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Research Article

Predictive Analytics in Smart Grids: Leveraging Machine Learning for Renewable Energy Sources

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Abstract

Stability testing and forecasting under various situations is very relevant since it is one of the most essential factors for evaluating the utility of smart grid architecture. A future smart grid design that can anticipate stability and avoid unwelcome instabilities is necessary due to the proliferation of both residential and commercial buildings as well as the incorporation of renewable energy sources into smart networks. To tackle the problems that come with integrating renewable energy sources, this research looks at how smart grid systems may be made more stable with an employ of predictive analytics and ML models. A simulated smart grid stability dataset containing 60,000 entries and 14 features from Kaggle. Three models were employed: ANN, CNN, and CART. The ANN model achieved superior results, with an accuracy of 98.7%, precision of 98.03%, recall of 98.02%, and F1-score of 98.02%. Comparison of ANN, CNN, and CART models demonstrated the ANN's efficacy in accurately forecasting grid stability. The results highlight the promise of DL models and other forms of ML in predictive analytics for making renewable energy smart grids more reliable.

Keywords: *Smart grid, renewable energy resource, Solar Energy, Predictive Analytics machine learning.*

1. Introduction

Solar energy helps people and communities in developing nations achieve energy balance and advancement by meeting both individual and collective energy needs. Renewable energy sources have the greatest potential to save the environment while simultaneously lowering emissions of greenhouse gases, a rapidly worsening issue. Many nations employ renewable energy to create next-generation technologies. Energy from renewable sources, including solar, biomass, hydro, and wind, is used in different ways in different countries [1][2]. There are many obstacles to integrating renewable energy sources into current networks, including outages, voltage swings, and energy losses[3]. These issues prompted the development of the smart grid. Much of the world's "grid network," or electrical distribution infrastructure, was constructed when power was reasonably priced. To meet the rising demand for power, the basic grid network has undergone slight improvements [4].

Smart grid technology emerges as a solution to these challenges, offering a modernised framework for energy generation, distribution, and management. By leveraging advanced infrastructure, smart grids enhance grid asset controllability, performance, observability, and security[5][6]. It overcomes the shortcomings of conventional grids by enabling control and monitoring in real-time, which in turn allows for the effective incorporation of renewable energy sources [7][8]. Predictive analytics allows grid operators to analyse massive volumes of data and predict energy needs and supply changes, which is vital in this context. With predictive analytics, smart grids can anticipate potential issues, optimise energy distribution, and maintain balance even in the face of variable renewable energy inputs[9].

Machine learning further strengthens predictive analytics in smart grids by providing algorithms capable of analysing complex data patterns and making accurate predictions[10]. Machine learning models can process data from different sources—like weather conditions, energy usage patterns, and grid infrastructure—to forecast energy generation, consumption, and potential grid instabilities. A steady and dependable energy supply is ensured by these predictive insights, which allow for proactive modifications to grid operations[11][12]. The integration of machine learning into smart grids thus represents a transformative approach, supporting the efficient and resilient management of renewable energy sources in modern power systems[13].

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Aim and Contribution of paper

The goal of this research is to use ML methods to create a prediction model that is both accurate and efficient for evaluating smart grid stability datasets. The main contributions of this study are:

Streamlined data preprocessing by utilising a high-quality, simulated dataset with no missing values or outliers, eliminating the need for imputation or extensive cleaning.

Retained all features without feature selection, ensuring that each contributes to the stability calculation and enhancing model comprehensiveness.

Developed a predictive model for assessing smart grid stability using Artificial Neural Networks (ANN), CART, and CNN.

Evaluated model performance employing metrics like F1-score, accuracy, recall, and precision, offering a detailed assessment of prediction reliability.

Structure of paper

The formatting for the remainder of the paper is as follows. Research the history of smart grids using renewable energy sources in Sections 1 and 2. A thorough explanation of the process is given in Section 3. Section 4 compares and contrasts the findings, analysis, and debate. Section 5 presents the results of the study as well as suggestions for further research.

Literature Review

Recent years have seen a rise in scholarly interest in the potential of predictive analytics applied to smart grids that generate electricity from renewable sources. The following are a few excerpts from relevant studies:

In this paper, Moloi, Hamam and Jordaan, (2020) examine a power distribution system that incorporates wind energy for the purpose of identifying and repairing fault patterns. The MATLAB/Simulink model incorporates a wind power energy supply and a decreased Eskom 22kV. The integrated model is able to produce a wide range of power system problem kinds. Our research into signal decomposition using LPA and fault classification and detection using SVM continued. Additionally, they evaluated how well the NBC performed. In order to identify and fix fault patterns in a power distribution system that incorporates wind energy, this study suggests a hybrid approach based on LPA and SVM. The suggested approach was further evaluated with the help of the ML tools WEKA and Orange. Depending on the classifier, the results might range from 98% to 99% accuracy[14].

In Al-Haija, Al Tarayrah and Enshasy, (2020) optimise the R_SNN model, which is a regression-based SNN with 20 hidden neurones, by determining the optimal values for the training parameters, such as weights and biases, to get the best possible results in terms of model fitting and time series data prediction. Time series data modelling and short-term renewable energy addition forecasting using the R_SNN (20) model were effective. After 50 epochs of NN training, the R_SNN (20) model achieved the maximum data fitting accuracy of 99% and the smallest loss-based MSE for model estimation. Renewable energy capacity additions are shown in the model as following a linear trajectory [15].

In Ghorbanian, Dolatabadi and Siano, (2019) introduced an XGBoost algorithm that capitalised on inertial sensors. A power system with 39 buses was subjected to this technology, and it attained a 97% accuracy rate. However, just one evaluation metric, namely accuracy, was used to determine how well the built algorithm performed. In addition, many smart grid models may benefit from power system modelling in real-time[16].

In this paper, Yao, Lim and Lai, (2017) a smart home's RES, ESS, and main grid are all shown in this hardware demonstration. In order to regulate the quantity of power used from the main grid, a SLFC is suggested for use in HEMS. This controller would take into account electricity pricing, energy stored in ESS, and load needs. The goal of automatically modifying the SLFC's parameters using a self-learning technique based on GA is to make the controller more resilient in a variety of home settings. To further increase the parameter learning efficiency of SLFC, efficient parameterisation approaches are also provided to represent the antecedent and consequent parts of the fuzzy rule base with fewer parameters. Thorough research has shown that by using the energy storage capacity of ESS, the suggested SLFC can achieve a reduction in energy costs of up to 37.70% [17].

This paper Xu et al., (2016) developed a smart grid-based ML platform that is both dispersed and networked. In addition to allocating renewable energy resources and providing short-term energy forecasts, it can also analyse occupant mobility. First, a real-time indoor positioning system that analyses Wi-Fi data can capture the occupant profile. Then, a real-time meter system that analyses electrical load data can extract the energy profile. Finally, a web-based distributed learning system that updates its data in real time is employed to combine the energy profile and the 24-hour occupant profile with prediction. Allocating solar energy sources to the secondary power grid in anticipation of peak demand on the primary grid is based on predicted occupant movements and energy consumption profiles. Utilising a general-purpose ML engine, the whole management flow may be executed on a distributed smart gateway network with constrained computational resources. Results from experiments conducted on real-world datasets demonstrate that the suggested energy prediction approach may achieve an accuracy gain of 14.83 percent when compared to the SVM method. Along with a 51.94% decrease in energy costs, the peak demand from the main electrical power-grid is decreased by 15.20% [18].

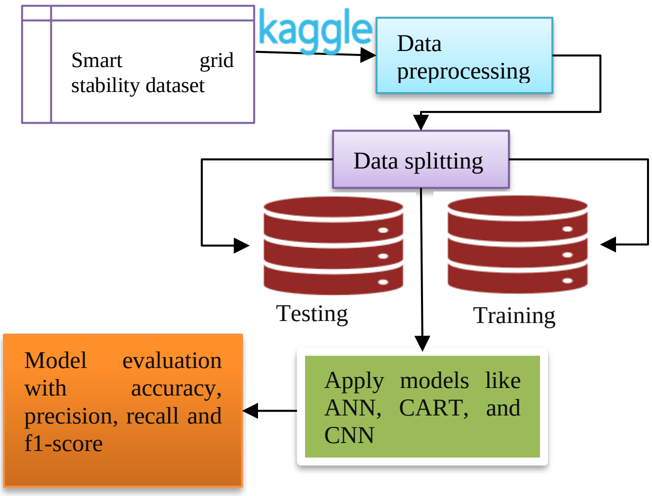
The background study of Predictive Analytics in Smart Grids for Renewable Energy Sources with its dataset, models, performance, and contribution is provided in Table I.

Table 1 Comparative Study on Predictive Analytics in Smart Grids for Renewable Energy Sources

Author	Data	Methods	Performance	Limitation/future work
Moloi, Hamam, and Jordaan (2020)	Simulated Eskom 22kV grid integrated with a wind power source modelled in MATLAB/Simulink	Hybrid Local Polynomial Approximation (LPA) and Support Vector Machine (SVM); tested on WEKA and Orange	Achieved 98%-99% accuracy in fault pattern recognition and detection	Limited focus on specific classifiers; future work could explore integrating other advanced ML techniques.
Al-Haija, Al Tarayrah, and Enshasy (2020)	Time series data for renewable energy additions for 2020-2025	Regression-based Shallow Neural Network (R_SNN) model with 20 hidden neurons	R_SNN (20) model accurately forecasts renewable energy additions with 99%.	Requires validation on more diverse datasets and longer forecasting horizons
Ghorbanian, Dolatabadi, and Siano (2019)	Power system data from a 39-bus network	XGBoost algorithm with inertial sensor input	Achieved 97% accuracy for fault detection in power systems	Only accuracy was used as an evaluation metric; future work should include additional performance metrics and real-time testing.
Yao, Lim, and Lai (2017)	Hardware demonstration with main grid, RES, and ESS	Self-Learning Fuzzy Controller (SLFC) optimised by Genetic Algorithm (GA)	SLFC achieved 37.70% energy cost savings by optimising electricity purchase and storage	Parameter tuning methods could be expanded; additional real-world testing needed under varying conditions.
Xu et al. (2016)	Real-life occupant and energy profiles (Wi-Fi data and electricity load data)	Distributed machine learning platform on smart gateways, using real-time Wi-Fi-based profiling and load data	Improved energy forecasting accuracy by 14.83%, reduced peak load by 15.20%, and achieved 51.94% energy cost savings.	Scalability and performance on larger, more diverse datasets need further investigation.

Research Methodology

A methodology for predicting smart grid stability begins with data collection, using a simulated dataset from Kaggle containing 60,000 rows and 14 features, where stability is calculated based on 12 features.



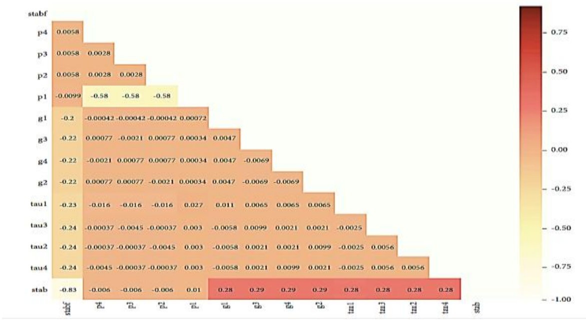
Flowchart for Predictive Analytics in Smart Grids for Renewable Energy Sources

A heatmap correlation matrix illustrates relationships among features, with the dataset showing minimal correlations and no outliers, as confirmed by box plots. Data preprocessing is streamlined due to the high-quality simulated data—no missing values, outliers, or categorical variables—allowing for direct application of the dataset in the model. A data is split 70-30 for training and testing purposes. An CART, CNN and ANN are used for smart grid system. The evaluation metrics—like F1-score, precision, recall, and accuracy—are computed using the confusion matrix values (TP, TN, FP, and FN) to evaluate how well the model predicts grid stability and to provide information about its resilience and efficacy. The overall steps of implementation are shown in Figure 1.

Below is a brief description of each component of Figure 1, "Predictive Analytics in Smart Grids for Renewable Energy Sources. "

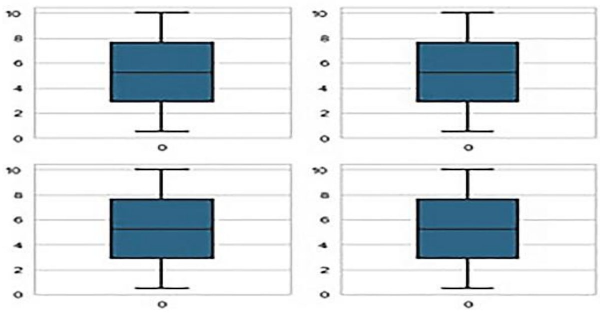
Data Collection

This dataset on smart grid stability is accessible for free on Kaggle. The dataset has 60000 rows and 14 characteristics. The first 12 attributes are averaged to generate the grid's stability value, which is then used to classify the grid as either stable or unstable. The attribute connections are displayed in Figure 2 using a heatmap.



Correlation matrix of the dataset features

Figure 2 shows a heatmap representing the correlation matrix between various features in a dataset. The features include stabf, p1 through p4, g1 through g4, tau1 through tau4, and stab. Each cell in the matrix displays the correlation coefficient between a pair of variables, ranging from -1 (darkest shades) to +1 (lighter shades), as indicated by the colour bar on the right. Lighter colours (those closer to white) indicate significant positive connections, whilst darker tones (those closer to brown) indicate strong negative correlations. For example, p1 and p2 have a moderately negative correlation of -0.58, while stab and tau1 show a strong positive correlation of 0.29. Most of the variables exhibit relatively weak correlations, as many coefficients are close to zero.



Box plot for no outliers

Figure 3 displays four identical box plots without any outliers, illustrating a consistent data distribution across the plots. Each plot has a box representing the interquartile range (IQR), with the median marked by a central line, and whiskers extending to a minimum and maximum values within an accepted range. A lack of outliers suggests that all values fall within the expected spread, indicating a potentially uniform or well-contained dataset.

Data Preprocessing

For the smart grid stability dataset, data preprocessing was streamlined due to the high-quality nature of the simulated data. As the dataset was synthetically generated, there were no missing values, making imputation techniques unnecessary[19][20]. All features were retained for analysis without applying feature selection algorithms, as each attribute contributes to the stability value calculation. Since the data consists entirely of numerical values, no categorical encoding was required. Additionally, the absence of outliers, confirmed through box plots, indicates a well-distributed dataset with consistent shape, variability, and median, allowing for straightforward modelling without the need for further data adjustments[21].

Data Splitting

The dataset is split into two halves, with 70% used for training and 30% for testing.

Artificial neural network (ANN) Models

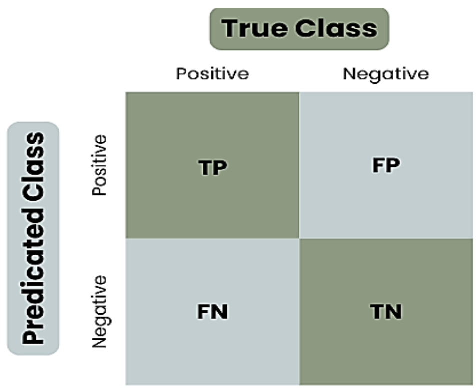
Three layers comprise an ANN: the input, hidden, and output layers. The hidden layer, which is the neural network's brains and is in charge of continuously changing the weights to enhance performance, receives input characteristics from the input layer[22][23]. The classes produced by the network are shown in the output layer. The neural network's output is affected by the learning process and propagation function. Equation 1 represents the propagation function, which allows you to control an inputs of a j-th neurone by an outputs of a preceding neurones[24].

$$P_j(t) = \sum 0_i(t) \times w_{ij} + b \quad (1)$$

where a propagation function is denoted by $pj\ (t)$, an output of a previous neurone by $Oi(t)$, a weight by wij, and a bias by b. In order for the neural network to produce a desirable output from a given set of inputs, the learning rule modifies the network's parameters. Using the learning rule as a guide, the learning process adjusts the network's weights to enhance output computation[25][26]. With intensive training and back-propagating the mistakes, the artificial neural network employs a high number of neurones with weights that are changed to increase the learning rate [27][28].

Evaluation metrics

This is the prediction model's last phase. Here, assess the prediction outcomes using a variety of assessment measures, such as f1-score, confusion matrix, and classification accuracy. A confusion matrix determines the statistical values that each measure is based on: TN, FP, TP, and FN. Figure 4 shows a matrix of perplexity.



Representation of confusion metrics

TN demonstrates that the model is accurate when it predicts the negative class.
A negative forecast for the positive class is indicated by the acronym FP.
TP is the outcome of accurately predicting the positive class.
The negative class is mispredicted by FN.

Accuracy: A ratio of accurate predictions to all of the testing dataset's predictions is known as accuracy. It is provided as (2).

$$Accuracy = \frac{\text{TP+TN}}{\text{TP+Fp+TN+FN}} \quad (2)$$

Precision: Precision may be defined as the ratio of accurate class activity predictions to all class predictions in the testing dataset. The expression for it is (3).

$$Precision = \frac{\text{TP}}{\text{TP+FP}} \quad (3)$$

Recall: Recall is the proportion of correctly identified positives for a given class to all actual class activities in the test dataset. It is expressed mathematically as (4).

$$Recall = \frac{\text{TP}}{TP+FN} \quad (4)$$

F1 score: It is used to assess a test's accuracy. The average of recall and precision is known as the F1 Score. [0, 1] is the range of the F1 Score. It informs you of the robustness and precision of your classifier. It is expressed mathematically as (5).

$$F1-score = 2 \times \frac{Precision \times Recall}{Precision+Recall} \quad (5)$$

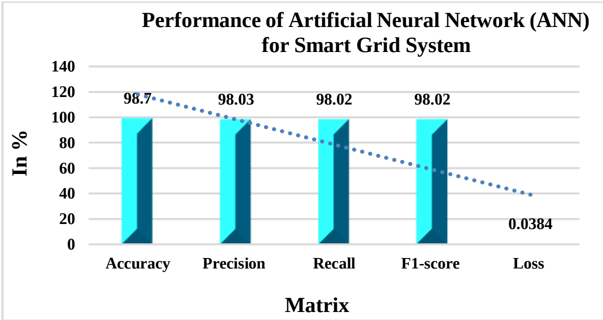
These metrics collectively provide insights into an accuracy and effectiveness of a model in predicting a target variable.

Results And Discussion

An experiment result of models like CART[29], CNN[30] and ANN is provided in this section. The following models are trained on the smart grid stability dataset and measured on Recall, accuracy, precision, and f1-score. In this section, firstly provide the ANN model performance for smart grid system. Then, comparison of model's performance on dataset. Table II provides the performance of the ANN model with graphical results including confusion matrix, learning curves of loss and accuracy, and ROC curves.

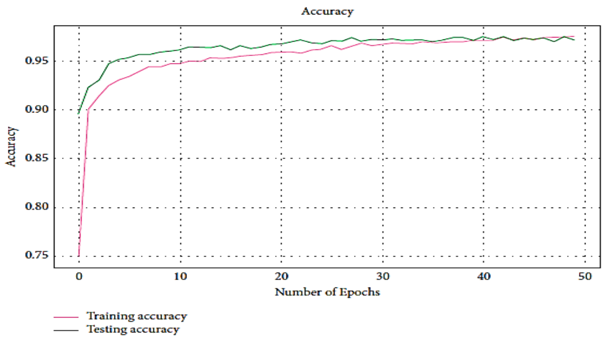
Table 2 ANN model efficiency across performance matrix

Performance matrix	Artificial Neural Network (ANN)
Accuracy	98.7
Precision	98.03
Recall	98.02
F1-score	98.02
Loss	0.0384



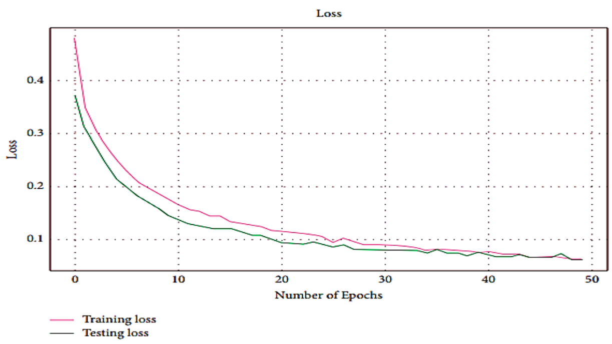
ANN model performance on smart grid stability dataset

Table II and Figure 5 above illustrate the ANN model's performance. This figure shows that ANN performs well overall and effectively classifies positive occurrences, with an accuracy of 97.36%, precision 98.03%, recall 98.02, F1-score of 98.02%, and loss0.0384.



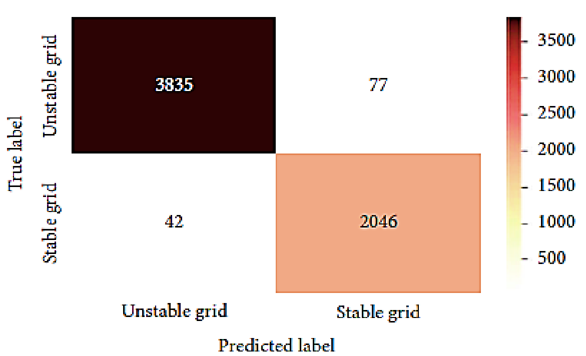
Accuracy curves for ANN model

Figure 6 displays the training and testing accuracy of a model across 50 epochs. Initially, both accuracies increase rapidly, with testing accuracy slightly surpassing training accuracy around the 10th epoch, indicating the model generalises well. As training continues, both accuracies converge and stabilise around 95%, showing minimal fluctuation. The close alignment of training and testing accuracy lines suggests that the model has not overfit the data and is likely well-optimised for both training and test sets.



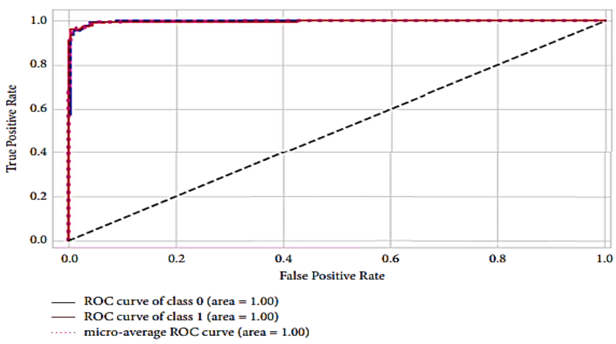
Loss curves for the neural network

Figure 7 displays a model's training and testing loss across 50 epochs. Both losses decrease steeply at first, showing rapid learning in the initial epochs. By around the 20th epoch, the loss values begin to converge and stabilise, with training loss slightly lower than testing loss, indicating good generalisation with minimal overfitting. Both losses reach values close to zero by the 50th epoch, suggesting the model is effectively minimising error for both training and test data.



Confusion matrix for the ANN

Figure 8 below displays a confusion matrix with two labels: the real label and the anticipated label. The confusion matrix assesses how well a model performs in dividing grid stability into two groups: unstable and stable. The matrix reveals that the model accurately predicted 3835 unstable grids and 2046 stable grids. However, it misclassified 77 unstable grids as stable and 42 stable grids as unstable.

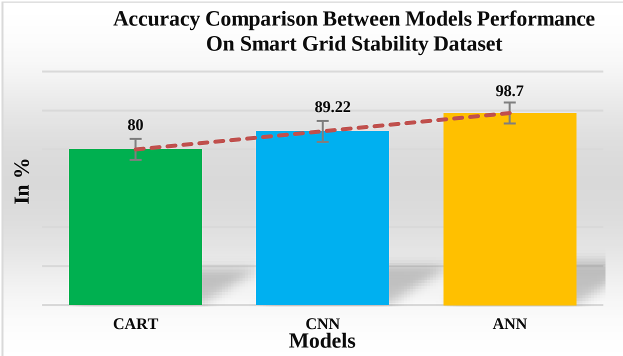


ROC curves for the neural network

Figure 9 displays the ROC curves for a classification model. The ROC curve visually shows a trade-off between TP rate (sensitivity) and FP rate (specificity) when the classification threshold changes. In this case, both the ROC curves for class 0 and class 1, as well as the micro-average ROC curve, exhibit an AUC of 1.00. This indicates that a model discriminates perfectly among two classes, achieving high sensitivity and specificity across all classification thresholds.

Table 3 Accuracy Comparison between ML and DL models for smart grid system

Model	Accuracy
Classification and Regression Trees (CART)	80
Convolutional Neural Network (CNN)	89.22
Artificial Neural Network (ANN)	98.7



Accuracy comparison between model

Comparisons of the smart grid system's model accuracy are shown in Figure 10, which is located above Table III. The ANN outperforms the other models significantly, with an accuracy of 97.36%. The CART model achieved 80% accuracy, and CNN improved to 89.22%. overall, the ANN model achieves the highest performance for smart grid systems.

Conclusion and Future Study

The rapid development of residential neighbourhoods and industrial parks has made smart grid technologies more and more crucial. Modernising electrical power networks and improving their efficiency, dependability, and adaptability are the goals of the Smart Grid system. It gathers data and generates forecasts for decision optimisation by integrating time series forecasting ML algorithms, networks, and smart sensors into the current grid transmission system. This study tested several ML and DL models on a simulated dataset to forecast smart grid stability. The analysis highlighted an effectiveness of an ANN compared to traditional ML models, like CART, ANN, and CNN. The ANN demonstrated exceptional performance, achieving an accuracy of 98.7%, with precision, recall, and F1-score values closely aligned at approximately 98.02%. These findings demonstrate the ANN's strong capacity to correctly categorise grid stability, which makes it a useful tool for smart grid applications. In contrast, the CART, and CNN models exhibited significantly lower performance metrics, with accuracies of 80% and 89.22%, respectively. This underscores the superiority of ANN in handling complex classification tasks in smart grid stability prediction. Future work may focus on integrating these models into real-time smart grid monitoring systems and exploring their adaptability to varying operational conditions and datasets.

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