An efficient smart grid stability prediction system based on machine learning and deep learning fusion model

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ABSTRACT

A smart grid is a modern power system that allows for bidirectional communication, driven mostly by the idea of demand responsiveness. Predicting the stability of the smart grid is necessary for improving its dependability and maximizing the efficacy and regularity of electricity delivery. Predicting smart grid stability is difficult owing to the various elements that impact it, including consumer and producer engagement, which may contribute to smart grid stability. This research work proposes machine learning (ML) and deep learning (DL) approaches for predicting smart grid sustainability. Five ML algorithms, namely support vector machine (SVM), decision tree (DT), K-nearest neighbor (KNN), random forest (RF), and logistic regression (LR), were applied for the prediction of smart grid stability. Later, the stacking ensemble and voting ensemble of ML algorithms were also applied for prediction. To further increase accuracy, a novel fusion model with DL artifical neural networks (ANN) and ML SVM was applied and achieved an accuracy of 98.92%. The experiment results show that the proposed model outperformed existing models for smart grid stability prediction.

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1. INTRODUCTION

Energy consumption is expected to increase significantly over the next several decades due to factors such as the world's increasing population and industrialization, as well as the expansion of the global economy. As a result of its versatility as an energy source and its widespread availability, electricity has risen to prominence in recent years. Electricity generation stems from a multitude of sources, encompassing thermal energy, solar power, hydroelectricity, nuclear reactors, wind turbines, and the extraction of fossil fuels. This diversity underscores its status as a pivotal energy source. Furthermore, as populations expand and societies progress, the associated surge in power requirements sets higher standards for energy generation. Smart grids have the capability to amalgamate consumer data to establish an efficient electricity distribution system. Smart grids harness renewable energy resources, rendering them a secure addition to the power grid. These grids evaluate real-time supply data through the collection of consumer demand information. Subsequently, they compute the electricity cost and convey this pricing data to customers, enabling them to make informed decisions regarding usage. Given the time-sensitive character of this process, ensuring the stability of a smart grid emerges as one of its principal imperatives. In a smart grid, information about how much power people want is collected, compared centrally to how much power is available now, and then the suggested price information is sent back to users so they can decide how much power to use. Since the whole process depends on time, predicting grid stability dynamically is not only a worry but also a big need. The goal is to comprehend and prepare for changes and disruptions in energy production and/or usage that are caused by people in the system. This should be done in a dynamic way, taking into account not only technical factors but also how participants react to changes in the energy price.

Applying machine learning (ML) and DL techniques to smart grid applications is not new. Alsirhani *et al.* [1] used a novel MLP-ELM strategy to predicting the reliability of smart grid networks by standardizing the results using a Z-score. Non-numeric values were transformed during preprocessing, and patterns were discovered via exploration. The results demonstrated that MLP-ELM outperformed conventional techniques, with 95.5% accuracy, 90% percent precision, 88% recall, and 89% F-measure, all of which point to its potential in improving smart grid dependability. Breviglieri *et al.* [2], the authors used a suite of optimized deep learning (DL) models to investigate the distributed smart grid control (DSGC) system across a broad input value range, with the goal of predicting the smart grid's stability without the use of limiting assumptions. The proposed DL models achieved good accuracy. The authors demonstrated that DL models provided novel insights into the simulated environment and it shown rapid adaptation that improves system stability.

The technique suggested in [3] aimed to address the difficulty of stability prediction in the presence of missing data. The loss of a sensor, network link, or other system might account for this missing variable. This work proposed a unique feed forward neural network (FFNN) model that can deal with missing inputs, which proved to be an effective solution to the problem. A star network with just four nodes was used to test the model's accuracy. Four different scenarios with missing input data were used in this analysis. For each scenario, a secondary neural network was trained to forecast the missing variables; these results were then used as input by the main neural network to make stability predictions. During training and testing, the sub-neural network performed the best, with a mean squared error (MSE) of 0.0001 and an R2 of 0.99. During training, the principal network's R2 was 0.9, while it was 0.97 during testing. The MSE for this network was 0.008. The models performed quite well across all four scenarios, with MSEs around zero and R-sqaured values close to one. A novel upgraded stacked GRU-RNN for univariate and multivariate scenarios was used to anticipate renewable energy (RE) production and electricity demand [4]. Multiple sensitive monitoring metrics or historical power consumption data are selected for the input dataset using correlation analysis. A simpler GRU, AdaGrad and configurable momentum are then built into a stacked GRU-RNN. The revised training approach and redesigned GRU-RNN structure improve training efficiency and robustness. Using its self-feedback connections and better training mechanism, the stacked GRU-RNN maps the specified variables to RE generation or electricity load. Two studies verify the suggested method: predicting wind power production using meteorological characteristics and modeling electricity demand using historical energy usage data. The experimental findings indicated that the suggested technique can provide accurate energy estimates needed for smart grid operations.

Naz *et al.* [5], the authors used the UMass Electric Dataset and two different ways to predict how much power would be used and how much it would cost. The suggested ELR method is better at making predictions than both CNN and LR. This has been proven using measures like MAPE, MAE, MSE, and RMSE on both the UMass Electric and UCI datasets. The dataset, which is multiple, is normalized and then split into a training set and a testing set. Recursive feature elimination (RFE), CART, and Relief-F are all used in feature engineering. ELR, which was made to make accurate predictions, does better than existing models, which is a big step forward for the accuracy of estimates for smart grid operations. Singh and Yassine [6], the energy demand was predicted with the help of CNNs. But CNN requires setting a number of levels, which makes it complicated in both space and time. Two improved ways are suggested to make the load and price of energy more accurate. Both methods use samples that have one variable or more than one. Also, both home data and data from utilities are analyzed together. Massaoudi *et al.* [7] automatically tuned hyperparameters using simulated annealing to improve the forecasting model. Simulations revealed that the suggested model made accurate predictions on a simulated electrical grid stability dataset. Comparisons show its advantages over cutting-edge solutions. Bingi and Prusty [8], the authors proposed neural network models trained with the damped least-squares technique for predicting the stability of smart grids. The results demonstrate the superior performance of the feed-forward neural network in terms of minimal error and highest R2 values for the considered system.

Tiwari *et al.* [9], the authors used a range of ML methods to guess the grid's security and keep it from breaking down. A Kaggle daatset was used in the tests. With 98% accuracy, the suggested model could predict load using the Bagging classifier method. Accurate predictions of how much power will be used are a key part of keeping the grid from going down, which makes the grid more stable and stronger overall. Ahmed *et al.* [10], the authors discussed how smart grid and green energy may be utilized combined to meet rising energy demand. They discussed the challenges of designing a smart grid with green energy. The authors also noted the importance of ML models over statistical models for nonlinear data. Mohsen *et al.* [11], the authors recommended employing a neural network to forecast the reliability of a smart grid. The dataset used is derived from DSGC system simulations. Testing the suggested neural network's efficacy yielded a loss rate of 0.06, accuracy of 97%, and a loss rate of 0.06 during training. Hong *et al.* [12], the authors introduced a short-term residence load forecasting system that use DL to exploit the spatio-temporal correlation found in load data from appliances. Paragraphs are used to explain the way in which a particular activity or set of actions are related to one another inside the same sequence of words. To learn the association among various power consumption habits for short-term load forecasting, a deep neural network and iterative ResBlock-based technique is developed. The effectiveness of the suggested forecasting method has been tested via experiments using real-world observations. The outcomes demonstrate that load data from appliances and iterative ResBlocks may both contribute to better predicting results.

Alazab *et al.* [13], a unique multidirectional long short-term memory (LSTM) approach is being developed to forecast the stability of the smart grid network. Results are compared to those achieved using other well-known DL methods, such as GRU and conventional LSTM and RNN. The experimental findings demonstrate that MLSTM performs better than the competing ML methods. Bose *et al.* [14], the authors addressed innovative smart grid AI applications. Automation of current wind generating system design and health monitoring in operation, fault pattern detection of an SG subsystem, and real-time simulator-based SG control are these applications. Many additional applications may be created from these examples. The article begins with a quick overview of AI basics relevant to these applications. Jindal *et al.* [15] used DT and support vector machine (SVM) classifiers to analyze power use data rigorously. Since the SVM classifier receives DT-processed data, the suggested technique is a two-level data processing and analysis strategy. Furthermore, the findings show that the suggested approach greatly lowers false positives and is feasible for real-time use. Önder *et al.* [16], the authors applied cascading of ML algorithms and achieved good results. The results shown that cascade methods outperformed conventional ML methods. Sallam [17] applied DL technique for smart grid stability prediction and achieved good results. A case study of ML models used to anticipate smart grid stability and difficulties that may arise when renewable energy is employed was described in [18]. The authors in [19] applied various ML techniques for smartgrid stability prediction and achived good results. They used ML models to predict power-grid synchronization stability [20]. The algorithms used in experiemnts are RF, SVM and artifical neural networks (ANN). Neelakandan *et al.* [21] are creating a stability prediction system using MHSA-LSTM. SOS optimization was used to optimize MHSA-LSTM model hyperparameters. The AHBFS and SOS algorithms greatly affect the MHSA-LSTM models for stability prediction. Several simulations illustrate AHBFS-ODLSP model adjustments and analyze their results. The AHBFS-ODLSP approach performs best with a 99% F score. Reddy *et al.* [22], neural networks, decision trees (DTs), and SVM were utilized in smart grid management systems and performed well. Maizana *et al.* [23] carried out a stability investigation of the smart grid management system on the campus building. The authors observed that the battery is acting as a source while the PLN and solar cells are providing the energy, or vice versa, and just one bus at the load is in an unstable or dangerous state. Aziz and Lawi [24] proposed ensemble ML methods for electrical grid stability and achieved good accuracy. The authors experimented with C 4.5 and CART algorithms and reported good results. Merza *et al.* [25] describe AI strategies built on DL algorithms that can use real-time measurement data to detect foreign direct investment (FDI) assaults on smart grids. Untraceable FDI assaults that bypass SVE defenses are countered with the help of the convolutional deep belief network (CDBN) design.

Most of the existing works proposed conventional ML models or DL models for stability prediction in smart grid. In this paper, the authors proposed novel fusion method of ML and DL algorithm for smartgrid stability prediction. The rest of the paper is organized as follows: Section 2 explains proposed method. Section 3 consists of results and discussion. Section 4 has a conclusion.

2. METHOD

The proposed architecture for smart grid stability perdiction system using ML and DL fusion is shown in Figure 1. Initially, a dataset was collected from UCI repository. The dataset contains the information about smartgrid with 12 features. The details of the dataset are described below.

2.1. Collection of smartgrid dataset

The dataset on smartgrid sustainability was collected from the UCI repository [26]. There are 10,000 samples of 12 independent features. Each network member's response time falls between 0.5 and 10 milliseconds for "tau1" to "tau4". Each participant's nominal power produced or used runs from -2.0 to -0.5

for consumers from "p1" to "p4". Between 0.05 and 1.00, 'g1' to 'g4' show the price elasticity coefficient for each network member. Features'stab' and'stabf' work together or separately. Later, several data preprocessing techniques were applied to clean the data and prepare it in the required format. In data preprocessing missing values are eliminated from dataset. Also, the dataset is checked for outliers. The collected dataset has no outliers. Finally, the cleaned dataset is ready for applying ML models.

Later, several ML algorithms were applied to the dataset. The algorithms used are SVM, logistic regression (LR), Random Forst and DT. The results obtained with ML algorithms are noted.

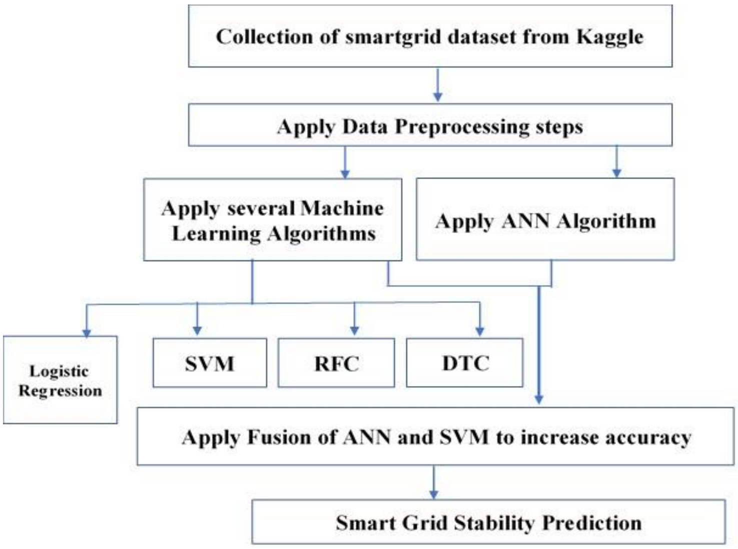

Figure 1. Proposed methodology

The use of various artificial intelligence (AI) methods, including ML and DL has been extensively observed in the paper pertaining to smart grids. These approaches have been employed to enhance the efficiency of energy consumption. In this work several ML algorithms and fusion of ML and DL ANN used for prediction of stability in smart grid. The algorithms used in this paper are described below.

2.2. Logistic regression

LR is a method in statistics and ML for making predictions between two discrete categories, often represented by the binary digits 0 and 1. The logistic LR input belongs to the positive class (1) given a set of input features. The logistic function, also called the sigmoid function, converts any real number to a value between zero and one, making it an excellent tool for modeling probability. Because of its interpretability and computational efficiency, It is widely used in a wide variety of contexts. It finds widespread use in fields as diverse as healthcare (disease presence prediction), marketing (customer churn prediction), and NLP (text classification), to name a few. As a starting point for more advanced classification methods like SVM and Neural Networks, its simplicity belies its effectiveness.

2.3. Decision tree

Popular for both binary and multi-class classification applications, DT Classification is a supervised ML approach. Each feature choice is represented by an internal node, and each leaf node represents a class label or a class distribution, in a tree-like structure that is generated by recursively partitioning the dataset into subsets based on the input features. The decision-making process starts at the root node and follows a path down the tree based on feature values until a leaf node is reached, which provides the final classification decision. DTs are interpretable and can handle both numerical and categorical data. They are prone to overfitting when the tree is deep and highly complex.

2.4. Random forest

Random forest (RF) is a powerful ensemble learning technique used for both binary and multi-class classification tasks. It is an extension of DT classification that mitigates some of the issues associated with single DTs, such as overfitting and high variance. In a RF, multiple DTs are constructed during training, each on a random subset of the data and with the ability to consider a random subset of features for making decisions at each node. This randomness and diversity in tree construction help improve the model's generalization ability and reduce the risk of overfitting. During prediction, each tree in the forest casts a vote, and the class with the most votes becomes the final prediction. RFs are known for their robustness, scalability, and ability to handle high-dimensional data.

2.5. Support vector classifier

Is a powerful supervised ML algorithm used primarily for binary classification tasks. Its fundamental idea is to find a hyperplane that best separates two classes in feature space while maximizing the margin between the nearest data points (support vectors) from each class to that hyperplane. SVMs are particularly well-suited for scenarios with limited training data, as they focus on the most informative data points (the support vectors) and are less prone to overfitting. They have found applications in various domains, including image recognition, text classification, and bioinformatics, where they are valued for their robustness and ability to generalize to new, unseen data. However, SVMs can be sensitive to the choice of hyperparameters, such as the kernel type and regularization parameters, and may require careful tuning for optimal performance. The model performance is estimated using several measures like accuracy, precision, recall, f1-score.

2.6. Model performance evaluation

Various metrics, like accuracy, precision, recall, and f1-score, were used to judge the model's success. How right the model is as a whole is measured by its accuracy. It's the number of correctly expected cases out of all the cases. Precision is the number of properly predicted positive observations divided by the total number of predicted positives. It assesses the accuracy of the positive predictions. Recall is crucial when the cost of false negatives is high. In medical diagnoses, for instance, it's essential to minimize false negatives even if it means more false positives. In summary, accuracy gives an overall picture, precision focuses on the accuracy of positive predictions, recall emphasizes the ability to capture all positive instances, and F1 score provides a balance between precision and recall. After applying ML techniues we achieved good results.To increase the performance, ANN technique was also applied.

2.7. Artifical neural networks

ANNs are based on the behavior of real neural networks, like the brain. In ANNs, artificial neurons or units, which are made up of nodes that are linked to each other, are arranged in layers. The three primary types of layers are the input layer, hidden layers, and output layer. The input layer receives raw data as input features, which are then transmitted through the network. Each input neuron corresponds to a feature in the data. Between the input and output layers, there can be one or more hidden layers. These layers are responsible for capturing and transforming the input data into a format that can be used to make predictions. Each neuron in a hidden layer processes information from the previous layer, applies weights to the inputs, calculates a weighted sum, and passes the result through an activation function. The activation function gives the model non-linearity, which lets it learn complicated trends in the data. The information processed by the hidden layers is sent to the output layer, which makes the final forecasts or classifications. The number of neurons in the output layer depends on the nature of the problem, with binary classification typically having one neuron with a sigmoid activation function and multi-class classification involving multiple neurons with softmax activation. The strengths of ANNs lie in their ability to learn and model complex relationships in data, making them suitable for various applications. Training an ANN involves modifying the weights and biases associated with each neuron,typically using techniques like backpropagation and gradient descent. DL, a subfield of ML, extends ANNs by using deep neural networks with many hidden layers, making them capable of tackling even more intricate and high-dimensional problems. To further improve the performace, fusion of ANN and SVM was applied and achived good resuts. Here the ouptuts of ANN models are given as input to SVM and prediction are made.

3. RESULTS AND DISCUSSION

3.1. Applying ML algorithms

The collected data contains 10,000 samples. It is divided into training and testing set with a ratio of 80,20. So, the training data dataset contains 8,000 samples and testing data contains 2,000 samples. Four ML algorithms namely LR, DT, RF, Support Vector Machine applied and results are tabulated. Later DL ANN applied. There are 3 hidden layers in proposed neural network model. The number of epochs in the model is 50. The results after applying ML algorithms are shown in Table 1. Figures 2 and 3 specify the precision, recall, f1 score, and accuracy values of ML models.

Table 1. Results of experiments with ML algorithms

Algorithm	Class	Precision	Recall	F1-Score	Accuracy
Log reg	0	0.84	0.88	0.86	81.4%
	1	0.77	0,70	0,73	
DT	0	0.92	0.93	0.92	89.8%
	1	0.77	0.70	0.73	
RF	0	0.95	0.97	0.96	94.6%
	1	0.94	0.91	0.92	
	0	0.98	0.99	0.98	97.8%
SVM	1	0.98	0.96	0.97	
	0	0.98	0.98	0.98	97.2%
ANN	1	0.96	0.97	0.96	

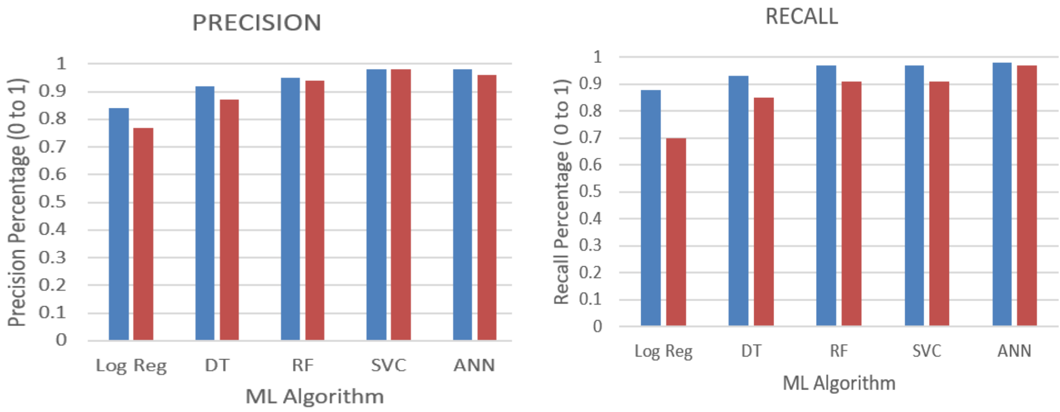

Figure 2. Precision, Recall of ML algorithms

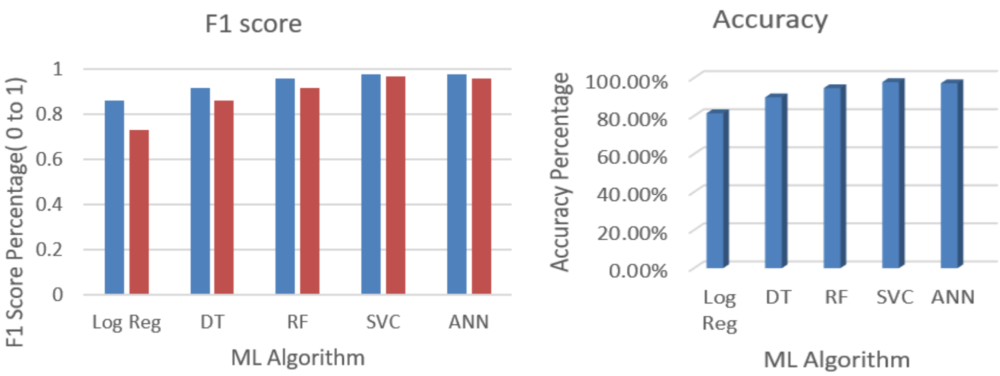

Figure 3. F1 score, accuracy of ML algorithms

From Table 1, it is observed that SVM given best results after applying ML algorithms. SVM given an accuracy of 97.8% where as ANN given next best accuracy of 97.2%. From Figure 2 it is observed that precision and recall values also good for SVM and ANN. From Figure 3, it is observed that accuracy and f1-score of SVC and ANN are better than remaining algorithms. So, after analyzing the results it is observed that SVM and ANN performed better in all aspects. To further increase the peformance of the model, an ensemble of SVM and ANN is proposed.

3.2. Applying SVM and ANN ensemble model

The process of amalgamating an ANN with a SVM for classification entails leveraging the feature extraction ability of the ANN and subsequently utilizing an SVM to conduct the classification task using these extracted features. Upon completion of training, the intermediary or final layers within the ANN are employed to extract pertinent features from the dataset, capturing crucial information essential for classification purposes. These derived features are subsequently utilized as inputs for an SVM, a distinctive classifier revered for its adeptness in defining effective boundaries within high-dimensional spaces.

Leveraging this information, the SVM undertakes the classification of the data, capitalizing on its proficiency in establishing optimal decision boundaries between distinct classes. This fusion amalgamates the strengths of both models: the ANN for its feature extraction capabilities and the SVM for its robust classification based on these extracted features, culminating in a potentially more accurate and potent classification system. After applying the ANN+SVM ensemble the accuracy enhanced to 98.9%. The recall and f1-score also better. The accuracy, f1-score comparison of proposed model with ML models is shown in Figure 4. The poposed model accuracy increased from 98% (SVM) to 98.9% (ANN+SVM).

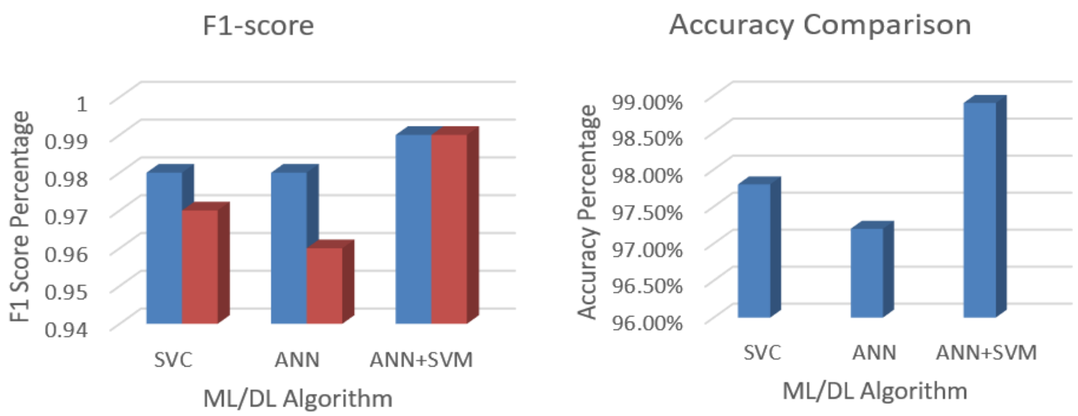

Figure 4. F1 score, accuracy of proposed model

3.3. Comparison with previous work

The comparison of proposed method with several previous works is shown in Table 2 and Figure 5. The SVM model [6] given an accuracy of 89.5%. The MLP+ELM method [1] given accuracy of 95,8%. The NN technique [11]s acquired an accuracy of 97%. Conventional ML models in [9] given accuracy of 98%. The proposed ANN+SVM model given an accuracy of 98.9%. It observed that proposed ANN + SVM outperformed existing works with an accuracy of 98.9%.

Table 2. Comparsion with previous work

Model	Accuracy
SVM [6]	89.5%
MLP-ELM [1]	95.8%
Neural networks [11]	97%
Convention ML models [9]	98%
Proposed method (ANN+SVM)	98.9%

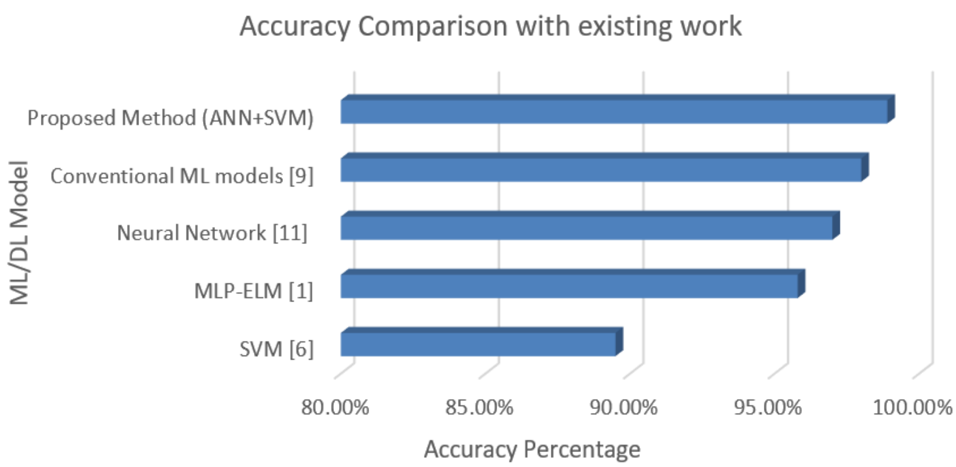

Figure 5. Comparsion with existing models

4. CONCLUSION

Smart grid stability prediction using ML offers several important benefits that contribute to the overall efficiency, reliability, and sustainability of electrical grids. Assessing and predicting stability of a smart grid stands as a pivotal factor for evaluating the efficiency of its design. In this paper, we proposed ML and DL algorithms for smart grid stability prediction. The dataset from Kaggle was downloaded for the experimentation. First, the dataset is pre-processed to prepare clean data. Later, several MLclassification algorithms were developed, namely LR, SVM, DT, RF, and ANN. Among these five, SVM and ANN given good accuracy. To further increase the accuracy, an ensemble of ANN and SVM implemented. With ANN and SVM fusion, the accuracy of the model increased to 98.9%. The experimental results have shown that the proposed method given good results for the smart grid stability predction when compared to conventional ML models. The proposed model tested on a dataset collected from Kaggle. In future, the proposed model can also be tested on several datasets related to smart gris stability to further articulate the performance of the fusion models.

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