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Performance Analysis of Machine Learning-Based Traditional and Ensemble Techniques for Smart Grid Stability Prediction

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***Abstract*—A smart grid is integral to the digitalized transformation of the electricity sector, employing self-sufficient systems that integrate information, telecommunication, and advanced power technologies. Artificial Intelligence (AI), particularly Machine Learning (ML), plays a crucial role in overcoming the limitations of traditional modeling techniques. ML enables intelligent decision-making in response to dynamic factors like changing customer energy demands or disruptions in power supply within smart grids. This paper compares Machine Learning-Based Traditional and Ensemble techniques for predicting smart grid stability, utilizing an augmented dataset from Kaggle. For optimization, various classifiers and Ensemble Techniques, including Bagging, Boosting, Stacking, and Voting, were implemented with hyperparameter tuning. The experimental study highlights that ML-based Ensemble Techniques, with optimized parameters, outperform individual traditional techniques, showcasing higher accuracy and overall superior performance. A comprehensive comparative analysis based on evaluation metrics such as accuracy, precision, recall, F1-score, and ROC emphasizes the potential of these techniques to enhance the efficiency of predicting smart grid stability.**

***Index Terms*—Smart grid Stability Prediction, Machine Learning Classifier, Ensemble Technique, Bagging, Boosting, Stacking, Hyper-parameter**

I. INTRODUCTION

The growth in population and urbanization around the world is predicted to raise energy consumption demands, which will impact the generation of electricity from sources like nuclear, thermal energy, photovoltaic, wind, and hydroelectricity. The distribution, transmission, and generation of power are crucial aspects of managing electricity. Electric grids are interconnected networks that transport energy and integrate electricity providers and consumers. Power plants, substations, transmission lines, and distribution lines make up these systems. Conventional grids are centralized, but when load increases, more overhead may be produced, which could result in poor power quality and necessitate the installation of new plants. Grids are not equipped with an adequate forecast system to anticipate intermittent power failures, their causes, response times, storage needs, and resource usage [1]. Data storage, cyberattacks, and power consumption are just a few of the technological difficulties and stability concerns that the integration of multiple technologies brings to SG. Sustaining grid stability for efficient and dependable operation is the primary problem. When the quantity of electricity provided and consumed in electrical networks is equal, this is the result. The power grid combines non-renewable and renewable resources to balance supply and demand to make sure that energy needs are met. Demand and supply must be balanced, and the integration of renewable energy into the grid is essential for this, but it also compromises grid stability because of things like power fluctuations and thefts. Grid stability is predicted using an intelligent machine-learning model [2].

Several Studies have been conducted defining DSGC in recent times, In 2015 and 2016 two of the studies were published on the same issue in the subsequent year [3]–[5]. The authors have conducted a comprehensive overview of DSGC, outlining its advantages and disadvantages. Based on those studies, the authors presented their succinct models and an extensive dataset at an exhibition to discuss SG stability. This allowed the scientists to conduct an evaluation of SG stability and resolve DSGC problems in a machine-learning data archive at the University of California, Irvine (UCI) [6]. In their research, they included an examination of the DSGC approach along with a simple decision tree model to forecast SG stability. Using Arzamasov's team's database (raw dataset) in 2019, the instability variables were examined in the research [2]. Researchers emphasized the importance of

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considering a description of the cyber-physical network. The stability prediction technique has been constructed using an integrated deep learning (DL) model. A modified version of Arzamasov's team's database was created by Paulo Breviglieri and uploaded to the Kaggle data repository later the following year. After that, the expanded dataset to produce a study in 2021 addressing the SG stability projection [7]. To examine the SG stability index, we suggested a set of machine learning methods that employ traditional algorithms using the unprocessed data set [8]. On the raw database, several machine learning algorithms have been suggested for predicting SG stability. In Ref. [9] offered the final study in the literature to use the raw dataset.

In addition to previous research that has been published in the literature using augmented datasets, the proposed study builds upon existing literature by incorporating augmented datasets in the prediction of smart grid (SG) stability. It specifically aims to contrast the effectiveness of advanced machine learning (ML) based traditional methods and combination techniques in addressing SG prediction challenges. By leveraging augmented datasets, the research endeavors to provide a comprehensive analysis of predictive models in the context of SG stability. To sum up, the following highlights key contributions to this work:

- ML-based ensemble techniques that achieve better accuracy, higher consistency, and reduced bias and variance error than traditional methods have been proposed for predicting the stability of the smart grid.
- A comparative analysis between ML-based traditional and ensemble techniques is presented.
- A novel ensemble method is presented to forecast the smart grid dataset's stability.

The paper categorizes the remaining sections into a total of five sections. Section II covers recent ML algorithm studies on smart grids, while Section III provides a detailed discussion of the suggested methodology. Section IV discusses experimental results, and Section V presents a conclusion and recommendations for further research.

II. METHODOLOGY

A. Dataset Description

The two standard identical datasets were used to estimate SG stabilization where the first one was the unprocessed data created by [10] and the following one was the expanded database [11]. Although the total sample of data across datasets varies in both operations, the first consists of 10,000 samples and the sample size is expanded to 60,000 using augmentation. The raw data sets are constructed using accurate model outcomes of stabilization processes a four-node architecture. Combining a generation center node with all three consumption nodes yields the "four" overall nodes. A reference 4-node star design with one power source (a centrally controlled generating node) providing electricity to three consuming nodes is evaluated in Fig. 1 to determine grid instability.

B. Data Pre-processing

Data preprocessing is a crucial step in machine learning analysis, ensuring accurate predictions by handling null values and negative columns. Data scaling transforms features' values to fit a specific range, choosing the appropriate method based on the problem and model. All features are numerical, so no feature coding is needed, as all data is originally numerical.

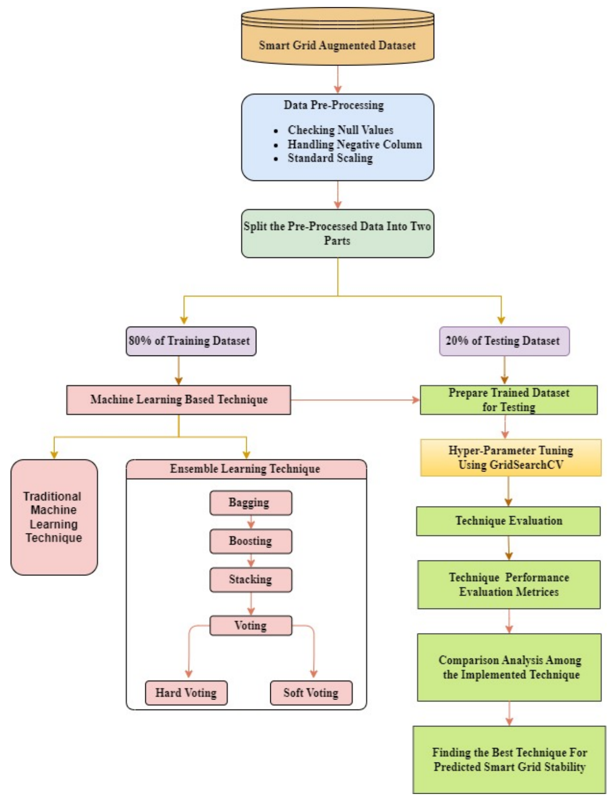


Fig. 1: The Proposed Design of Smart Grid Stability.

C. Traditional Techniques for Stability Analysis

The ML-based classifiers like Logistic Regression (LRC), Random Forest classifiers (RFC), Decision Tree classifiers (DTC), Gradient Boosting classifiers (GBC), Support Vector Machine classifiers (SVMC) and K-Nearest Neighbors classifiers (KNNC), Ada Boost classifiers (ABC), Gaussian Naïve-bayes (GNBC), Quadratic Discriminant Analysis classifiers (QDAC), Ridge Classifier (RC), Passive Aggressive classifiers (PAC) were used in this study.

D. Ensemble Techniques for Stability Analysis

Ensemble methods combine a set of learners using algorithms like decision trees or neural networks. By utilizing a single learning method, they generate homogeneous ensembles; alternatively, they can create heterogeneous ensembles with a variety of learners. These methods are effective and efficient, reducing variances, combining multiple models, and reducing prediction spread [12], [13]. Four ensemble models were used in this study.

TABLE I: Predictive Features of Electrical Grid Stability.

Features No.	Name of Features	Nature of Features	Features Description	Types	Min	Max
1	tau1	Input	The power producer's reaction time in seconds	Numerical	0.5	10
2	tau2		Electricity user 1's reaction time in seconds		0.5	10
3	tau3		Electricity user 2's reaction time in seconds		0.5	10
4	tau4		Electricity user 3's reaction time in seconds		0.5	10
5	p1		Nominal power produced		-2.0	-0.5
6	p2		Nominal power consumption by user 1		-2.0	-0.5
7	p3		Nominal power consumption by user 2		-2.0	-0.5
8	p4		Nominal power consumption by user 3		-2.0	-0.5
9	g1		Gamma coefficient proportional to elasticity price of producer		0.05	1.00
10	g2		Gamma coefficient proportional to elasticity price of user 1		0.05	1.00
11	g3		Gamma coefficient proportional to elasticity price of user 2		0.05	1.00
12	g4		Gamma coefficient proportional to elasticity price of user 3		0.05	1.00
Two Dependent Variable	Stab	Output	The typical differential equation root's largest real part {System is linearly stable (if negative); linearly unstable (if positive)}	-	-	-
	Stabf	Output	'Stable' or 'Unstable'	Categorical (binary) label	0	1

1) Bagging: Bagging is the process of reducing variance, handling, missing variables, and error to a significant minimum. In our work, the bagging approach is used to calculate the testing portion of the ML model classifier, which includes LRC, RFC, DTC, GBC, SVMC, KNNC, ABC, GNBC, QDAC, RC, and PAC. The Bagging model's classification formula is displayed. EQ. (1) [14].

$$f'(x) = sign(\sum_{i=1}^{T} fi(x)) \tag{1}$$

Here $f'(x)$ is the average of $fi(x)$ for $i = 1, 2, 3, \ldots .T$.

2) Boosting: The method known as "boosting" makes use of a weighted average to operate with many techniques, making the weak learners become strong learners who increase the accuracy of separate models that generate the loss functions [15]. To create a hybrid model, this research uses the boosting approach in the ML classifier, such as LRC, RFC, DTC, GBC, and GNBC training and assessing the validation component. The proposed equation is shown below [16].

$$\frac{1}{n}\sum_{i}^{n} I(y_j g(x_i) < 0) \leq \prod_{t=1}^{T}\sqrt{1 - 4Y_t^2} \tag{2}$$

Here,Y_t= $\frac{1}{2} - \epsilon_t$,(how much f_t is on the weighted sample).

3) Stacking: Stacking is a technique that trains an individual model by combining the predictions of multiple algorithms, resulting in a fresh prediction. In this study, a stacking technique using Logistic regression as a meta-algorithm was applied, combining various ML models to make a final prediction. The final estimator, which can be any machine learning model or estimator, is used to aggregate the predictions of the base models into a final prediction that improves predictive performance compared to individual models. Fig. 2 depicts the suggested stacking ensemble training approach for smart grid stability prediction of smart grid stability.

4) Voting: An ensemble voting classifier effectively aggregates the results of many classifiers to predict the class according to the largest voting majority, was employed in the study. The classifier was applied to various classes, including

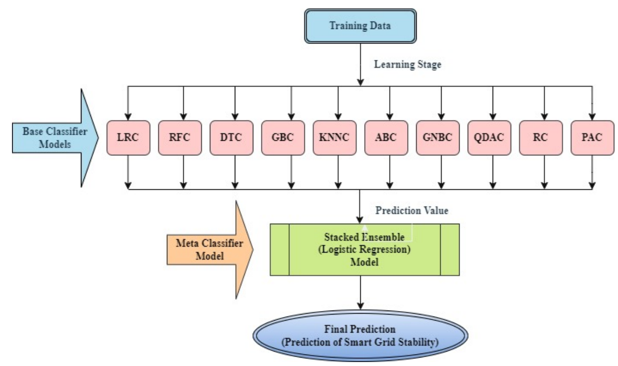


Fig. 2: Proposed Ensemble Stacking Technique.

LRC, RFC, DTC, GBC, KNNC, ABC, GNBC, and QDAC, to achieve an efficient score. The hard ensemble classifier was found to be the most efficient. In this case, each classifier B would vote with the lion's share to determine the class mark Y.

$$Y = mode\{B1(x), B2(x), \ldots, Bm(x)\} \tag{3}$$

Soft voting predicts class labels based on predicted probabilities for a classifier, recommended only for well-calibrated classifiers [17]. To get the average probability score [18], which may be advised for modified classifiers, it takes into account the uncertainty of each classifier.

$$Y = argmax_i \sum_{j=1}^{m} W_j P_{ij}, i \in 0, 1, [j = 1, 2, ...m] \tag{4}$$

Where W_j is the heap that can be doled out to the j^{th} classifier.

III. RESULTS AND DISCUSSIONS

The section demonstrates the evaluation outcomes of traditional and ensemble-based machine learning classifiers on the features of the dataset for predicting smart grid stability.

A. Hyper Parameter Optimization of Classifier

Hyperparameter tuning is a technique used in this study to control the learning process and generate a generalized outcome through cross-validation. The GridSearch CV approach was used to define the best parameter set, resulting in better testing accuracy. Fig. II shows the best parameters for general classifiers [19].

TABLE II: Hyper Parameter Tuning.

Machine Learning Model	Hyper-Parameter Tuning
Logistic Regression	{'C': 1}
Random Forest	{'max_depth': None, 'mini_ samples split': 5, 'n_estimators': 30}
Decision Tree	{'criterion': entropy, 'maxi_ depth': None}
Gradient Boosting	{'learning rate': 0.2, 'max_depth': 7, 'n_ estimators': 150}
Support Vector Machines	{'C': 10, 'kernel': rbf}
k-Nearest Neighbors	{'n_neighbours': 7, 'weights': distance}
Ada boost Classifier	{'learning rate': 0.2, 'n_ estimators': 150}
Gaussian Naïve Bayes	No hyperparameters to tune for Gaussian Naïve Bayes
Quadratic Discriminant Analysis	{'reg parameter': 0.2}
Ridge Classifier	{'alpha': 0.1}
Passive Aggressive Classifier	{'C': 0.01, 'max_iter': 1000}

B. Evaluation Outcomes of Traditional Machine Learning Classifiers

The evaluation metrics of different traditional machine-learning models are shown in Fig. 3a. SVMC has the highest accuracy (98.63%), indicating the lowest overall misclassification rate. PAC has the lowest accuracy (80.25%), while SVMC has the highest precision (98.82%). GNBC has the lowest precision (80.49%). SVMC has the highest recall (99.03%), indicating its effectiveness in capturing all positive instances. RC has the lowest recall (83.26%). SVMC has the highest F1-Score (98.47%), combining precision and recall. RFC has the highest ROC (98.78%), indicating strong discrimination ability, while QDAC has the lowest ROC (49.13%), suggesting poor discrimination. SVMC consistently performs well across multiple metrics, while RFC shows strong overall performance.

C. Comparison Between Ensemble Bagging and Traditional Machine Learning Classifiers

Fig. 3b shows a comparison result between Ensemble bagging and traditional machine learning classifiers represent two different approaches to building predictive models. We applied individual Ensemble bagging methods on 11 traditional machine learning classifiers but some ensemble bagging models generally outperform traditional models in accuracy across all classifiers. Ensemble bagging models tend to have higher precision and recall compared to traditional models, indicating a better ability to correctly classify positive instances and avoid false positives. Ensemble bagging models tend to have higher precision and recall compared to traditional models, indicating a better ability to correctly classify positive instances and avoid false positives. Ensemble bagging models show higher F1 scores, suggesting a better balance between precision and recall. Ensemble bagging models exhibit higher ROC values, indicating better trade-offs between true positive rate and false positive rate. When compared against conventional machine learning designs, ensemble bagging methods like Random Forest and Gradient Boosting perform better concerning accuracy, precision, recall, and F1 score. Other applied bagging methods are very close compared to the traditional machine learning methods but we proposed for Smart grid stability prediction ensemble bagging method because having their ability to better performance, more robust and prone to overfitting, higher consistency, and reduce bias and variance error.

D. Comparison Between Ensemble Boosting and Traditional Machine Learning Classifier

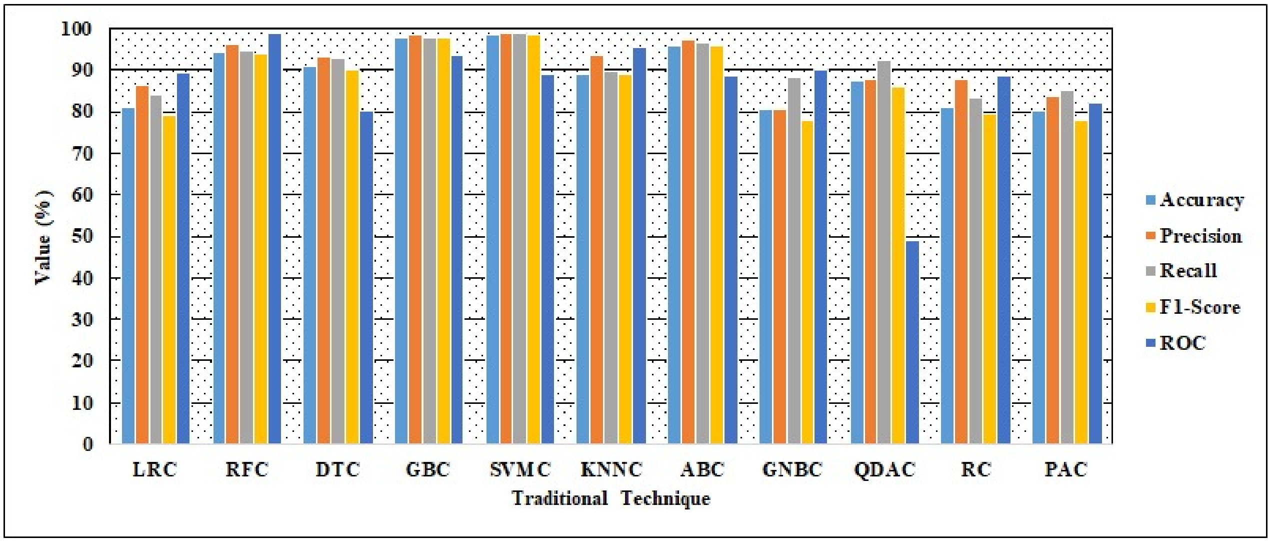
In Fig. 3c shows a comparison result between Ensemble boosting and traditional machine learning classifiers. We applied the individual Ensemble boosting method on 5 traditional machine learning classifiers. The highest accuracy is observed in the Boosted GBC with 97.41%, followed closely by the GBC with 97.67%. These two models outperform the others in terms of accuracy. The highest precision is achieved by the Boosted GBC with 97.08%, followed by the GBC with 98.49%. Both GBC and Boosted GBC have the highest precision values among all models. The highest recall is observed in the Boosted RFC with 91.76%, followed closely by the RFC with 94.63%. These two models perform better in terms of recall compared to the other models. The highest F1-Score is achieved by the Boosted GBC with 96.39%, closely followed by the GBC with 97.58%. Both GBC and Boosted GBC exhibit the highest F1-Score values. The highest ROC is observed in the Boosted RFC with 99.57%, followed closely by the Boosted GBC with 99.86%. These two models have the highest ROC values among all models. Some ensemble boosting method consistently performs well across all metrics compared to the traditional machine learning classifier and others results are close. We suggested the Ensemble Boosting Method compared to the traditional machine learning classifier based on their useful characteristics for predicting smart grid stability.

E. Comparison Between Ensemble Stacking Method and Traditional Machine Learning Classifiers

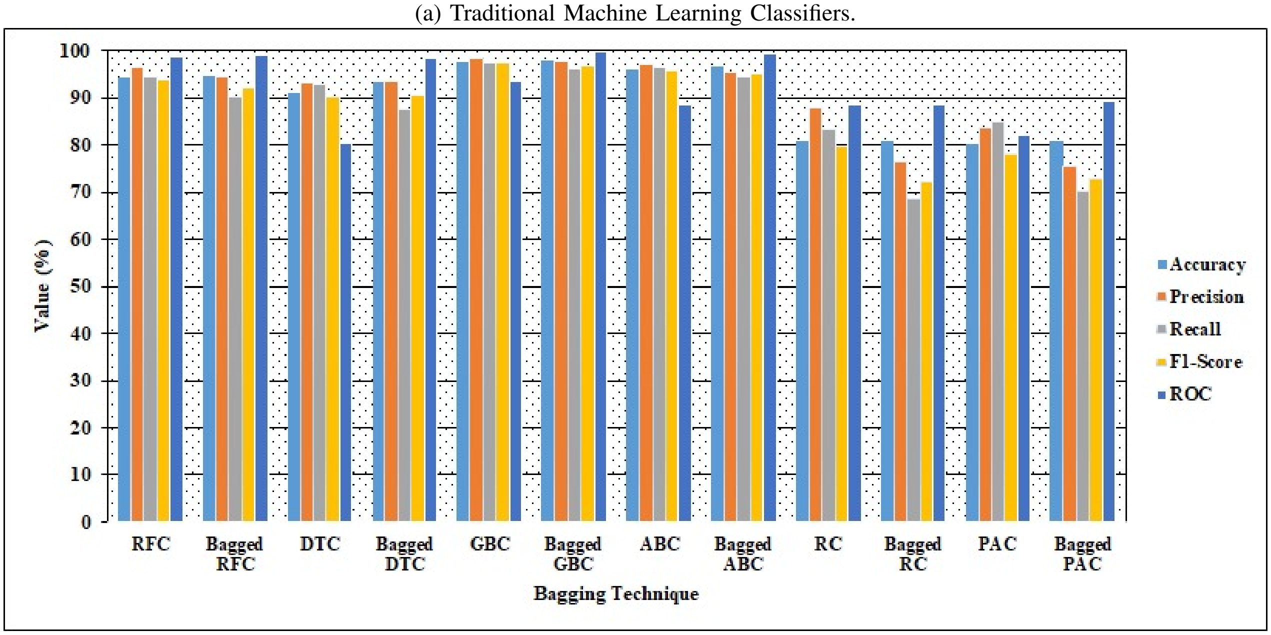
The ensemble stacking method was applied using traditional machine learning as a base classifier, the output response was very consistent where higher accuracy, precision, recall, F1-Score, and ROC scores of the ensemble stacking method compared to the single traditional classifier as shown in Table III.

TABLE III: Evaluation Outcomes.

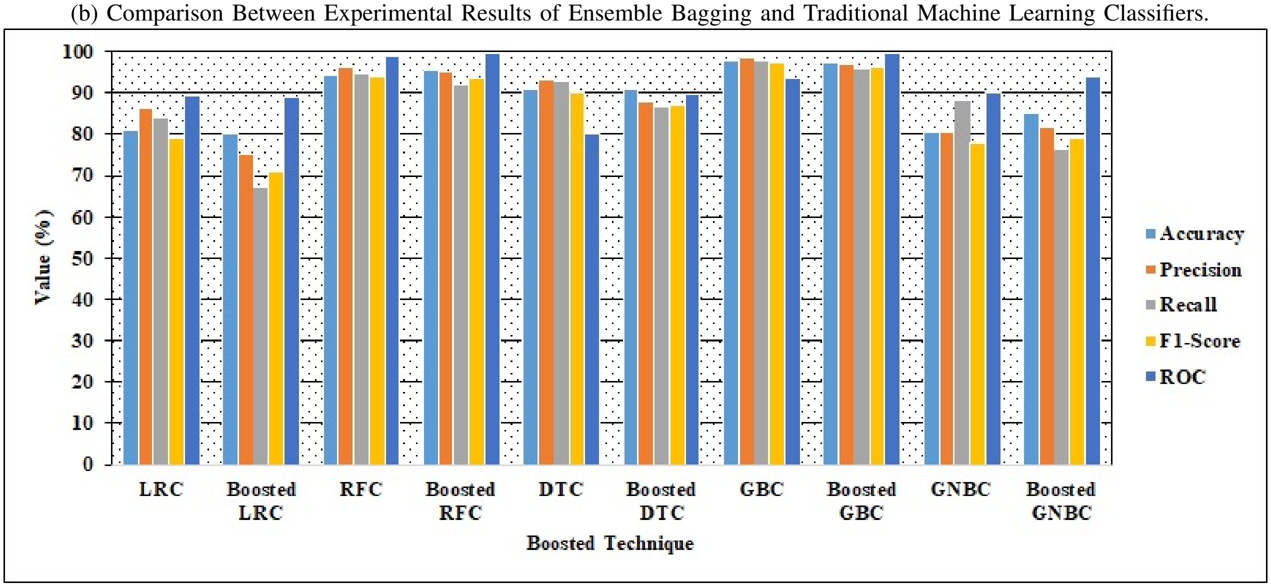
Model	Accuracy	Precision	Recall	F1-Score	ROC
Ensemble Stacking Classifier	97.77%	97.12%	96.68%	96.90%	99.81%



(a) Traditional Machine Learning Classifiers.



(b) Comparison Between Experimental Results of Ensemble Bagging and Traditional Machine Learning Classifiers.



(c) Comparison Between Experimental Results of Ensemble Boosting and Traditional Machine Learning Classifiers.

Fig. 3: Experimental Result.

F. Experiment Result of Ensemble Voting Classifier

The ensemble hard and soft voting methods were applied using traditional machine learning as a base classifier where the output response is shown in Table IV. We get consistently higher accuracy, precision, recall, F1-Score, and ROC scores of ensemble hard and soft voting methods compared to the traditional classifier. So we also suggested an ensemble voting method compared to the traditional machine learning classifier.

TABLE IV: Evaluation Outcomes.

Model	**Accuracy**	**Precision**	**Recall**	**F1-Score**	**ROC**
Hard Voting	95.23%	95.90%	90.68%	93.22%	94%
Soft Voting	95.26%	93.95%	92.87%	93.41%	99%

G. Comparative Analysis

Comparison with similar literature in terms of output response in depicted in V.

TABLE V: Comparison with Similar Literature

Study	Proposed Models	Datasets	Accuracy	
This study	Machine Learning-Based Ensemble Techniques	(60,000) (Augmented)	Bagged RFC	94.59%
			Bagged GBC	97.78%
			Bagged ABC	96.56%
			Bagged DTC	93.33%
			Boosted RFC	95.39%
			Ensemble Stacking Classifier	97.77%
			Ensemble hard Voting Classifier	95.23%
			Ensemble Soft Voting Classifier	95.26%
2023 [3]	Multi-:Layer Perceptron-Extreme Learning Machine	10,000	95.8%	
2023 [2]	Cost-Sensitive Stacked Ensemble Classifier	10,000	98.6%	
2022 [6]	Ensemble Bagging Technique	10,000	90.16%	
2022 [7]	XG Boost	10,000	94.7%	

IV. CONCLUSION

This study compares traditional and ensemble techniques based on ML and our proposed techniques excelled in testing, with Bagged GBC leading at 97.78%, closely followed by Ensemble Stacking Classifier at 97.77%. Bagged ABC and Boosted RFC showed strong accuracies of 96.56% and 95.39% respectively, while Bagged RFC achieved 94.59%. Hard and soft voting classifiers achieved impressive accuracies of 95.23% and 95.26% respectively, outperforming individual ML classifiers for predicting the stability of the smart grid. The suggested approach is tested using the smart grid augmented dataset from the UCI Machine Learning Repository.

The effectiveness of ensemble techniques based on ML has been compared with traditional techniques and proved that using ensemble techniques has been better compared to the other any individual traditional ML-based classifier. The dataset is not very large, based on the limits of the current work. However, SGs produce enormous amounts of data in real-time. Future research could involve the application of efficient feature engineering-based models and using updated algorithms on real-time SG data to address this issue.

REFERENCES

[1] B. Zhao, L. Zeng, B. Li, Y. Sun, Z. Wang, M. Shahzad, and P. Xi, "Collaborative control of thermostatically controlled appliances for balancing renewable generation in smart grid," *IEEJ Transactions on Electrical and Electronic Engineering*, vol. 15, no. 3, pp. 460–468, 2020.

[2] K. Ramasamy, A. Sundaramurthy, and D. Velusamy, "Assessment and classification of grid stability with cost-sensitive stacked ensemble classifier," *Automatika*, vol. 64, no. 4, pp. 783–797, 2023.

[3] A. Alsirhani, M. M. Alshahrani, A. Abukwaik, A. I. Taloba, R. M. Abd El-Aziz, and M. Salem, "A novel approach to predicting the stability of the smart grid utilizing mlp-elm technique," *Alexandria Engineering Journal*, vol. 74, pp. 495–508, 2023.

[4] A. I. Ikram, A. Ullah, D. Datta, A. Islam, and T. Ahmed, "Optimizing energy consumption in smart homes: Load scheduling approaches," *IET Power Electronics*, 2024.

[5] A. I. Ikram, M. Shafiullah, M. R. Islam, and M. K. Rocky, "Techno-economic assessment and environmental impact analysis of hybrid storage system integrated microgrid," *Arabian Journal for Science and Engineering*, pp. 1–18, 2024.

[6] F. Aziz and A. Lawi, "Increasing electrical grid stability classification performance using ensemble bagging of c4. 5 and classification and regression trees," *International Journal of Electrical and Computer Engineering*, vol. 12, no. 3, pp. 2955–2962, 2022.

[7] M. Ibrar, M. A. Hassan, K. Shaukat, T. M. Alam, K. S. Khurshid, I. A. Hameed, H. Aljuaid, and S. Luo, "A machine learning-based model for stability prediction of decentralized power grid linked with renewable energy resources," *Wireless Communications and Mobile Computing*, vol. 2022, pp. 1–15, 2022.

[8] C. Li, "Retracted: Stability analysis of distributed smart grid based on machine learning," in *IOP Conference Series: Earth and Environmental Science*, vol. 692, no. 2. IOP Publishing, 2021, p. 022125.

[9] M. Massaoudi, H. Abu-Rub, S. S. Refaat, I. Chihi, and F. S. Oueslati, "Accurate smart-grid stability forecasting based on deep learning: Point and interval estimation method," in *2021 IEEE Kansas Power and Energy Conference (KPEC)*. IEEE, 2021, pp. 1–6.

[10] V. Arzamasov, K. Böhm, and P. Jochem, "Towards concise models of grid stability," in *2018 IEEE international conference on communications, control, and computing technologies for smart grids (SmartGridComm)*. IEEE, 2018, pp. 1–6.

[11] P. Breviglieri, T. Erdem, and S. Eken, "Predicting smart grid stability with optimized deep models," *SN Computer Science*, vol. 2, pp. 1–12, 2021.

[12] A. Sharma and A. Suryawanshi, "A novel method for detecting spam email using knn classification with spearman correlation as distance measure," *International Journal of Computer Applications*, vol. 136, no. 6, pp. 28–35, 2016.

[13] Z.-H. Zhou, *Ensemble methods: foundations and algorithms*. CRC press, 2012.

[14] H. Drucker, C. Cortes, L. D. Jackel, Y. LeCun, and V. Vapnik, "Boosting and other ensemble methods," *Neural computation*, vol. 6, no. 6, pp. 1289–1301, 1994.

[15] R. Islam, A. R. Beeravolu, M. A. H. Islam, A. Karim, S. Azam, and S. A. Mukti, "A performance based study on deep learning algorithms in the efficient prediction of heart disease," in *2021 2nd International Informatics and Software Engineering Conference (IISEC)*. IEEE, 2021, pp. 1–6.

[16] A. Lemmens and C. Croux, "Bagging and boosting classification trees to predict churn," *Journal of Marketing Research*, vol. 43, no. 2, pp. 276–286, 2006.

[17] A. Mahabub, "A robust technique of fake news detection using ensemble voting classifier and comparison with other classifiers," *SN Applied Sciences*, vol. 2, no. 4, p. 525, 2020.

[18] X. Deng, Q. Liu, Y. Deng, and S. Mahadevan, "An improved method to construct basic probability assignment based on the confusion matrix for classification problem," *Information Sciences*, vol. 340, pp. 250–261, 2016.

[19] S. Tajmen, A. Karim, A. Hasan Mridul, S. Azam, P. Ghosh, A.-A. Dhaly, and M. N. Hossain, "A machine learning based proposition for automated and methodical prediction of liver disease," in *Proceedings of the 10th International Conference on Computer and Communications Management*, 2022, pp. 46–53.