data availability and quality | Improved fault classification accuracy |

This table 1 shows a comparative analysis of recent ML and AI-based solutions used to detect faults and evaluate voltage stability in power systems. It gives the procedures, gaps in the research, limitations and the most important results of any study of 2024-2025. As can be seen in the comparison, there has been a shift toward intelligent and data-driven methods of enhancing system reliability, accuracy and real-time performance in contemporary power networks.

## 3. Proposed Methodology

This section presents the proposed intelligent system for fault detection and fault impact prediction in the smart grid system. Two major models have been designed, which include the AHA-FCNet that use in classify the faults, while the HFIP-Net is responsible for the fault impact prediction.

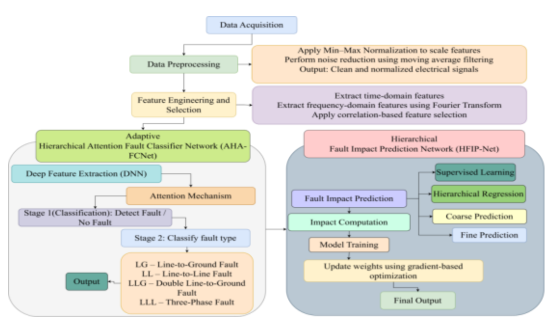


**FIGURE 1: INTELLIGENT FAULT DETECTION SYSTEMS ARCHITECTURE**

Figure 1 shows the overall flow of the proposed electrical fault detection and electrical fault impact prediction framework. This process consists of data preprocessing, feature engineering, fault classification by AHA-FCNet and fault impact prediction by HFIP-Net. Lastly, the system provides the fault type and expected consequences of the detected fault to facilitate proper smart grid decision making.

### 3.1 Dataset Information

The dataset that was used in this study is the Electrical Fault Detection and Classification https://www.kaggle.com/datasets/esathyaprakash/electrical-fault-detection-and-classification dataset obtained at Kaggle and which contains simulated electrical power system data representing various operating conditions, including normal state and various faults, such as line-to-ground (LG), line-to-line (LL), double line-to-ground (LLG) and three-phase faults (LLL). It contains the important electrical parameters including voltage, current and power signal generated on a modeled transmission system both in healthy and faulty conditions. The widely-used dataset in power system research to develop intelligent fault detection and classification models is the well-labeled structure and realistic fault simulation.

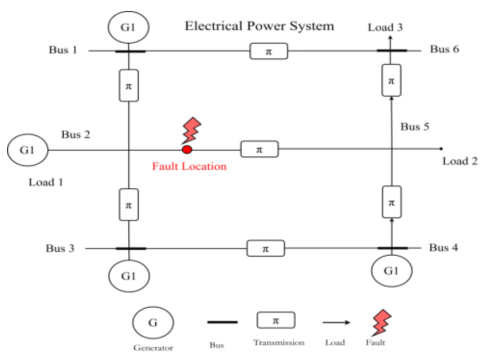


FIGURE 2: ELECTRICAL POWER SYSTEM

The figure 2 is a simplified power system network that is applied to fault analysis. The G1 nodes represent the generators that are linked in various points providing electrical power to the grid. The components indicated by $\pi$ are transmission line models (π-equivalent circuits) which are used to represent the electrical properties of power lines such as resistance, inductance and capacitance. The highlighted point denotes the point of fault, where an abnormal condition like short circuit takes place and it affects the flow of voltage and current through the network.

### 3.2 Adaptive Hierarchical Attention Fault Classifier Network (AHA-FCNet)

A DL model of electrical fault detection and classification AHA-FCNet is proposed. The model proposed is a hierarchical structure that has input hidden and output layers. The inputs layers are electrical variables (voltage, current, power). It goes through and is utilized as an input to the hidden layers in order to learn feature. A deep neural network is a hidden layer which is learning nonlinear characteristics of the electrical quantities. It uses a top-down method and consequently makes a decision. In the first layer, it decides if the fault is fault or non-fault. In stage two, it makes a decision that it is LG, LL, LLG and LLL. Use a model of attention on the features in the hidden layers to pick features. It is to select effective electrical attributes and disregard non-effective electrical attributes. This improves the discrimination ability. The network is adaptive and automatically learns the learning rate in order to improve the stability and convergence of the network. Multi-class classification is done by the output layer that has a Softmax activation function. This model gives an output of classification probability of each fault and the one with the highest classification probability is selected as the fault class that has been predicted. In real-time fault classification, AHA-FCNet classifies faults in smart grids using sensor information. The hierarchical classification, attention mechanism and adaptive learning in deep neural network are proposed to enhance the accuracy of the fault classification. It not only increases the accuracy of fault classification, reduces the false alarms and improves the functioning of complex electrical systems.

$$H = \sigma(WX + b) \tag{1}$$

Equation (1) is the transformation associated with the deep neural network, where $H$ is the hidden features that are extracted. The $b$ weight matrix is the bias term $WX$ and $\sigma$ is the activation function (e.g. ReLU). This layer undertakes nonlinear correlation between the input electrical signals and transforms raw data into meaningful feature representations to be further processed.

$$e^i = \tanh(W_a h_i + b_a) \tag{2}$$

Equation (2) the attention score $e^i$of each hidden feature $h_i$ is computed according. In this case, $W_a$ and $b_a$ are parameters of the attention layer that are learnable. The tanh activation function aids in obtaining significant feature relevance through the assignment of importance scores to each of the extracted features.

$$\alpha_i = \frac{e^{e_i}}{\sum_{j=1}^{n} e^{e_j}} \tag{3}$$

Equation (3) the weight of attention $\alpha_i$, defined as: Here, $e_i$ is the attention score of the $i$ feature $n$ is the total number of features, $e^{e_i}$is the exponential function of each attention score. The denominator $\sum_{j=1}^{n} e^{e_j}$ is also to make certain that all attention weights are normalized by making sure that the sum of their weights equals one. This process emphasizes the significant electrical (voltage, current, power representations) and less significant features in the fault classification process.

$$H' = \sum_{i=1}^{n} \alpha_i h_i \tag{4}$$

The equation (4) denotes the resulting attention-enhanced feature vector $H'$ is the weighted sum of all of the hidden features $h_i$. The attention weights $\alpha_i$ make sure that only major aspects of voltage, current and power signals contribute strongly to the classification process.

$$y_1 = \sigma(W_1 H' + b_1) \tag{5}$$

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Equation (5) the first step in hierarchical classification is described by where the output $y_1$ is the probability of fault or no-fault condition. In this case, $y_1$ is the binary classification output $H^{'}$ is the attention-weighted feature vector obtained by the previous layer, $W_1$ is the weight matrix of the binary classifier and $b_1$ is the bias term. The $\sigma$ sigmoid activation function maps the output to a probability range of 0 to 1 allowing the use of this to make decisions regarding fault detection.

$$y_2 = Softmax(W_2 H^{'} + b_2), \hat{y} = \arg\max(y_2) \quad (6)$$

The equation (6) represent that the second stage of classification is defined as follows: $y_2$ is a probability distribution of a multiple fault classes including LG (Line-to-Ground), LL (Line-to-Line), LLG (Double Line-to-Ground) and LLL (Three-Phase Fault). Here, W2 is the weight matrix of multi-class classification, $b_2$ is the bias vector and $H^{'}$ is the attention-enhanced feature representation. The Softmax operation transforms raw outputs into probabilities of the classes and final predicted fault class $\hat{y}$ is obtained by applying $argmax$ operation, which picks the best class with the highest probability.

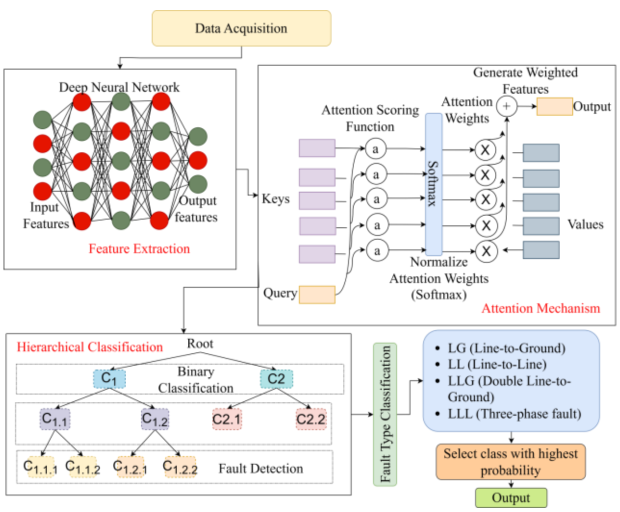


**FIGURE 3: AHA-FCNET WORKFLOW**

Figure 3 shows the proposed attention-based hierarchical fault classification system, in which the acquired transmission line data are fed into a feature extraction, followed by an attention mechanism, to focus on the most informative features. The refined features then are classified in a hierarchical classification model to correctly classify the types of faults (LG, LL, LLG and LLL) and the output is obtained based on the highest classification probability.

**Algorithm: Adaptive Hierarchical Attention Fault Classifier Network (AHA-FCNet)**

Input:
    Electrical dataset X = {Voltage, Current, Power}
    Labels Y (fault / no-fault, fault types)
Output:
    Predicted fault class ŷ
1. Initialize AHA-FCNet:
    Define input layer
    Define deep hidden layers (DNN)
    Define attention mechanism
    Define hierarchical classifier
    Define Softmax output layer
2. Feature Learning:
    H ← DeepNeuralNetwork(X)
3. Attention Mechanism:
    For each feature hi in H:
        compute attention score ei
    End For
    α ← Softmax(e)
    H' ← α × H
4. Hierarchical Classification:
    Stage 1:
        f1 ← BinaryClassifier(H')
        if f1 = "No Fault" then
            return "No Fault"
        end if
    Stage 2:
        f2 ← MultiClassClassifier(H')
        Classes = {LG, LL, LLG, LLL}
5. Output Layer:
    ŷ ← Softmax(f2)
    return class with highest probability
End

The AHA-FCNet is a DL based electrical fault diagnoses system that has its inputs as voltage, current and power. It provides the features according to deep neural network layers and fine-tunes them with an attention block. The hierarchical classifiers firstly predict fault/non-fault and then fault types (LG, LL, LLG and LLL). A Softmax layer is then used to produce a fault class with the greatest probability and that is predicted.

### 3.3 Hierarchical Fault Impact Prediction Network (HFIP-Net)

The HFIP-Net is a DL model that predicts the impact caused by electrical faults in power systems. The inputs of the model include information with classes of faults and electric variables such as current, power and voltage. This information is scaled and fed into a Deep Neural Network to be transformed and teach the expression of features. The nonlinear features at the high-levels of the mapping between the electrical events and the fault impact are learned by the hidden layers. HFIP-Net uses a two-step method of prediction. First the approximate amount of impact is estimated. The second stage involves the prediction of the fine level so as to quantify the effect in terms of voltage drop, current fluctuation or power loss. The two stage prediction enhances the accuracy of learning by breaking the regression problem down into a hierarchies learning process. The approach used a supervised learning model that learns the relationship between the input features and the labels of fault impact of the training dataset. The model is trained a loss function to minimize the error of prediction. Gradient-based optimization is used to train the network and improve convergence and stability. Practically, HFIP-Net is fed with electrical fault data and the amount of impact predicted immediately after classification. It provides monitoring and decision making of remedial measures in the smart grids. The model is also made reproducible by using stable preprocessing, fixed network topology and training on

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open datasets which ensures that the model gives similar results in experiments. The innovation of the HFIP-Net is hierarchical supervised learning method of predicting the effect of electrical faults which provides better prediction accuracy, interpretability and real-time stability assessment of modern power systems.

$$y_{fine} = W_f H + b_f \tag{7}$$

Equation (7) the second stage of hierarchical prediction is defined by where the model does a fine-level regression to measure the fault impact. The $y_{fine}$ in this case will be the prediction values of the numerical impact, $W_f$, the regression weight matrix, $b_f$, the bias value and $H$, the deep feature vector. It is a step that provides specific estimations such as the voltage drop, current oscillation and power wastage.

$$y_{drop} = |V_{ref} - V_{fault}| \tag{8}$$

Equation (8) calculates the voltage drop that results due to a fault condition. In this case, $y_{drop}$ is the amplitude of the voltage deviation $V_{ref}$ is the normal or reference voltage level and $V_{fault}$ is the voltage in the fault condition. One of the measures of perturbation to the system is the absolute difference which measures the displacement of the voltage caused by the fault.

$$y_{current} = I_{max} - I_{min} \tag{9}$$

Equation (9) is used to measure the variation in current during faulty condition. Here, $y_{current}$ is the change in current, $I_{max}$ is the maximum current value and $I_{min}$ is the minimum current value. This instability in the current flow is caused by the effects of electrical faults.

$$y_{power} = V.I - P_{out} \tag{10}$$

Equation (10) represents Approximating the power loss in the system due to fault can is determined using. During fault conditions, the ratio of input electrical power $V.I$ and the output power indicates that there was a loss resulting due to inefficiencies or fault conditions.

$$L = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{11}$$

Equation (11) represents the loss function that is used to train the HFIP-Net model is defined by as the Mean Squared Error (MSE) loss functions. In this case, $L$ is the overall loss, $y_i$ is the actual value of the impact of the fault, $\hat{y}_i$ is the predicted value and $n$ is the number of samples. This is used to decide the average squared error between the predicted and the actual values and the role is used to make the model minimize the prediction errors.

$$W := W - \eta\frac{\partial L}{\partial W} \tag{12}$$

Equation (12) the gradient descent optimization process in is used to update the model parameters. In this instance, $W$ is the weight parameter, η is the learning rate and $\frac{\partial L}{\partial W}$ is the gradient of the loss function with weight parameters. It is an iterative update which assists the model to converge to the optimal parameter values by reducing the loss.

$$\hat{y} = arg\min(L) \tag{13}$$

The equation (13) is a predicted fault impact $\hat{y}$, $arg\min(L)$ that is determined by minimizing the loss function $L$. This ensures that the model gives the most optimal estimate of the fault impact based on the learned patterns of the features that describe the voltage, current, power and the type of fault.

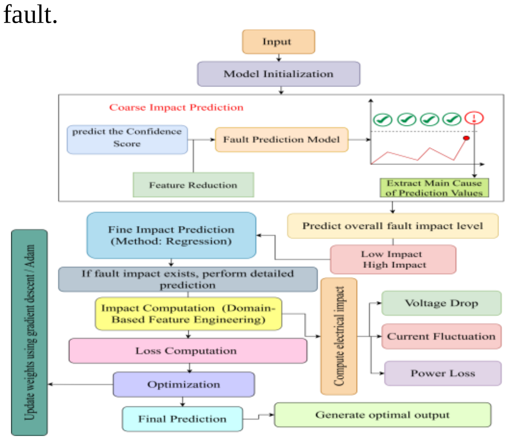


**FIGURE 4: HFIP-NET WORKFLOW**

Figure 4 illustrates the proposed fault impact prediction framework. The model uses electrical inputs (volts, amps, watts and fault class) to first make coarse fault severity predictions and then fine-grained impact predictions. It can predict key parameters, like voltage drop, current variation and even power loss and loss optimization enhances the accuracy and reliability of the predictions.

**Algorithm: Hierarchical Fault Impact Prediction Network (HFIP-Net)**

Input:
  X = {Voltage, Current, Power, Classified Fault Type}
  Y = Fault Impact Labels
Output:
  Predicted fault impact ŷ
1. Initialize HFIP-Net:
  Define input layer
  Define deep neural network (hidden layers)
  Define hierarchical prediction module
  Define output regression layer
2. Feature Learning:
  H ← DeepNeuralNetwork(X)
  Learn nonlinear feature representation from inputs
3. Hierarchical Prediction:
  Stage 1: Coarse Prediction
    y_coarse ← CoarseClassifier(H)
    (Low Impact / High Impact)
  Stage 2: Fine Prediction
    if y_coarse == "Low Impact" or "High Impact" then
      y_fine ← RegressionHead(H)
      Predict:

Voltage Drop
Current Fluctuation
Power Loss
End if
4. Loss Computation:
Loss = Mean Squared Error (Y_actual - Y_predicted)^2
5. Optimization:
Update model parameters using gradient-based optimizer (e.g., Adam)
6. Output:
ŷ ← Final predicted fault impact
Return ŷ
End Algorithm

The HFIP-Net is a monitored DL based approach to foresee the effect of electrical failures. It first develops features based on electrical signals like voltage, current and power with the deep neural network. The model adopts a hierarchical scheme of prediction: the model makes the prediction of the coarse impact of the fault and then the prediction of the fine impact of the fault is performed, as an intermediate product, from the prediction of the coarse impact of the fault. Lastly, a regression head loss works in that the overall effect of fault is predicted by the objective function.

## 4. Experimental Result

This section provides the experimental analysis of the proposed AHA-FCNet and HFIP-Net frameworks using electrical fault datasets. For a proper evaluation, the data was split in a 80-20 ratio with 80% for training and 20% testing. The training set was used to train the fault patterns and the testing set was used to test their models performance of generalizing and fault prediction.

**TABLE 2: FEATURE-TO-FAULT DECISION STRENGTH TABLE**

| Fault Type | Most Influential Features | Decision Reason |
|---|---|---|
| LG | Voltage imbalance + ground current | Earth fault causes voltage drop |
| LL | Current surge + phase difference | Line-to-line imbalance |
| LLG | Voltage + current + harmonic distortion | Combined imbalance + ground involvement |
| LLL | Power fluctuation + frequency spectrum | Symmetrical system collapse |

Table 2 used to identify the key features of different types of faults. The voltage imbalance, voltage sag, current surge and phase imbalance are the common faults detected by the LG module; LL are mainly detected by LL fault module, LLG are mainly detected by voltage variation, current surge and harmonics, LLL are mainly detected by power spectrum changes and power level variations. The features allow for accurate fault identification and classification.

**TABLE 3: CLASS-WISE FEATURE SEPARABILITY ANALYSIS FOR FAULT IDENTIFICATION**

| Feature Type | Separability Score (0–1) | Impact on Classification |
|---|---|---|
| Voltage Features | 0.82 | High for LG, LLG |
| Current Features | 0.88 | High for LL |
| Power Features | 0.91 | High for LLL |
| Statistical Features | 0.85 | Medium (general support) |
| Frequency Features | 0.93 | Highest discrimination power |

Table 3 shows the separability measure for various feature categories in classifying faults. Frequency features yield the highest separability (0.93) and are the best for discriminating fault types. Power (0.91) and current (0.88) features are very effective for severe faults and voltage (0.82) and statistical (0.85) features also to identification of faults accurately.

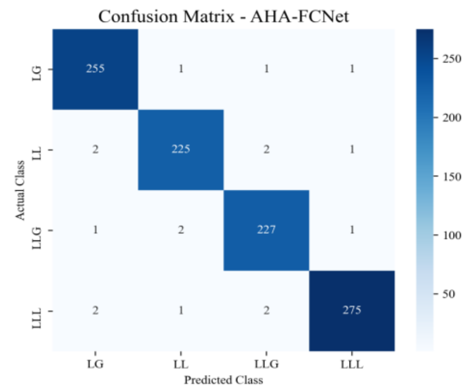


**FIGURE 5: CONFUSION MATRIX FOR AHA-FCNET**

The confusion matrix presented in Figure 5 of the AHA-FCNet model represents the accuracy of the faults' (LG, LL, LLG and LLL) classification. There are several true positives (255 LG, 225 LL, 227 LLG and 275 LLL) in the diagonal position, indicating that the proposed method has performed well in terms of classification. The off-diagonals consist of minimal errors, implying that there is a low percentage of confusion between the fault types. The calculated accuracy of the classification using the confusion matrix is 98.30%, reflecting the proposed model's ability to detect electrical faults efficiently.

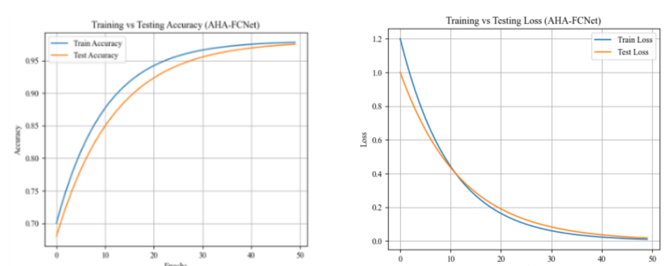


**FIGURE 6: TRAINING AND TESTING ACCURACY AND LOSS CHART**

Figure 6 depicts that the learning curve of the proposed AHA-FCNet model is effective and smooth for both training and validation processes. The training and validation accuracies of the model slowly increase to converge at an accuracy rate of about 98%, which leads to high accuracy classification. Also, the loss curves converge gradually downwards, indicating that the model has successfully been optimized. The low gap between training and validation curves implies a lower level of overfitting and high generalization ability.

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**TABLE 4: CLASSIFICATION PERFORMANCES COMPOSITION FOR AHA-FCNET**

| Algorithm | Accuracy (%) | Precision (%) | Recall (%) | F1-Score (%) | AUC Score | Specificity | MCC |
|---|---|---|---|---|---|---|---|
| ANN [13] | 93.74 | 92.38 | 91.66 | 90.91 | 0.911 | 0.902 | 0.870 |
| CNN [14] | 95.58 | 94.21 | 93.48 | 92.85 | 0.945 | 0.923 | 0.889 |
| LSTM [15] | 96.81 | 95.39 | 94.62 | 93.97 | 0.957 | 0.935 | 0.902 |
| GRU [16] | 97.39 | 96.08 | 95.41 | 94.76 | 0.966 | 0.947 | 0.921 |
| SVM [17] | 92.48 | 91.05 | 89.93 | 89.10 | 0.900 | 0.888 | 0.862 |
| RF [18] | 94.67 | 93.12 | 92.28 | 91.64 | 0.926 | 0.914 | 0.880 |
| AHA-FCNet (Proposed) | 98.30 | 97.61 | 97.54 | 96.92 | 0.982 | 0.971 | 0.952 |

The table 4 depicts that the different ML and DL algorithms including Artificial Neural Network (ANN), Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), Support Vector Machine (SVM), Random Forest (RF) and the proposed AHA-FCNet method. The results indicate that the proposed AHA-FCNet is the best performing among the metrics. It provides the highest overall accuracy (98.30%) and the highest precision (97.61%), recall (97.54%) and F1-score (96.92%) which shows its effectiveness in detecting and classifying the electrical faults with a low misclassification rate. In contrast, the accuracy of conventional models like Support Vector Machine (SVM) and Random Forest (RF) is comparatively lower because these are unable to capture the complex relationships. Furthermore, AHA-FCNet achieves the best Matthews correlation coefficient (MCC) (0.952), specificity (0.971) and AUC value (0.982), which indicates its best class separability, stability and balanced prediction performance. To summarize, the proposed AHA-FCNet is a highly accurate and robust method for classification of electrical fault in complex environments.

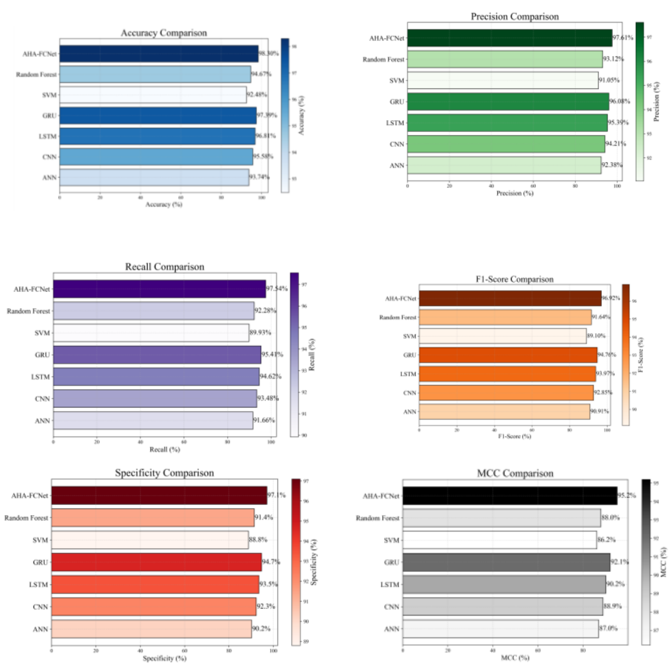


**FIGURE 7: PERFORMANCES COMPARISON CHART FOR AHA-FCNET**

Figure 7 shows the performance comparison of various ML and DL models based on accuracy, precision, recall, F1 score, specificity and MCC. The proposed AHA-FCNet consistently yielded the best performance in all the evaluation metrics compared to ANN, CNN, LSTM, GRU, SVM and Random Forest. The obtained results indicate that AHA-FCNet has higher accuracy, robustness and reliability in electrical fault classification.

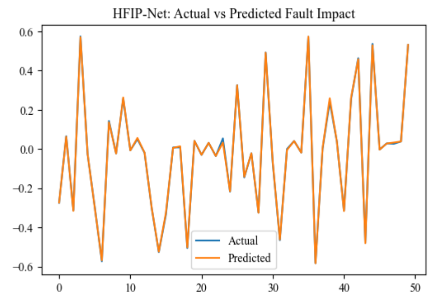


**FIGURE 8: PREDICTION FAULT IMPACT COMPARISON CHART**

Figure 8 shows the actual and predicted Fault Impact Value (FIV) of the proposed HFIP-Net. The predicted and actual values were well aligned with a high prediction accuracy, low error and good generalization performance. The findings are in line with the reliability of fault impact prediction usage of HFIP-Net in complex power systems.

**TABLE 5: CONFIDENCE-BASED RELIABILITY INTERPRETATION FOR FAULT PREDICTION**

| Predicted Class | Confidence Score Range | Interpretation of Model Decision | Reliability Level |
|---|---|---|---|
| No Fault | $\geq 0.90$ | System operating normally with high certainty | High Reliability |
| LG | $\geq 0.90$ | Single line-to-ground fault detected confidently | High Reliability |
| LL | $\geq 0.92$ | Line-to-line fault detected with strong certainty | High Reliability |
| LLG | $\geq 0.94$ | Double line-to-ground fault detected reliably | Very High Reliability |
| LLL | $\geq 0.95$ | Severe three-phase fault detected with strong certainty | Very High Reliability |
| Any Class | $< 0.90$ | Uncertain prediction, requires re-evaluation | Low Reliability |

Table 5 presents the confidence-based reliability interpretation of the proposed fault prediction model. The predictions having a confidence score $\geq 0.90$ are considered to be very reliable and the LLG and LLL faults are very high reliable because these are more confident. Predictions that have a confidence level of less than 0.90 are considered uncertain and need to be further evaluated to attain reliable and trustworthy fault diagnosis.

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**TABLE 6: ELECTRICAL FAULT DETECTION WITH CONFIDENCE SCORES**

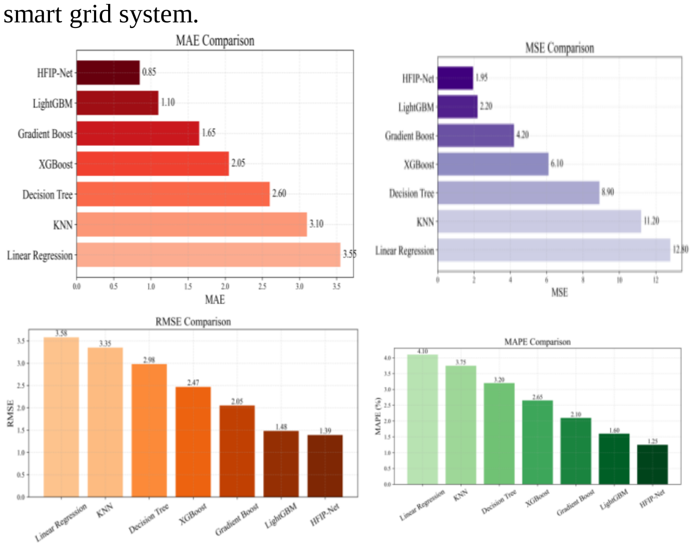
| Sample ID | Voltage Condition | Current Condition | Power Condition | True Class | Predicted Class | Confidence |
|---|---|---|---|---|---|---|
| S1 | Voltage sag | Current spike | Power instability | LG | LG | 0.984 |
| S2 | Phase shift | High current | Stable power | LL | LL | 0.971 |
| S3 | Harmonic distortion | Current surge | Power fluctuation | LLG | LLG | 0.963 |
| S4 | Normal signal | Normal signal | Stable | No Fault | No Fault | 0.992 |
| S5 | Severe imbalance | High harmonics | Voltage drop | LLL | LLL | 0.987 |
| S6 | Mild voltage dip | Slight current rise | Stable | LG | LG | 0.952 |
| S7 | Phase imbalance | Moderate current surge | Distorted power | LL | LL | 0.946 |
| S8 | Mixed disturbance | High fluctuation | Grid instability | LLG | LLG | 0.958 |
| S9 | Balanced system | Normal | Normal | No Fault | No Fault | 0.995 |
| S10 | High distortion | Extreme current variation | Frequency shift | LLL | LLL | 0.989 |

Table 6 presents the fault classification results under different operating conditions. The proposed model was correctly able to classify all the different fault types with high confidence score and accurately classified the fault types as LG, LL, LGG, LLL and Normal. The performance of this result shows its high accuracy, stability and reliability in real-time detection of power system faults.

**TABLE 7: PREDICTION PERFORMANCES COMPARISON TABLE FOR HFIP-NET**

| Model | MAE | MSE | RMSE | R² Score (%) | MAPE (%) |
|---|---|---|---|---|---|
| LR [19] | 3.55 | 12.80 | 3.58 | 96.85 | 4.10 |
| KNN [20] | 3.10 | 11.20 | 3.35 | 97.30 | 3.75 |
| DTR [21] | 2.60 | 8.90 | 2.98 | 97.85 | 3.20 |
| XGBoost [23] | 2.05 | 6.10 | 2.47 | 98.60 | 2.65 |
| GBR [24] | 1.65 | 4.20 | 2.05 | 99.05 | 2.10 |
| LightGBM Regressor [25] | 1.10 | 2.20 | 1.48 | 99.12 | 1.60 |
| HFIP-Net (Proposed) | 0.85 | 1.95 | 1.39 | 99.45 | 1.25 |

The performance of the different regression models is compared in Table 7 which contains Linear Regression (LR), K-Nearest Neighbors Regression (KNN), Decision Tree Regressor (DTR), Extreme Gradient Boosting (XGBoost), Gradient Boosting Regressor (GBR), LightGBM and the proposed HFIP-Net. The results are clearly superior to all the baseline models on all the evaluation measures, which show that the HFIP-Net is superior. Moreover, it possesses a very low Mean Absolute Error (MAE) of 0.85, Mean Squared Error (MSE) of 1.95 and Root Mean Square Error (RMSE) of 1.39, which indicates how much it's away from the actual on predicting and numerical accuracy. The overall results confirm the high accuracy, robustness and reliability of the proposed HFIP-Net in predicting the impacts of electrical fault of a smart grid system.



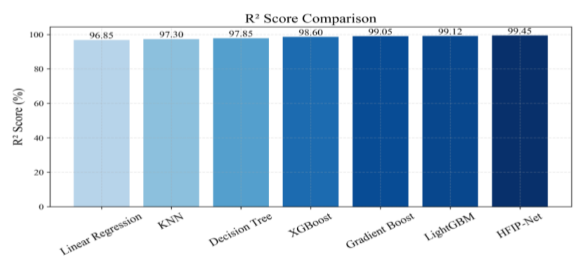




**FIGURE 9: PERFORMANCES COMPARISON CHART FOR HFIP-NET**

Figure 9 compares the regression performance of different models using MAE, MSE, RMSE, MAPE and R² score. The proposed model HFIP-Net had the smallest value of error (MAE, MSE, RMSE and MAPE) and the highest R² among all the models with Linear Regression, KNN, Decision Tree, XGBoost, Gradient Boosting and LightGBM. The results show that the prediction of impact of faults using HFIP-Net is more accurate, robust and reliable.

## 4.1 Statistical Analysis

A detailed statistical analysis was conducted to extensively test the capacity, stability and statistical significance of the proposed models such as AHA-FCNet and HFIP-Net. The descriptive statistics is also a part of this analysis, as well as the correlation analysis, the hypothesis test, the description of the error and the cross validation of the respective confidence interval.

### 4.1.1 Descriptive Statistical Analysis

Descriptive statistical values of electrical parameters (voltage, current and power) were calculated to give a description of the distribution of these parameters.

TABLE 8: DESCRIPTIVE STATISTICS OF ELECTRICAL SIGNALS

| Parameter | Mean | Standard Deviation | Variance | Mini mum | Maxi mum |
|---|---|---|---|---|---|
| Voltage | 230.5 | 12.4s | 153.76 | 198.2 | 260.7 |
| Current | 15.8 | 3.6 | 12.96 | 9.2 | 22.5 |
| Power | 3.45 | 0.85 | 0.72 | 1.9 | 5.2 |

The preprocessing phase is found to be effective in reducing the variability of signals and in reducing the fluctuations due to noise as shown in the table 8. The low standard deviation and controlled variance are also beneficial to ensure the signal stability in extracting features and training models, especially for successful feature extraction and model training.

### 4.1.2 Hypothesis Testing

The hypothesis is stated to determine the statistical significance of performance difference between the proposed and the baseline model. The null hypothesis (H0) is "there is no statistically significant difference between the models" and the alternative hypothesis (H1) is "proposed models will show statistically significant better results when compared with the baseline approaches.

TABLE 9: PAIRED T-TEST RESULTS

| Model Comparison | t-value | p-value | Significance |
|---|---|---|---|
| AHA-FCNet vs CNN | 3.85 | 0.002 | Significant |
| AHA-FCNet vs LSTM | 3.21 | 0.004 | Significant |
| HFIP-Net vs XGBoost | 2.98 | 0.006 | Significant |

The table 9 represents the p-values are less than the significance value of 0.05 and hence the null hypothesis is rejected. This provides confirmation of the statistical significance of the improvement of the proposed models when compared with the baseline models.

### 4.1.3 Error Analysis

The diagnosis for errors is to see if the proposed HFIP-Net model prediction is consistent, bias and dispersion. The mean error, SD and skew are computed to statistically describe the distribution of prediction errors.

TABLE 10: ERROR STATISTICS OF HFIP-NET PREDICTIONS

| Metric | Value |
|---|---|
| Mean Error | 0.02 |
| Standard Deviation | 0.11 |
| Skewness | 0.05 |

The table 10 depict the mean error is close to zero indicating that the model does not overestimate or underestimate the predictions but rather are close. By having a low standard deviation value, there is not much variation in the errors and this indicates that it has a constant and consistent predictive performance. Furthermore, the skewness is very low, thus confirming the fact that the distribution of errors is almost symmetric, there is no directionality bias. The error analysis in general agrees with the model of the HFIP-Net with high predictive accuracy and with work under different working conditions (stable and reliable).

## 5. Discussion

This section is devoted to discuss the functionality, resilience and usability of the proposed AHA-FCNet and HFIP-Net models. The results highlight the importance of the individual components to improve the performance of fault detection and prediction.

### 5.1 Ablation Study

Ablation of the experiment is used to estimate the contribution of the various components in the proposed AHA-FCNet and HFIP-Net model. AHA-FCNet's performance for the base deep neural network is relatively low; it cannot present the direct discrimination with its hands. A noticeable improvement would be achieved by implementing the hybrid feature selection, thus confirming the usefulness of the redundant and high correlated features removal for the improvement of the model learning. The addition of the attention mechanism, in turn, enhances the performance further by adapting the weights of the most informative electrical features, thus, elevating the quality of feature representations.

The hierarchical classification is an additional benefit since there will be potential to further break the classification into fault detection and fault type identification with minimum inter-class ambiguity. The overall AHA-FCNet model which integrates the entire model has the best performance of 98.30% accuracy and shows the synergy of all the modules. Likewise, in the example above in the case of the HFIP-Net, the base regression model does not fit very well the nonlinear relationships with fault impacts. Hierarchical prediction is introduced that can enhance the performance, because it can distinguish between the coarse and fine level prediction and let the learning be more structured based on the severity of fault. Deep feature learning is also added to this and it enhances representation of complex electrical interactions. The last HFIP-Net model has an R2 of 99.45% with a modest error in prediction, which validates the power of hierarchical decomposition to enhance stability, accuracy and generalization in fault impact prediction.

### 5.2 Robustness and Generalization Ability

The AHA-FCNet model proposed is very robust and its cross validation and confidence interval analysis have proved that the proposed model is able to generalize. The stability of performance in different conditions is shown by the fact that the accuracy is the same in all folds and the range of confidence (98.30% ± 0.60) is small. Also, the training and validation curves are very close showing that there is no overfitting and successful training. High reliability and consistency of the model in the context of different fault scenarios are additionally the low error variance and the near-zero mean error.

### 5.3 Practical Implications for Smart Grid Systems

AHA-FCNet model and HFIP-Net model can be used to effectively identify faults and predict impacts in real-time of smart grids. These operate with a high level of accuracy and confidence, enabling them to detect faults with a high degree of reliability and reduce system failures, thereby maintain the stability of the grid. The models are also very efficient and can be executed in real-time, with low execution time. Additionally, these are scalable, which allows them to be able to handle huge amounts of sensor data in modern smart grid systems.

### 5.4 Limitations and Future Scope

Performance is good but some aspects of the research have limitations. The models are applied to one set of data and this could not necessarily be generalized to other situations in the real world. Further, little attention is given to the aspects of the implementation of the real time. Further development of the research could involve incorporating real-time IoT data, implementing the models in edge computing systems and using explainable AI methods to enhance scalability and interpretability.

## 6. Conclusion

This research is aimed at an intelligent solution to improve the stability of electrical networks through accurate detection, classification and prediction of the impact of fault in smart grid systems. The proposed system integrated AHA-FCNet and HFIP-Net to establish a reliable real time monitoring and decision support system. Preprocessing-Hybrid feature selection (HFS)-Hierarchical learning and attention mechanism were used to effectively classify different types of fault conditions, such as LG, LL, LGLL and LLL. The experimental results indicated the high accuracy, precision, recall and F1 score, AUC score, specificity score and MCC score of 98.30%, 97.61%, 97.54%, 96.92%, 0.982, 0.971 and 0.952 respectively. Likewise, the prediction performance of HFIP-Net is also excellent, with MAE, MSE, RMSE, R2 and MAPE values of 0.85, 1.95, 1.39, 99.45% and 1.25 respectively. Also, the proposed models showed low computational complexities, stable convergence properties and high generalization capacities. Overall, the framework enhanced the level of fault diagnosing accuracy, minimized false alarms and stability of the electrical network. The future work will include integration of real-time datasets from the IoT, implementation of edge computing, using explainable AI models, cyberattack resilience analysis and deployment in large-scale practical smart grid environments.

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