



Original Article

Machine Learning-Powered Fault Detection System for Smart Grid Equipment with Predictive Analytics

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Abstract - As the backbone of modern business and society, a more sustainable and efficient electrical grid is necessary for efficient energy management. Evaluate and predict stability under different conditions since smart grid stabilization is one of the most crucial qualities that might be utilized to assess the effectiveness of smart grid architecture. For smart grid systems to remain stable, operate efficiently, and provide a steady supply of electricity, reliable defect detection is crucial. This study presents a data-driven approach using a neural network (NN) model for fault detection, leveraging the Smart Grid Stability dataset. The proposed NN model is implemented in a Python-based Jupyter Notebook environment and evaluated using standard performance metrics. The results of the experiment show good classification performance, with 98.02% accuracy, 98.92% precision, 98.03% recall, and 98.47% F1-score. Further analyses (confusion matrix, accuracy/loss curves, and ROC curves) support the model's generalizability and resilience. The NN model performs better than the existing state-of-the-art machine learning models (Logistic Regression, Random Forest, and Gradient Boosting) when compared to all important metrics. In general, the results indicate that the suggested NN model provides a trustworthy, saleable, and effective solution for intelligent fault detection in smart grid environments.

Keywords - Electrical Power Systems, Smart Grid Equipment, Fault Detection, Predictive Analytics, Grid Reliability, Machine Learning (ML), Smart Grid Stability Dataset.

1. Introduction

Electrical power systems are the mainstay of modern society, they allow power production, distribution, and transmission from a range of sources, including hydro, solar, wind, and nuclear, and thermal energy. With the global increase in demand for energy occasioned by rapid industrialization, urbanization and population growth, the importance of having strong, efficient, and scalable infrastructure for providing power becomes more pressing than ever. Traditional electrical grids are, at the very least, increasingly pressured by changes in demand, old infrastructure, and a lack of adaptability. To address these challenges, the smart grids have become the next generation of power system management [1]. These grids are equipped with modern technologies including real-time monitoring, smart meters, renewable energy integration, and two-way communication to improve visibility, automation and control across the electricity network [2]. Important elements in a smart grid are energy generation equipment, transformers, substations and distribution systems that are linked together and becoming more and more digitized should have the ability to dynamically adjust to grid circumstances.

Nevertheless, the introduction of heterogeneous and dispersed electricity elements enhances the system's susceptibility to various faults such as equipment failure, overloads, communications mistakes, and interference from intermittent renewable sources. These faults in smart grids can spread very quickly, causing blackouts, degraded power quality, and costing a lot of cash. Therefore, it's critical that errors be detected in time with accuracy to ensure the safety of the grid and high performance levels [3]. In order to make a fault detection system for smart grid equipment, not only should it be able to detect existing faults, but also predict eventual failures (before they happen) [4]. This is the point where predictive analytics comes into play. Once historical data is analyzed and a pattern in equipment behavior is established, predictive analytics allows early fault prediction and pre-emptive maintenance, which minimizes downtime and increases the reliability of the system.

A predictive method to problem detection in smart grids is made possible by predictive analytics, which makes using statistical models and previous data to predict future occurrences. By examining previous fault data, predictive models can detect likely fault points and determine when and where faults are likely to happen, which would allow grid operators to prepare pre-emptively [5][6]. This is a more effective method than the conventional ones that only come in after a fault has occurred [7][8]. Through the analysis of large amounts of real-time data, AI and ML offer advanced solutions for problem detection in smart grids by identifying intricate patterns that are invisible to conventional techniques [9][10]. AI/ML algorithms are able to cope with varied datasets that are produced by smart grids, which makes them preferable for such complex systems [11][12]. DL models are particularly efficient with spatial and temporal data streams produced by smart grid sensors and devices. These intelligent systems can learn complicated relationships in the data to facilitate real-time, automated fault detection and prediction.

1.1. Motivation and Contribution of the Study

The growing complexity of contemporary smart grid systems, as a result of renewable energy sources integration, distributed generation, and the presence of real-time data monitoring, has made fault detection increasingly difficult. Conventional fault detection methods do not always prove adequate to counter the dynamic behavior of such grids. While ML models have the capability to analyse mega datasets and detect complex patterns, their use holds enormous promise in enhancing the detection of faults in such sophisticated systems. This research paper is driven by the need to investigate and assess data-driven Smart grid systems can benefit from proactive problem detection and mitigation using ML models for fault detection, which can also stabilize and sustain the grid. Based on the Smart Grid Stability dataset, the research is aimed at comparing various ML models to determine which ones work best for defect detection. Below are the primary contributions of this study:

- Utilized Smart Grid Stability dataset to tackle the issue of defect detection in a smart grid setting.
- Developed a thoroughly painstaking data pre-processing pipeline that encompassed missing value handling and deletion of outliers to make data quality possible.
- Applied data-scaling to normalize value of features and enhance the performance of model.
- Improved the efficiency and interpretability of the model by using CFS to find the most pertinent characteristics.
- Proposed and implemented a classification model based on NN adapted to smart grid fault detection tasks.
- Performed comparative performance analysis through F1-score, recall, accuracy, and precision to evaluate how well the suggested approach works.

1.2. Justification and Novelty

This study defends its approach using a practical, real-world smart grid stability dataset; hence, it is applicable to power system monitoring. The dataset undergoes a rigorous preprocessing pipeline, addressing key challenges such as outliers, missing values, and data consistency using methods like imputation, outlier removal, and feature scaling. This study's originality comes from its incorporation of correlation-based feature selection to identify significant attributes, coupled with the application of a NN, GBM, LR, and RF models to improve fault detection. Unlike traditional methods, this study optimizes data-driven insights to enhance monitoring accuracy, ensuring scalability and robustness for real-world smart grid applications.

1.3. Structure of the paper

The structure of this paper is as follows: Section II provides the background study on fault detection in smart grid systems. The research approach for this study is detailed in Section III. Section IV presents the experimental results and analysis of the models' performance. Finally, Section V outlines the conclusion and potential future work of this study.

2. Literature Review

This section reviews the existing literature on the classification and detection of fault in smart grid equipment using ML approaches. The comparative analysis of ML approaches for fault detection based on their key findings, limitations, and future work, is provided in Table I.

Alhanaf, Balik and Farsadi (2023) Fault mitigation and smart grid self-healing depend on efficient fault localization, classification, and detection. DL can automatically identify fault categories and derive fault characteristics from the raw voltage and current data for three phases. Controlling dynamic fault currents has become increasingly challenging for conventional relaying systems due to the rise of dispersed generators. A number of DNN techniques have been put forth for the purposes of defect localization, classification, and detection. This study presents unique defect detection approaches using ANN and 1D-CNN. Their methodology exceeds current methods in terms of accuracy and efficiency by using sensor information, including measurements of current and voltage. The demonstration of the IEEE 6-bus system results for fault classification and fault localization for ANN and 1D-CNN were 98.25% and 96.85%, respectively [13].

Firos et al. (2023) identification of transmission line faults the power system's autonomous and efficient problem detection continues to be a significant problem in intelligent fault diagnostics. The creation of intelligent defect diagnostic methods that utilize ML has attracted a lot of attention in recent years. Various ML methods for defect categorization are showcased. After being cleaned and merged, Kaggle data is used. The ML models that are employed include RF, NB, and SVM. The best model is identified using the assessment metrics. With an accuracy rate of 97.77%, experimental results show that the NB will perform better than alternative methods for identifying electricity transmission line faults [14].

Baradieh et al. (2023) method for defect identification and classification that compares and applies twelve supervised ML classifiers. The PV output current characteristics matrix was built using statistical analysis. PV arrays exhibiting LL and LG faults were analyzed under difficult technical and environmental circumstances, and partial shading faults involving single, double, and triple-shaded modules were differentiated from full PV shading. Following the implementation of three cross-validation techniques, the Extra Trees classifier outperformed the others in terms of fault identification and provided a 94.44% accuracy rate for fault classification using the RF Classifier [15].

Adhikari, Prakash and Sharma (2023) Forecasting of energy is a crucial component in overcoming the challenges of smart grid mechanisms, which include functions such as demand-side management, load reduction, and desirable allocation. The most significant obstacle battling today's grid has to do with efficient forecasting management for restricted predictive inconsistencies, a comprehensive and application-focused review of advanced prediction strategies for smart grid systems, as well as the latest advances in the use of ML and DL methodologies. It also discusses the significance of hybridized techniques in improving the accuracy of forecasts an hourly energy consumption database has been carried out to evaluate the effectiveness of ML and DL techniques [16].

Abdelkhalek, Ravikumar, and Govindarasu (2022) the attack surface against these systems increased as a result of the smart grid. In order to initiate further effective mitigations, ML algorithms can identify intrusions at a fine granularity. It created DER-specific datasets using a data augmentation technique and retrieved 84 distinct IT/OT statistical variables using traffic thresholds based on patterns and DER physics. The suggested ADS system trains five DER-specific anomaly detection machine learning algorithms using a model-based methodology. For smooth integration in the assessment environment, the best approach is then serialized in an open-source format. This was done using a testbed HIL, CPS DER scheme with about 100 DER inverter models. The system's FPR was 0.28%, its detection accuracy was 98.4%, its detection latency was 5 μ s, and its FNR was 1.32% [17].

Massaoudi et al. (2021) field of smart grids (SG) has great promise for effective energy management and high system resilience. This continuous transformation is changing quickly, necessitating the use of several sophisticated approaches to handle the large amounts of data produced by different units. SG is closely linked to DL as a new technology for creating a more intelligent and decentralized energy paradigm and integrating high intelligence in supervisory and operational decision-making. Motivated by DL-based prediction approaches' impressive results, this work attempts to provide a thorough summary of the most recent advancements in DL in SG systems from a broad perspective. Additionally, investigate the process underlying some of the popular DL algorithms using the taxonomy. Then highlight the distributed computing, edge intelligence, and federated learning technologies that enable DL in SG. The RNN model's total accuracy percentage is 98.23% [18].

Table 1: Comparative Analysis of Literature Review on Fault Detection in Smart Grid Using ML

Author	Dataset	Models	Key Findings	Limitations	Future Work
Alhanaf, Balik and Farsadi (2023)	IEEE 6-bus system	ANN, 1D-CNN	98.25% accuracy for fault classification, 96.85% for fault location	Focus on specific network structure; limited to three-phase voltage and current data	Extend to other grid configurations and include multi-phase data analysis
Firos et al. (2023)	Kaggle dataset	SVM, NB, RF	NB model achieved 97.77% accuracy for fault detection	Dataset preprocessing and feature selection not discussed in depth	Explore hybrid ML models for enhanced accuracy and robustness
Baradieh et al. (2023)	PV output data	Extra Trees, RF, statistical analysis	94.44% accuracy for fault classification	Limited focus on PV arrays under specific shading conditions	Expand analysis to other fault types and environmental conditions
Adhikari, Prakash and Sharma (2023)	Hourly energy consumption data	ML, DL, hybrid techniques	Comprehensive review of ML/DL for energy forecasting	Lack of practical implementation and real-world validation	Develop hybrid predictive models for various smart grid functions
Abdelkhalek, Ravikumar and Govindarasu (2022)	DER-specific dataset	Data augmentation, ML algorithms	98.4% detection accuracy, low latency and false positive rates	Specific to DER environments; limited generalizability to other smart	Integrate ML-based detection systems in broader smart grid infrastructure

				grid components	
Massaoudi et al. (2021)	SG data	DL algorithms, RNN, federated learning	RNN achieved 98.23% accuracy in SG data prediction	Broad focus without specific fault detection application	Apply DL frameworks for decentralized grid fault detection and mitigation

3. Methodology

The research design is to evaluate data-driven ML models for identifying faults in smart grid networks. The following steps of the research design are outlined in the flowchart in Figure 1. Initially, the Smart Grid Stability dataset is collected and subjected to data pre-processing, involving handling of missing values and outlier removal. Data scaling is then performed to standardize the dataset, followed by feature selection with CFS to identify significant attributes relevant to fault detection. In order to evaluate the dataset is then split into training (75%) and testing (25%) sets for the model. A NN model is suggested and used for classification. In order to identify the best method for defect detection in smart grid equipment, the performance of these models is assessed using the F1-score, recall, accuracy, and precision

The flowchart's general procedures for fault in the smart grid system are shown below:

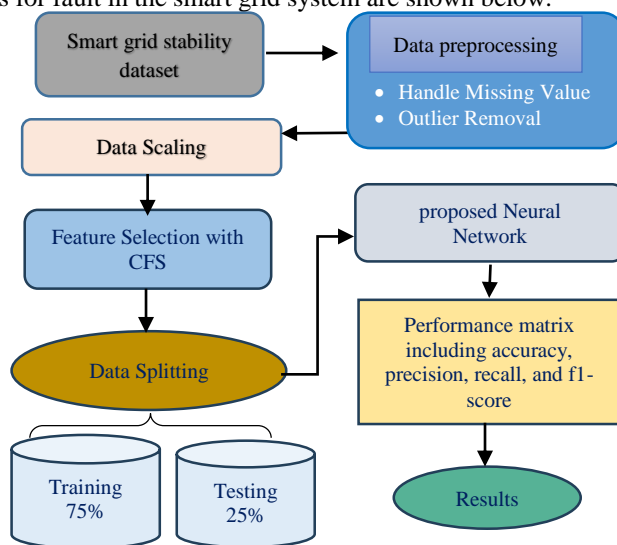


Fig 1: Flowchart for Fault in a Smart Grid System

3.1. Data Collection

The Smart Grid Stability dataset from Kaggle contains 60,000 samples, with two classes: stable (36.2%) and unstable (63.8%). It includes data from simulations of grid stability using a four-node star network design, with one energy source and three consumption nodes. The dataset features 12 predictive variables: four for nominal power (p1 to p4), four for reaction times (tau1 to tau4), and four for energy price elasticity (g1 to g4). Two dependent parameters, "stab" and "stabf," indicate grid stability and whether the system is stable or unstable, respectively. The scatter plot of the data is shown in Figure 2.

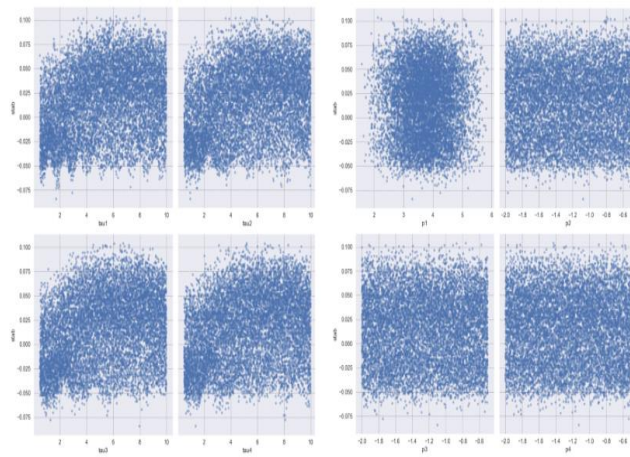


Fig 2: Scatter Plot of Features of Raw Dataset

Figure 2 Show the eight scatter plots in a 2x4 grid, visualizing the relationship between a common y-axis variable "tau0" (approx. -0.075 to 0.100) and eight distinct x-axis variables ("tau1" to "tau4", "p1" to "p4" with varying ranges); the scattered blue points indicate a lack of strong linear correlation between "tau0" and each of the independent variables. Fault analysis in smart grid systems is crucial for ensuring reliable and stable operation.

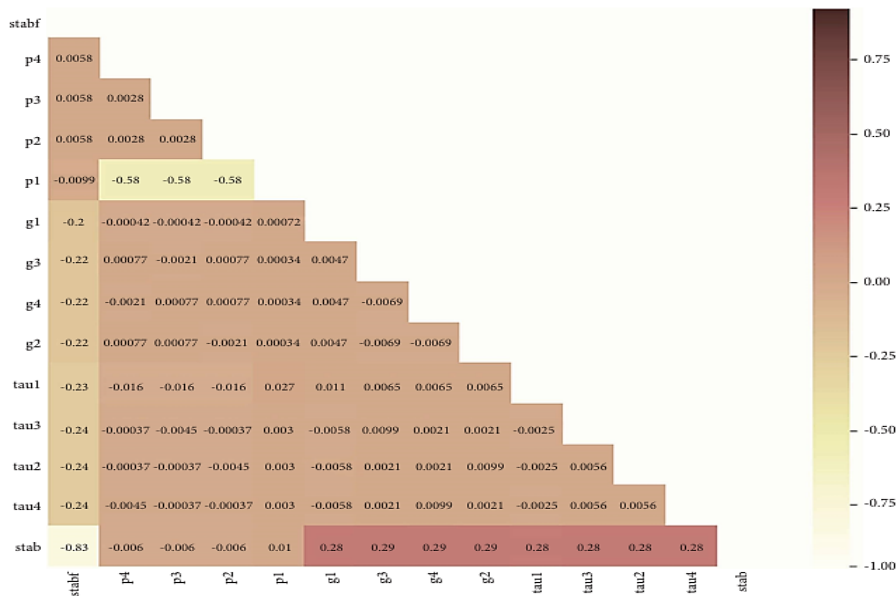


Fig 3: Correlation Matrix of the Dataset Feature

Figure 3 displays pairwise correlation coefficients between multiple variables, with rows and columns labelled as "p1" through "p7" and "task1" through "task5". The correlation values are represented by both numeric annotations (showing the precise coefficient values) and color coding, with a gradient scale ranging from approximately -1.00 (dark red) to +1.00 (dark brown), as the color bar on the right side indicates. The diagonal elements show perfect correlation (1.0) as expected. The matrix appears symmetrical across the diagonal, which is characteristic of correlation matrices. This type of correlation analysis is particularly valuable for Smart grid systems problem diagnostics.

3.2. Data Preprocessing

The step of preparing data for smart grid failure detection involves several essential steps. The dataset is first inspected to identify missing values, which are handled using techniques like mean imputation. Outliers are detected, Numerical features are then scaled to ensure uniform ranges, and the CFS method is applied to retain the most relevant attributes. The following pre-processing steps are listed below:

- **Handle missing value:** Missing data in smart grid fault detection can lead to biased model predictions and reduced accuracy. Appropriate techniques such as mean imputation, median imputation to maintain data integrity and reliability
- **Outlier Removal:** Outliers in smart grid fault detection data can distort model training and degrade prediction accuracy. Techniques interquartile range, and isolation forests are applied to detect and eliminate anomalies, ensuring data integrity.

3.3. Data Scaling

The numeric features are normalized to ensure all values are within a standard range, the technique is straightforward, and the range of values is defined as 0 to 1 [19]. The following is the formula for a universal value normalization. It transforms each numeric feature into the range [0, 1], it is a normalized Equation (1).

$$\hat{z} = \frac{z - z_{min}}{z_{max} - z_{min}} \quad (1)$$

Z is original value and Z_{min} is min value of z and Z_{max} is maximum value of z.

3.4. Feature Selection with CFS Method

The following premise underpins the estimation of feature subsets via CFS, provide for great feature subsets in classification [20], but showed little to no correlation with the other characteristics. Features that are highly correlated have a nearly identical impact on the variables that are dependent on them. A linear correlation coefficient c between the two variables (X, Y) may be represented by the Equation (2).

$$C = \frac{\sum_i(x_i - \bar{x}_i)(y_i - \bar{y}_i)}{\sqrt{\sum_i(x_i - \bar{x}_i)^2} \sqrt{\sum_i(y_i - \bar{y}_i)^2}} \quad (2)$$

At this point, the averages of X and Y are represented by \bar{x}_i and \bar{y}_i , respectively. In addition, when X and Y are associated, c is adjusted between -1 and 1. If X and Y don't depend on each other at all, then c is 0.

3.5. Data Splitting

The pre-processed dataset is used to build a training set and a testing set. Seventy-five percent of the two are used to train the model. The remaining 25% is used as the testing set to evaluate the model's performance.

3.6. Proposed Neural Network

The NN design that has been suggested is shown in Figure 4. Three hidden layers, an input layer, and an output layer make it up. Included among the 288 neurons and 12 characteristics that make up the input layer [21]. First, each input data feature is subjected to a hidden layer, which employs a ReLU activation function to extract data features [22]. There are two hundred and eighty neurons in this hidden layer, twenty-four neurons in a subsequent twelve neurons in a final hidden layer with a ReLU function, and another hidden layer with a ReLU function. In order for the neural network to detect additional characteristics that could have been overlooked by the earlier hidden layers, a final hidden layer is added. A dropout is used after the first hidden layer with a 25% drop rate from its neurons to alleviate the problem of overfitting.

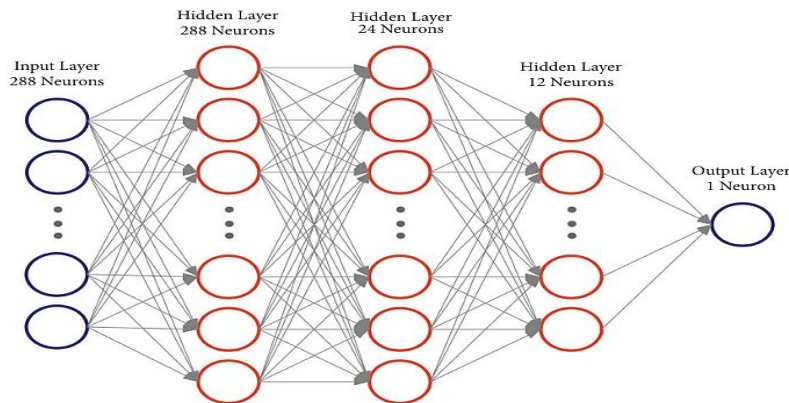


Fig 5: Schematic Diagram of Neural Network

This NN employs the Adam optimizer method. This technique in Figure 4's neural network determines the ideal weights for the network while minimizing mistakes and increasing training accuracy. A loss function called binary cross-entropy is used to measure the difference between expected and actual values.

3.7. Performance Metrics

The performance of the suggested NN is examined using a number of measures throughout the assessment process. These metrics include precision, recall, accuracy, and F1 score. The statistical information on which each metric is based is generated by a confusion matrix. The following is a definition of the confusion matrix words TP, TN, FP, and FN.

- True positive (TP): shows the quantity of positive components that were accurately anticipated to be positive.
- True negative (TN): shows the number of things that were accurately predicted but adversely.

- False positive (FP): demonstrates the percentage of negative components that were accurately expected to be positive.
- False negative (FN): shows the percentage of components that were positively predicted but turned out to be negatively.

Accuracy: A common tool for evaluating a model's effectiveness based on accuracy is the confusion matrix. Equation (3) has been utilized to determine the accuracy of the model:

$$Accuracy = \frac{TN + TP}{TP + TN + FP + FN} \quad (3)$$

Precision: The proportion of TP among all expected positives is known as precision. Stated differently, accuracy is the number of instances that the classifier recognised as positive, it is represented as Equation (4):

$$Precision = \frac{TP}{TP+FP} \quad (4)$$

Recall: The proportion of TP among all true positives is known as a recall. The model's recall has been computed, it is represented Equation (5):

$$Recall = \frac{TP}{TP+FN} \quad (5)$$

F1-score: The F-measure is the geometric median of recall and accuracy. Recall (R) and precision (P) couldn't coexist. The F1 score can be defined as follows Equation (6):

$$F1 = \frac{2*(precision*recall)}{precision+recall} \quad (6)$$

Roc-curve: The area under the ROC curve (AUC) is the integral of the FPR times the TPR. Tis metric value, or AUC, is always in the range of 0 and 1. A NN capacity to differentiate between different classes of smart grid stability is shown by a high AUC score. Accordingly, the optimal neural network for classification AUC in Equation (7) is the one with the biggest area under the ROC curve.

$$AUC = \int_0^1 TPRd(FPR) \quad (7)$$

According to Equation (8), the TPR is the ratio of TP to the sum of TP+FN. The ratio of FP to the total of FP+TN in Equation (9) is the FPR.

$$TPR = \frac{TP}{TP+FN} \quad (8)$$

$$FPR = \frac{FP}{FP+TN} \quad (9)$$

Their selection was based on how well The assessment measures include area under the curve, F1-score, accuracy, recall, and precision assessed and analyzed NN performance.

4. Result and Discussion

The experiment environment and this section present the findings of the suggested models. The suggested neural network is experimentally built in this Jupiter Notebook environment using the Python programming language. A PC running Microsoft Windows 10 The neural network is operated using an Intel Core i7 CPU with 16GB of RAM running at 2.2 GHz. Utilizing a smart grid stability dataset, the effectiveness of the suggested models was examined. Table II presents the results of an evaluation of each model's accuracy, precision, recall, and F1-score. The model demonstrates exceptional performance metrics across accuracy, is 98.02%, precision is 98.92%, recall is 98.03%, and F1-score is 98.47%, indicating its robustness in effectively classifying instances with minimal false positives and negatives. These results emphasize the NN model's dependability and effectiveness in detecting issues with smart grid hardware.

Table 2: Neural Network Performance on the Smart Grid Stability Dataset for Fault Detection

Matrix	Neural Network
Accuracy	98.02
precision	98.92
Recall	98.03
F1-score	98.47



Fig 6: Plot Accuracy Curve for Neural Network

Figure 5 shows the Accuracy curve illustrating the model's performance during training. The graph shows training accuracy (pink line) and testing accuracy (green line) plotted against the number of epochs. Both metrics rapidly improve from initial values around 75% and 90%, respectively, converging to approximately 97% by the end of training. The testing accuracy consistently exceeds training accuracy, suggesting excellent generalization capability for power fault detection in the smart grid.

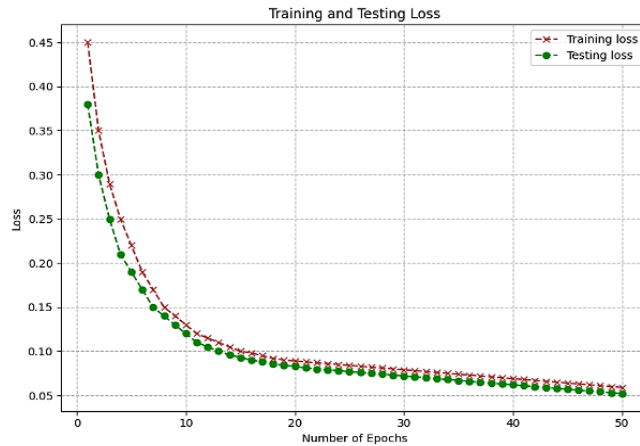


Fig 7: Plot Loss Curve for Neural Network

Figure 6 show the loss curve showing the training (pink line) and testing (green line) loss values against the number of epochs during model training. The graph demonstrates consistent convergence from initial loss values of approximately 0.45 and 0.38, respectively, to final stabilized values around 0.07, indicating successful optimization without overfitting. This validates the neural network's learning effectiveness for power fault detection in the smart grid.

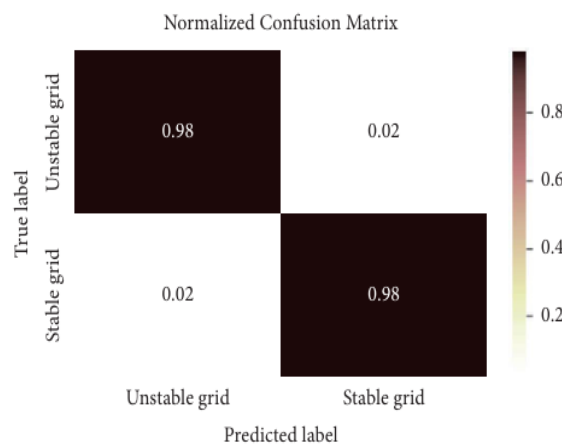


Fig 8: Confusion Matrix for Neural Network

The neural network's normalised confusion matrix model in show in Figure 7 for smart grid stability classification. The matrix shows 98% correct classification rates for both stable and unstable grid conditions, with only 2% misclassification between classes.

The dark diagonal elements represent high prediction accuracy, while the lighter off-diagonal elements indicate minimal errors, demonstrating excellent performance for power fault detection in the smart grid.

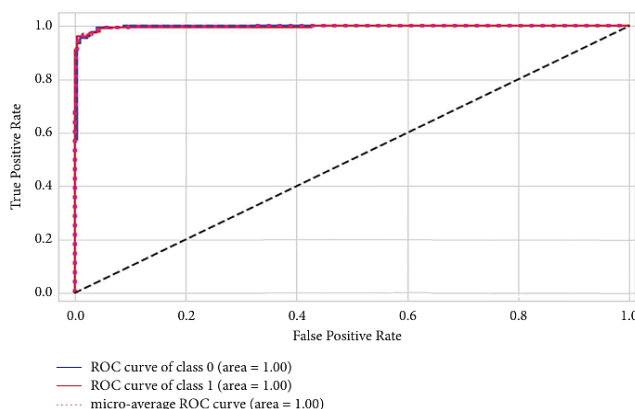


Fig 9: ROC Curve for the Neural Network

Figure 8 displays three overlapping curves (class 0, class 1, and micro-average) all achieving perfect AUC scores of 1.00, demonstrating optimal discrimination capability significantly outperforming random classification (diagonal dashed line) for fault detection on the smart grid.

Table 3: Comparative Analysis for Fault Detection in Smart Grid between Propose and Existing Models

Matrix	GBM [23]	LR[24]	RF [25]	NN
Accuracy	95	80.4	95	98.02
precision	-	84.3	95	98.92
Recall	-	81.2	94	98.03
F1-score	96.22	85	95	98.47

Table III of the comparison study shows how well a number of machine learning models operate for fault detection in smart grid systems. The NN model has a high accuracy of 98.02%, along with a precision of 98.92% and a recall of 98.03%. At 95% accuracy, the GBM model obtains a noteworthy F1-score of 96.22%. LR shows relatively lower accuracy at 80.4% and precision at 84.3%, with an F1-score of 85% and an 81.2% recall. The RF model performs admirably, with 95% F1-score, 94% recall, 95% accuracy, and 95% precision. These findings reflect that the NN and GBM models are superior to all other methods in overall accuracy and F1-score, which points to their usefulness in identification of faults in smart grid systems.

The Neural Network-based fault detection model proposed has several major advantages, such as high accuracy, robustness against data variability, and the ability to manage large-volume data efficiently. Its learning mechanism increases the quality of predictive performance by accurately detecting patterns of fault while reducing both FP and FN. In comparison to traditional approaches, the NN model delivers better classification metrics, which effectively guarantees reliable detection of faults in smart grid equipment. Such benefits make it a promising answer for ensuring operational stability and avoiding disruptions in the smart grid systems.

5. Conclusion and Future Work

Faults in smart grid systems are unplanned occurrences of breakages or abnormalities in the operation of equipment or networks that may lead to power outages, equipment failure, or unsteady state in the system. In a smart grid design, one of the smartest methods to forecast stability is to attenuate unexpected instability. Making use of the Smart Grid Stability data, this study proposed and supported an NN method for fault identification in smart grid systems. By extensive data pre-processing, feature selection, and training using a Python-based Jupiter environment, the study produced highly promising results. The NN model achieved an precision: 98.92%, recall: 98.03%, accuracy: 98.02%, and F1-score: 98.47%, and performed immensely better than the traditional ones like LR, RF, and GB Machines. Though the proposed neural network model has high performance, this study restricts itself to a static set of data and offline analysis, which may not reflect the dynamic nature of smart grid systems in real time. Additionally, the model's performance was evaluated under a controlled environment without considering noisy or adversarial data. Future work will focus on deploying the model in real-time smart grid settings, incorporating live data streams, and exploring hybrid or ensemble deep learning techniques to further enhance accuracy and robustness under varying operational conditions.

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