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| RESEARCH ARTICLE

Revitalizing the Electric Grid: A Machine Learning Paradigm for Ensuring Stability in the U.S.A

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| ABSTRACT
The electric grid entails a diverse range of components with pervasive heterogeneity. Conventional electricity models in the U.S.A. encounter challenges in terms of affirming the stability and security of the power system, particularly, when dealing with unexpected incidents. This study explored various electric grid models adopted in various nations and their shortcomings. To resolve these challenges, the research concentrated on consolidating machine learning algorithms as an optimization strategy for the electricity power grid. As such, this study proposed Ensemble Learning with a Feature Engineering Model which exemplified promising outputs, with the voting classifier performing well as compared to the rainforest classifier model. Particularly, the accuracy of the voting classifier was ascertained to be 94.57%, illustrating that approximately 94.17% of its predictions were correct as contrasted to the Random Forest. Besides, the precision of the voting classifier was ascertained to be 93.78%, implying that it correctly pinpointed positive data points 93.78% of the time. Remarkably, the Voting Classifier for the Ensemble Learning with Feature Engineering Model technique surpassed the performance of most other techniques, demonstrating an accuracy rate of 94.57%. These techniques provide protective and preventive measures to resolve the vulnerabilities and challenges faced by geographically distributed power systems.

| KEYWORDS

Electricity Power Grid, Voting classifier, Gradient booster, Random forest, Machine learning algorithms

| ARTICLE INFORMATION

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1. Introduction

In the recent past, the national electric power grid in America has been experiencing a transformative shift targeted at establishing a reliable, efficient, secure, and stable smart electric grid, coinciding with the national energy sustainability objectives. Acting as the fundamental infrastructure of contemporary society, the electric power grid comprises the entire network of machinery and wires that link electricity sources to users. The smart grid employs advanced digital information, communication, and control technology to fortify the reliability and efficiency of the system (Henderson et al, 2019). Tremendous smart grid algorithms and technologies have been crafted within the framework of the new smart grid paradigm. Nevertheless, before their execution, it is imperative to test and validate these technologies meticulously (Amin & Singer, 2018). To affirm this, simulation and modeling of consolidated smart electric grid frameworks provide an efficient approach for validating and testing these smart grid algorithms.

According to Bomfim (2020), to accomplish the vision of a Smart Grid in USA, it is pivotal to effectively incorporate communication systems, real-time data delivery, digital information, embedded software, and real-time control decision-making. These spheres transcend beyond conventional advancements in power engineering algorithms. Nevertheless, there is still a lack of high-fidelity frameworks in a position to simulate the activities between the electric grid and the communication and control infrastructure components, particularly for large-scale systems. Modeling the interdependencies of the infrastructure complementing the power grid, encompassing communication networks, control systems, sensors, and software, presents a substantial challenge. Currently, there are distinct gaps in effectively modeling the consolidated smart grid system extensively and efficiently.

1.1 Background

As per Henderson et al. (2019), the electric grid comprises a diverse range of elements with pervasive heterogeneity. This heterogeneity is apparent in various elements, comprising physical elements such as power generation equipment, transmission lines, and computational elements, as well as organizational and human components. Moreover, the multitude of simulations undertaken across distinct domains, such as network systems and planning optimization, further leads to the increased diversity of required models.

The complication and sophistication of modeling the dynamics and operation of the electric grid emanates from a wide range of incidents, comprising network formulation and planning of operating strategies, regulation of the transmission system, control strategy design, production unit dispatching, as well as dependability and vulnerability analysis (Heptonstall & Gross, 2021). The aggregate activities of the electric grid are impacted by the interplay of computational, physical, and human/organizational elements. As smart grid schemes proceed to evolve, the heterogeneity and complexity of the system are anticipated to increase in multiple ways.

According to Hasan (2021), granted the instrumental role that electric power grids have in our community, it has become very significant to comprehend the sophisticated phenomena that lead to the rise of blackout safety and insecurity incidents. Researchers and scholars have attempted various approaches to resolve these challenges. One avenue comprises undertaking simulations that consider the automation/control layer and electromagnetic processes that govern the grid. Nevertheless, such simulations are extremely challenging and can only be undertaken on a reduced scale. On the other hand, when investigating blackouts, our attention lies in understanding the behavior of the entire electric power grid as a unified entity. Moreover, these simulations are relatively time-consuming, while it is highly instrumental to get real-time insights regarding how the system responds to external disturbances.

1.2 Problem Statement

Nguyen et al. (2020), indicate that traditional electricity models encounter a substantial challenge in terms of affirming the stability and reliability of the power system, notably in the confrontation of different contingencies and strains. Recent occurrences worldwide have illustrated the vulnerabilities of geographically distributed power systems, demanding the implementation of robust preventive and protective techniques such as Machine learning Techniques. As per MD Robikul (2024), across history, upholding the stability and security of power systems has always been a difficult task. Operators of conventional power systems frequently struggle with effective network monitoring, depending on consumer reports of faults. Despite the tremendous innovations in contemporary power systems, reports and evidence signify that the international power system has encountered an increasing number of security and stability challenges.

2. Literature Review

Power grids have for a long time been a renowned framework system in the domain of synchronization concepts within the arena of network dynamics. As the field has advanced, an escalating number of investigators have attempted to apply insights and concepts from previous theoretical research to resolve power grid-specific challenges (Roy & Naur, 2016). This need emanates from the fact that, despite the comprehensive engineering literature on power mechanisms, there is still a substantial gap in comprehending how the collective dynamics in power grids are impacted by the large-scale network structure. While previous literature has concentrated on the detailed modeling of relatively small test frameworks, recent research in computational power, data processing tools, and theoretical developments in network synchronization have inspired possibilities for assessing large-scale properties of power grid systems (Specht, 2022). The stability of intended states, particularly the synchronization stability of power generators, is of substantial concern for power grids. This condition is pivotal for affirming the normal operation of the generators.

2.1 Understanding Power Grid

Zhang (2020), contends that a power grid refers to a connected framework of electrical devices crafted to transmit power from generators to consumers. When one views this framework as a network, one considers nodes as points where power is inserted by generators or retrieved by consumers and points where power is reallocated among connected transmission lines. Links in the network exemplify electrical connections between sets of nodes, which can be transformers or transmission lines.

In this network depiction, the physical framework of the power grid is portrayed in Figure 1(A), which exhibits a simple illustration with two power-inserted nodes (1 and 2) linked to a single power-receiving node (3) via two transmission lines. It is essential to mention that transmission lines have COMPONENTS, which are generally portrayed by sophisticated numbers, and the parallel conductors of these lines have distinctions between them.

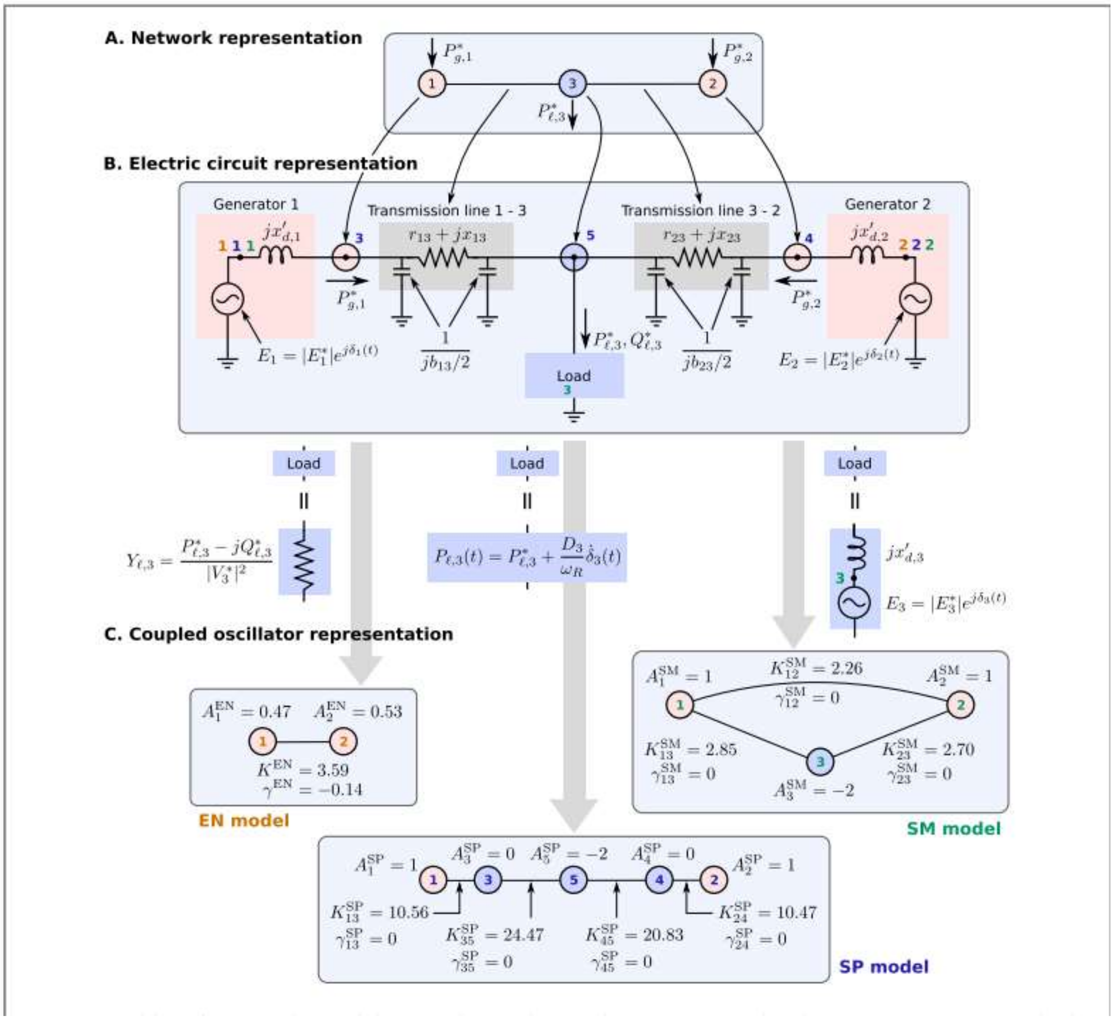


Figure 1: Showcases the modeling of a power-grid network system.

As per Figure 1, In (A), a simple portrayal of the network is demonstrated, where nodes signify loads or generators, and links exemplify transformers or transmission lines. This specific example comprises two generators (nodes 1 and 2) and one load node (node 3). (B) Portrays the electrical attributes of the elements within a similar network. The load node can be portrayed in three distinct ways, each conforming to a different model (Huhta, 2021).

On the other hand, (C) presents the framework portrayed as a network of joint oscillators, relying on the load representation selected in (B). For the provided parameter values, the network aspects follow equations (28)-(30) for the SP, EN, and SM models, accordingly), with the particular values of Ai, Kij, and γij. It's imperative to mention that every dynamical framework has its definition of nodes, which varies from the one utilized in (A). In (B), the nodes are portrayed as black dots and stamped with blue, orange, and green indices for the SP, EN, and SM models, accordingly. A similar color scheme is employed for the node indices in (C). Particularly, in the SP framework, the terminals of the generators are taken as load nodes with zero power utilization (nodes 3 and 4), distinct from the internal nodes of the generators (nodes 1 and 2), culminating in a 5-node representation (Huhta, 2021).

In power framework analysis, the π model is predominantly adopted to depict transmission lines. As per this model, the two nodes are linked by an impedance, and there are two capacitors (with equivalent capacitance) that link both sides of the impedance to the ground. Figure 1(B) demonstrates this framework for the transmission line 1-3, which comprises two capacitors with an impedance of $1/(j\omega C)$, where j denotes the imaginary unit and ω is the angular frequency (Huhta, 2021). On the other hand, transformers are portrayed by a framework where the voltages on both aspects of the transformer uphold a constant ratio, which can be complicated valued to account for potential phase transformations in voltage. In this setting, we employ the standard approach of depicting the framework parameters for transformers and transmission lines in terms of equivalent admittances, which are the inverses of impedances.

To portray the whole physical network framework, one can utilize the (complex-valued) admittance matrix Y. This matrix has the symbol $Y = [Y_{ij}]$ where Y_{ij} is the negative of the admittance existing between nodes i and j (when i is not equal to j), and Y_{ii} is the summation of all admittances linked to node I, encompassing the shunt admittances to the ground, which are elements of the models for transformers and transmission lines.

2.2 The Current State of the Electricity Sector in America

As per the Worldometer, electricity consumption in America was approximately 4,050 terawatt-hours as of 2022, among the highest values in the period under assessment. The Americas' portion of the electrical grid in North America had a nameplate capacity of 1,213 GW and generated 3,988 TWh as of 2022. According to Hasan (2023), Historically, the American electricity sector has functioned under a vertically consolidated utility model. In this framework, a single utility organization was in charge of generating, distributing, and transmitting electricity to consumers within a particular geographic region. This framework presented a regulated monopoly, with the utility organizations being the exclusive electricity provider in its service region. In the 1990s, some states in America started to restructure and regulate their electricity markets. This encompassed separating the generation, distribution, and transmission functions of the electricity sector to present competition. The objective was to promote efficiency, lower prices, and offer consumers more choices.

As per Hasan (2022), ensuring the stability and security of the power system is a tremendous challenge confronted by electricity organizations in America. Recent occurrences worldwide have underscored the need for robust preventive and protective measures to resolve stability and security issues in geographically dispersed power systems. Previously, operators of the old power system battled to effectively monitor the network, frequently depending on reports from officials and faults from consumers. Nevertheless, despite the advancements in contemporary power systems, reports and evidence indicate that security and stability challenges have increased globally. Constant system monitoring is fundamental for pinpointing security violations promptly. It is essential to ensure consistent vigilance since breaches can happen within minutes or seconds.

In this paper, the researcher will concentrate on three renowned models adopted in different countries across the globe, all models either adopt: The Effective Network (EN) framework, the Structure-Preserving (SP) system, or the Synchronous Motor (SM) system. Each framework represents a network of interrelated phase oscillators, and their dynamics are regulated by equations of the following form.

$$\frac{2H_i}{\omega_R}\ddot{\delta}_i + \frac{D_i}{\omega_R}\dot{\delta}_i = A_i - \sum_{j=1, j\neq i} K_{ij} \sin\left(\delta_i - \delta_j - \gamma_{ij}\right),$$

In the provided equations, ω_R denotes the reference angular frequency of the model. The oscillators are attributed to inertia constant H_i and subsequent damping constant D_i. The variations among the three frameworks can be witnessed in the descriptions of parameters A_i, K_{ij}, and γ_{ij}, and in the number of phase oscillators encompassed. The phase angle δ_i denotes either a generator or a load. Even though all three models consider n_g generators as oscillators, their key distinctions depend on how they model the loads, which portray independent or aggregated users drawing power from particular points in the transmission network. In the EN model, the loads are depicted as constant impedances instead of oscillators, with the concentration on synchronizing the generators as second-order oscillators. In contrast, the SP framework treats all load nodes as first-order oscillators ($H_i = 0$), and every generator is portrayed by two oscillators, comprising one for its terminal, which is the point linking the generator to the rest of the network.

2.3 Comparing and Contrasting Electricity Grid Models Adopted in Different Nations

Year	*Model Adopted*	*Country*	*Shortcomings*
2022	*The Grid-Independent Model*	*India*	*-High initial costs of installation and maintaining infrastructure.* *- Lacks the scalability of centralized power production.* *-Reliability Challenges*
2016	*Centralized Model*	*Canada*	*-Vulnerable to disruptions such as cyber-attacks or equipment failures.* *-Lack of flexibility since they are tailored to function on a large scale.* *-Negative environmental implications since they highly depend on fossil fuel which in turn leads to air pollution*
2021	*Decentralized Model*	*Germany*	*-Difficulty in coordinating multiple units or divisions.* *-Narrow Product Lines.* *- Deploying and upholding. decentralized frameworks can be relatively costly.*
2020	*Hybrid Model*	*Australia*	*-Complexity and integration challenges.* *- Challenges to grid stability and reliability.* *-Transition and compatibility issues.*
2023	*The Smart Grid Model*	*Denmark*	*-Privacy and security issues* *- The sophistication of a smart grid framework can lead to technical challenges.* *-Affordability and equity issues*

3. Methodology

The methodology in this study combines multiple Machine Learning algorithms. Most notably, random forest, decision tree, Gradient booster classifier, voting classifier, and XGBoost are ensembled in this research. Each of these algorithms presents unique capabilities and strengths, reinforcing the overall performance of the ensemble classifier. Moreover, the methodology adopted in this model incorporated the Stevens Multi Performance Comparison of Machine Learning Algorithms for Load Forecasting in Smart Grid. This methodology is crafted particularly for load forecasting in the setting of smart grids. It comprises an extensive evaluation framework that facilitates a comprehensive comparison of distinct machine-learning algorithms. The Stevens Multi Performance Comparison methodology takes into consideration multiple performance metrics to evaluate the efficiency of distinct algorithms in load forecasting. These metrics may comprise precision, accuracy, recall, F1 score, and others, offering a holistic view of the algorithms' performance across distinct dimensions.

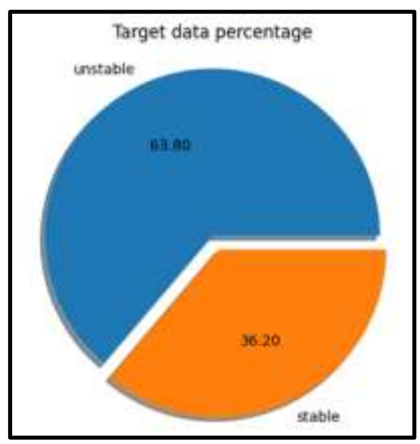
3.1. Dataset Information

The evaluation entailed undertaking experiments with different input values adopting a methodology identical to the one presented in the research paper titled Taming instabilities in power grid networks by decentralized control, by Schäfer, Benjamin, et al. (2016). In these tests, specified input values were kept constant. The average time for the evaluation was set at 2 seconds, implying that data was averaged on a 2-second interval. The joint strength was set at 8 s^-2, signifying the rate at which distinct elements in the system interact. In particular, the damping was set to 0.1 s^-1, indicating the rate at which oscillations in the model are minimized. These fixed input values present a consistent baseline for contrasting the results of the analysis across different scenarios.

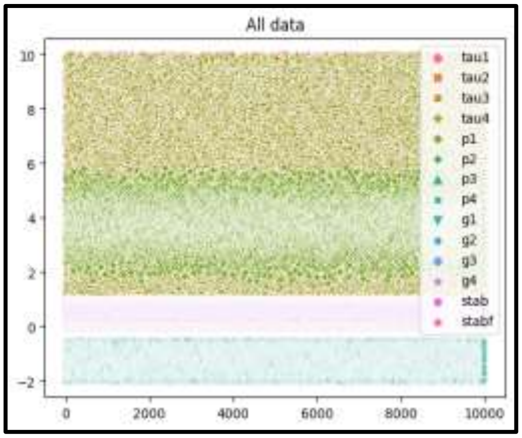
Variable Name	Role	Type	Demographic	Description	Units	Missing Values
tau1	Feature	Continuous				no
tau2	Feature	Continuous				no
tau3	Feature	Continuous				no
tau4	Feature	Continuous				no
p1	Feature	Continuous				no
p2	Feature	Continuous				no
p3	Feature	Continuous				no
p4	Feature	Continuous				no
g1	Feature	Continuous				no
g2	Feature	Continuous				no
g3	Feature	Continuous				no
g4	Feature	Continuous				no
stab	Target	Continuous				no
stabf	Target	Binary				no

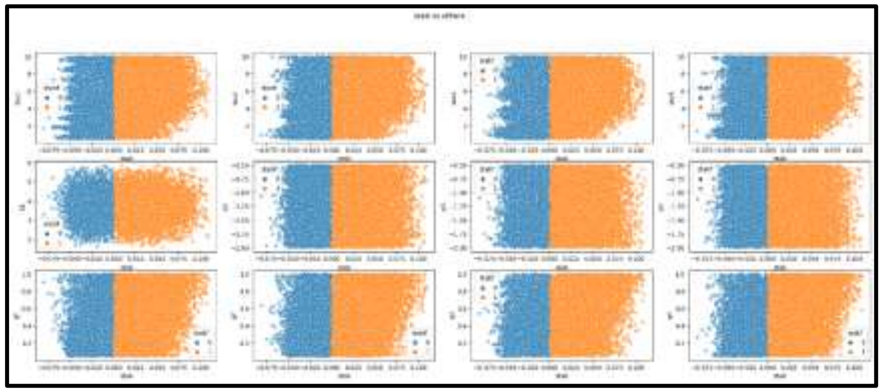
3.2 Data Preparation

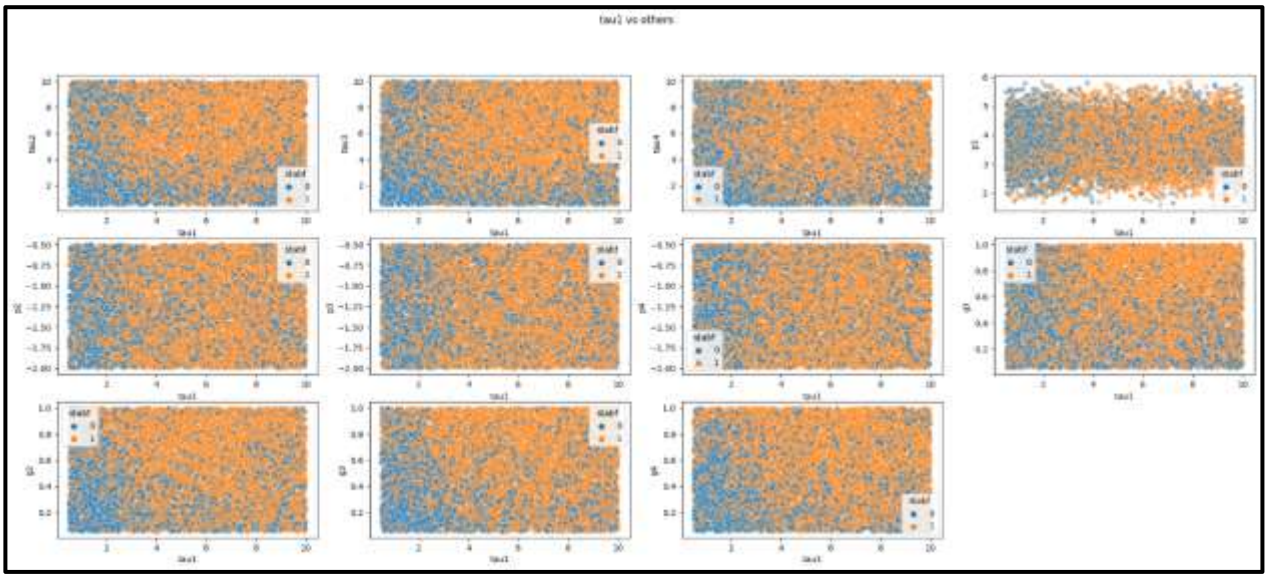
The first step started with loading the dataset from a CSV file into a Pandas Data Frame, followed by undertaking an Exploratory Data Assessment (EDA). The second step, the EDA phase comprises showcasing the number of columns and rows in the dataset, portraying the first few columns of the dataset, exhibiting information regarding the dataset, entailing data types and missing values, and presenting a statistical overview of the dataset. The third phase entails Data Visualization, pie charts are created to visualize the scattering of the target variable 'stabf', and the resulting chart image is saved to a file using plt. savefig(). This comprehensive process allows for a thorough understanding of the dataset and its characteristics.

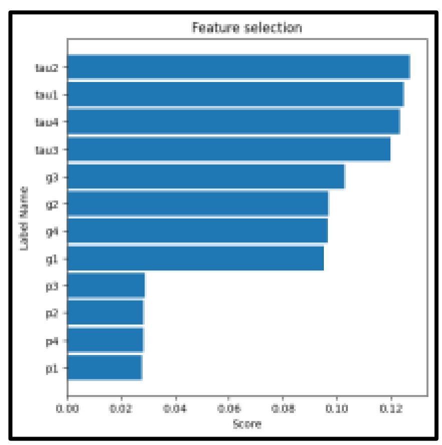


The fourth step entailed the Label Encoding phase, where a label encoder was fitted to the 'stabf' column. Subsequently, the stabf column was then transformed using the label encoder. The resulting label encoder was saved using joblib. dump(). The fifth step encompassed presenting data visualization, where scatter plots were created to showcase all data points, and the subsequent scatter plot image was documented. In the sixth step, scatter plots were presented to compare and contrast each feature with 'tau1' and color-coded by 'stabf' as showcased in the figure below:









seventh phase comprised defining the target variables and defining the features. Subsequently, a random forest classifier of 200 trees was initialized, where the model was trained using the target and features. Finally, the researcher visualized the feature's importance by utilizing the horizontal bar charts as showcased below:

4. Implementation

4.1 Model creation and training

This study comprised experimenting with four models, most notably, (1) Ensemble learning without Feature Engineering model, (2) Ensemble learning with Feature Engineering, (3) Gradient Boosting Classifier, and (4)Random Forest Classifier, to ascertain which model is suitable in terms of streamlining electricity power grid.

Model #1: Ensemble learning without Feature Engineering model.

In this experiment, a Random Forest model was trained for binary classification without feature engineering. The procedure entailed model selection, target and feature definition, model training, determining the number of estimators, and portraying feature significance. The Random Forest Classifier with approximately 200 decision trees was chosen for model training, known for its capability to handle complex datasets and robustness. Firstly, the target variable 'stabf' portraying the system's stability is described, and the features are exhibited by excluding the target variable. The model is then trained using the defined features and target variable. Secondly, the quantity of decision trees in the Random Forest is fixed at 200. Thirdly, model evaluation was employed, where the trained model was evaluated on a test or validation set using various metrics. Fourthly, the process comprised visualizing the feature significance by employing a horizontal bar chart, and the feature significance plot was displayed as images visualizing.

Model #2: Ensemble learning with Feature Engineering

Firstly, the Ensemble Learning with Feature Engineering procedure was initialized comprising three classifiers, most notably, Gradient-Boosting-Classifier, Random-Forest-Classifier, and XGB-Classifier for ensemble learning. Secondly, a voting classifier was then developed with a soft voting strategy, consolidating predictions according to the predicted probabilities from the three classifiers. Thirdly, a pre-trained ensemble framework was then loaded, facilitating predictions without necessarily retraining. Thirdly, the model made predictions on the test set upon dropping particular features, and the outcomes were preserved. The fourth step, entailed visualizations using a bar chart portraying training and test accuracy, a heatmap for the bar chart, and a confusion matrix, showcasing precision, recall accuracy, and F1 score on the test set. These visualizations provided insights regarding the ensemble model's evaluation and performance metrics.

Model #3: Gradient Boosting Classifier

The first step entailed initializing a Gradient Boosting Classifier. Gradient Boosting is an ensemble learning technique that establishes a series of weak learners, normally decision trees, and integrates their predictions to enhance overall performance. Secondly, a pre-trained Gradient Boosting Classifier framework was loaded utilizing the joblib.load() function. This facilitated the adoption of a previously saved framework for making predictions without retraining. The third stage comprised employing the trained Gradient Boosting Classifier framework to make predictions on the test set (x_test). The fourth stage comprised creating bar charts to visualize and display both the training and test accuracy of the Gradient Boosting Classifier. The accuracy scores were presented as percentages.

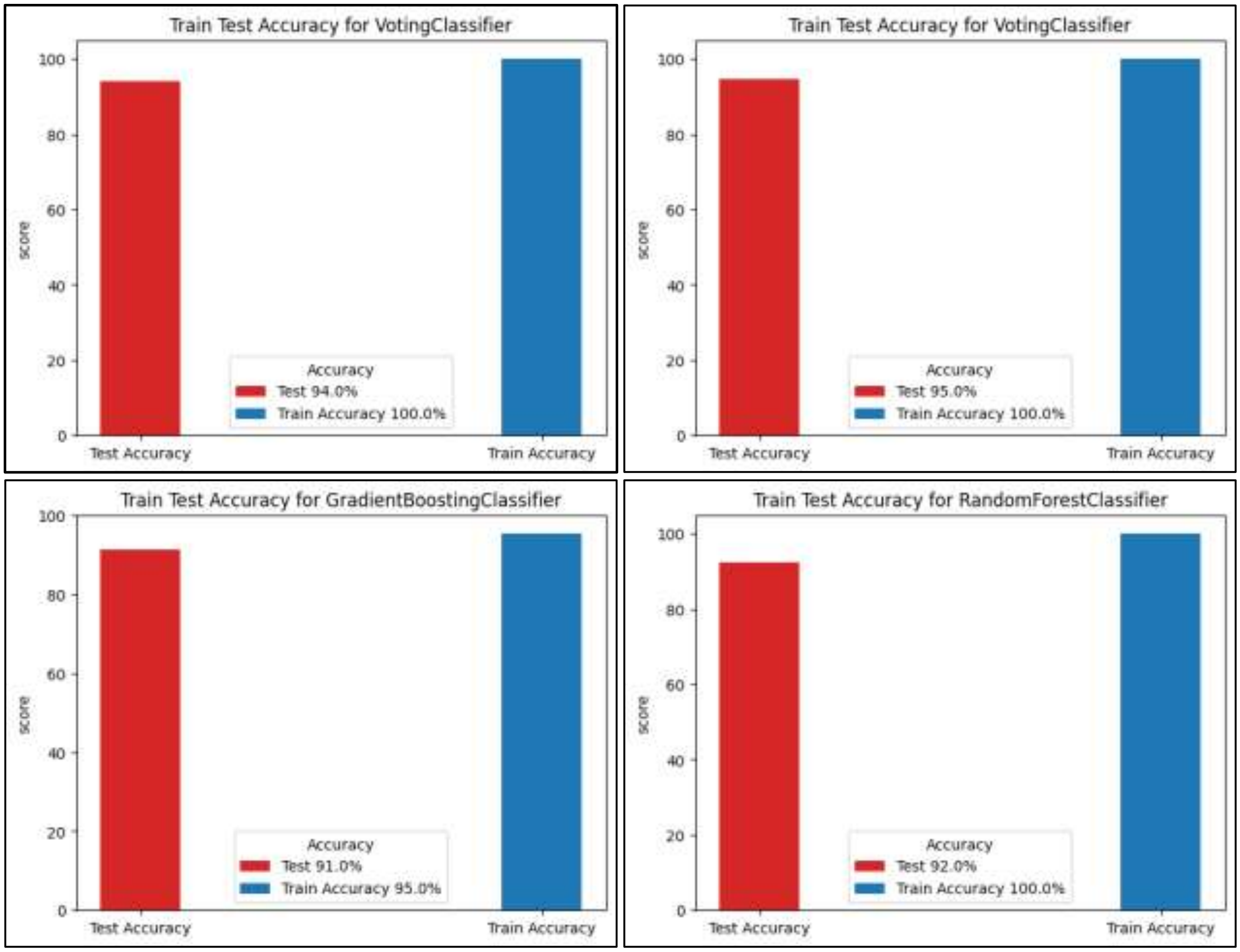
Model# 4: Random Forest Classifier

Model 4 entailed initializing the Random Forest Classifier. Secondly, a pre-trained Random Forest Classifier framework was loaded using the joblib.load() function. The third step encompassed employing the trained Random Forest Classifier framework to make predictions on the test set (x_test). Fourthly, bar charts were created to display both the training and test accuracy of the Random Forest Classifier. The fifth stage entailed portraying the confusion matrix for the Random Forest Classifier on the test set utilizing a heatmap. In the final stage, bar charts were created to exhibit the precision, accuracy, recall, and F1 score of the Random Forest Classifier on the test set.

4.2 Results and Discussion

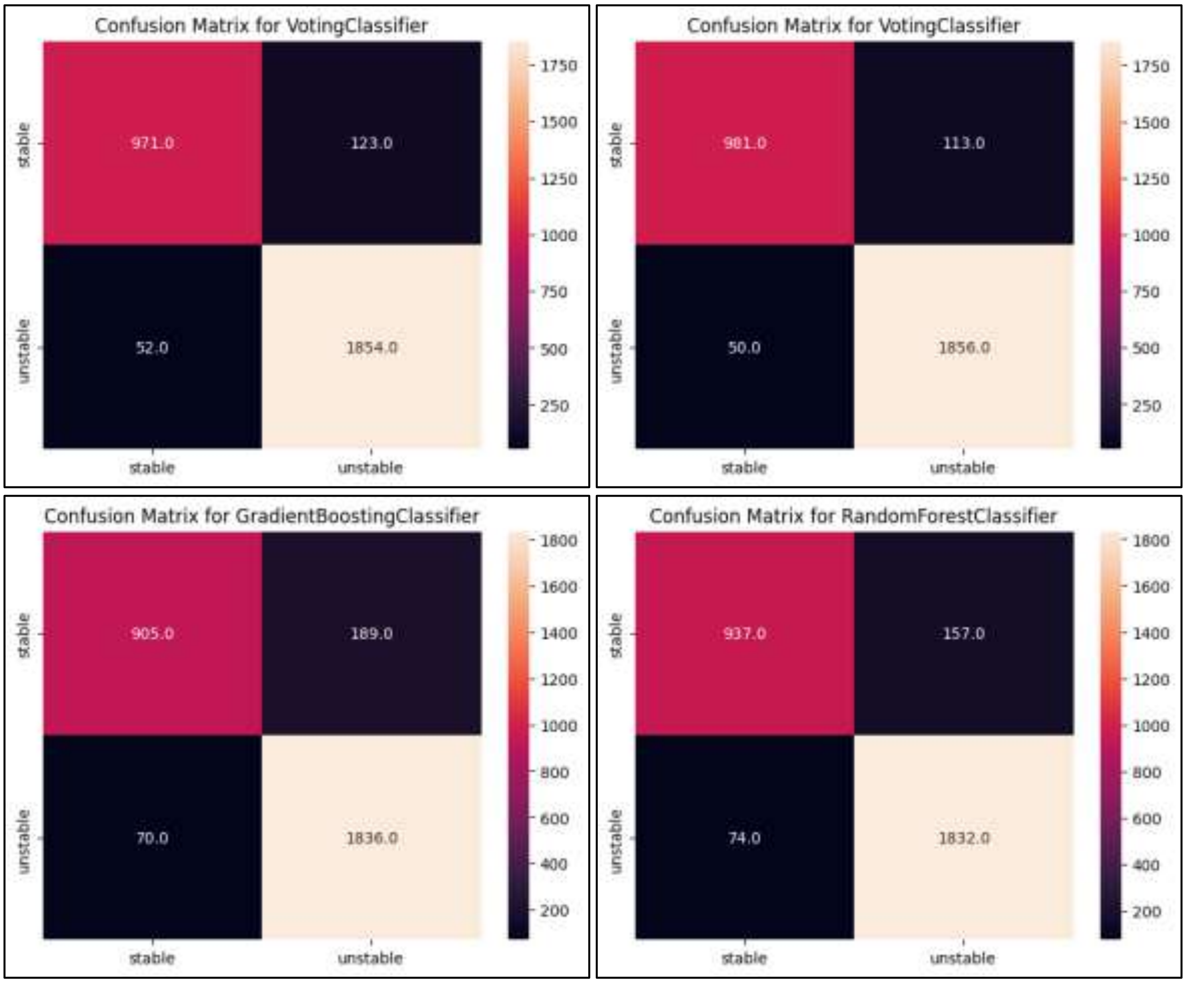
The following sections present the outcomes of the experiment conducted using the four models. In particular, this section will present the train test accuracy, confusion matrix test, as well as the precision, accuracy, recall, and F1 score tests.

Train Test Accuracy



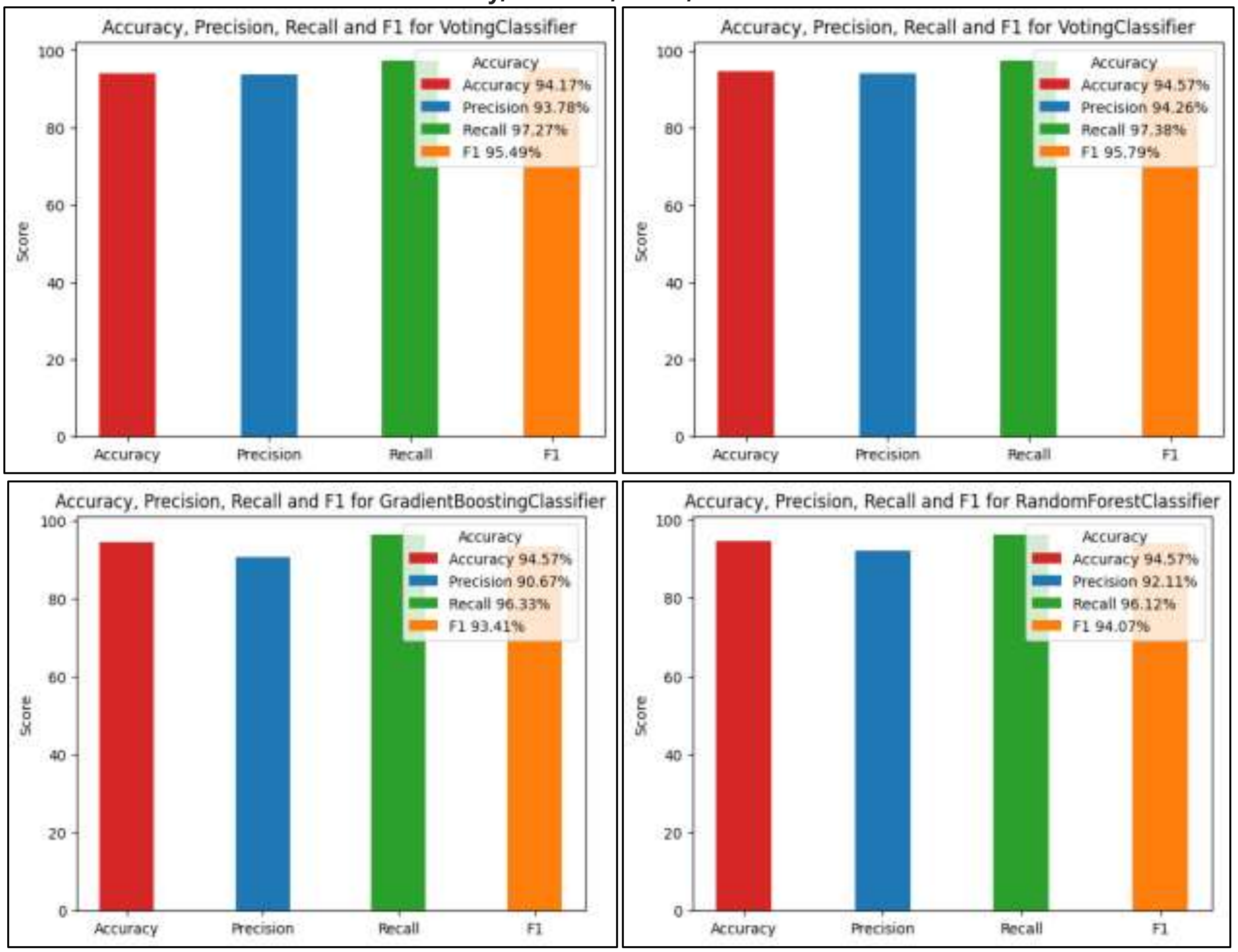
From the train test accuracy for the voting classifier, it was evident that the test accuracy for the voting classifier for the ensemble learning without Feature Engineering was 94% & the Train accuracy (100%). On the other hand, as for the ensemble learning with feature engineering, the test accuracy was 95% and train accuracy was 100%, implying that the ensemble learning with feature engineering was relatively accurate at predicting incidents. By contrast, concerning the gradient boosting classifier, the test accuracy was ascertained to be (91%) and Train accuracy (95%), implying that it was less accurate in predicting incidents. Finally, as for the random forest classifier the results were as follows (Test result-92% & Train Accuracy-100%).

Confusion Matrix Test



The Figure above showcases the confusion matrix for different model classifiers applied to the 80% training dataset. The results illustrated that the voting classifier for the ensemble learning without Feature Engineering accurately classified 971 samples as stable, and 1854 samples as unstable, performing well as compared to other models. Conversely, ensemble learning with feature engineering accurately classified 981 samples as stable and 1856 samples as unstable, performing well as compared to other models. The gradient boosting classifier was able to classify 905 of the samples as stable and 1836 as unstable. Lastly, the random forest classifier categorized 1832 of the sample as unstable and 937 of the sample as stable.

Accuracy, Precision, Recall, and F1 Score



As regards the precision, recall, accuracy, and the F1 score of the Random Forest Classifier, the outcome was as follows accuracy was 94.57%, precision (92.11), recall (96.12%), and F1 score (94.07%). As for the gradient boosting classifier, the outcome was as follows: Accuracy (94.57%), Precision (90.67%), Recall (96.33%), and Fi Score (93.41%). As for the voting classifier for the ensemble learning feature engineering, the outcome was as follows: Accuracy (94.57%), precision (94.26%), recall (97.38%), and F1 score (95.79%). Overall, the ensemble learning with feature engineering demonstrated exceptional performance.

4.3 Proposed Model

Overall, this study proposed the Voting Classifier for Ensemble Learning with Feature Engineering Model, the output demonstrated that the voting classifier was performing relatively well as far as the train test accuracy was concerned. Besides, the accuracy was relatively high as compared to the Random Forest Classifier and the gradient boosting classifier, besides, the recall and precision were also better, as well as the F1 score was also excellent. Remarkably, the Voting Classifier for the Ensemble Learning with Feature Engineering Model technique surpassed the performance of the majority of other techniques, demonstrating an accuracy rate of 94.57%. This exemplified a substantial elevation in accuracy when contrasted to the majority of the techniques evaluated.

4.4 Final Output

To obtain the final output the researcher employed 8 questions, to determine the range, and eventually showcase the output sample below this page

Questions

Response time of respondents (real from the range [0.5,10]s), tau1(τ)

Response time of respondents (real from the range [0.5,10]s), tau2(τ)
Response time of respondents (real from the range [0.5,10]s), tau3(τ)
Response time of the respondents (real from the range [0.5,10]s), tau4(τ)
Coefficient (gamma) relative to price elasticity (real from the range [0.05,1]s^-1), g1(γ)
Coefficient (gamma) relative to price elasticity (real from the range [0.05,1]s^-1), g2(γ)
Coefficient (gamma) relative to price elasticity (real from the range [0.05,1]s^-1), g3(γ)
Coefficient (gamma) relative to price elasticity (real from the range [0.05,1]s^-1), g4(γ)

5. Benefits of Adopting the Proposed Model in America

Cybersecurity and Resilience: Ensemble voting can reinforce the cybersecurity and resilience of the electric grid in the USA. By integrating multiple frameworks with diverse data sources and algorithms, ensemble learning can enhance anomaly detection, intrusion detection, and threat prediction capabilities.

Environmental Benefit: Ensemble voting classifier will certainly assist in terms of optimizing renewable energy consolidation and grid management in the USA, leading to better utilization of clean energy sources.

Economic Benefit: Ensemble learning methods, and consolidate multiple frameworks, which enhances the efficiency and accuracy of predictive and forecasting modeling in the electric grid. By adopting these methodologies, grid operators and utilities in the USA can make more informed decisions concerning energy generation, distribution, and consumption.

Public Health and Safety: Ensemble voting classifier, incorporated with feature engineering, can certainly fortify public safety and health in the setting of the electric grid in the U.S.A. By assessing historical data and real-time sensor data, ensemble learning frameworks can pinpoint anomalies and patterns correlated with potential grid failures or hazards.

6. Conclusion

Traditional electricity models encounter a substantial challenge in America in terms of affirming the stability, security, and reliability of the power system, notably in the confrontation of different contingencies and strains. This study explored different electric grid models adopted in different nations and their shortcomings. To counter the challenges faced by the traditional electricity models, this study focused on integrating machine learning algorithms as an optimization strategy for the electricity power grid. Overall, this study proposed the Ensemble Learning with Feature Engineering Model, the output demonstrated that the voting classifier was performing relatively well. Overall, the ensemble learning with feature engineering demonstrated exceptional performance accuracy.

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