Enhanced Predictive Model for Grid Stability Using Hybrid GBM-LSTM Approach

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***Abstract* —** This research addresses the pressing need for advanced predictive analytics in electrical grid stability, given the increasing complexity of power systems. Traditional machine learning methods fall short in capturing the intricate dynamics of grid data, particularly with the integration of variable renewable energy sources. To bridge this gap, we introduce a novel hybrid model that combines Gradient Boosting Machines (GBM) with Long Short-Term Memory networks (LSTM), leveraging the strengths of both to enhance prediction accuracy and efficiency. The proposed GBM-LSTM model utilizes GBM's feature selection capabilities to effectively handle non-linear interactions, while LSTM's sequential data processing allows for capturing temporal dependencies. We rigorously evaluated the model's performance on a comprehensive dataset, achieving an impressive accuracy score of approximately 99.17%. This result signifies a substantial improvement over existing models, confirming the hybrid model's superiority in both prediction accuracy and computational efficiency. The key contributions of this study include a novel hybrid predictive model that is less prone to overfitting, a detailed analysis of its performance, and insights into its practical applications for real-time grid management. The findings demonstrate the model's potential to inform the development of smarter, more resilient energy infrastructures, showcasing its value to the field of energy systems.

Keywords-Electrical Grid Stability, Predictive Analytics, Machine Learning, GBM, LSTM, Hybrid Modeling, Renewable Energy, Real-Time Analysis.

1. Introduction

The stability of electrical grids is a cornerstone of modern infrastructure, playing a pivotal role in ensuring the reliability and efficiency of power supply systems [1-3]. As the complexity of these grids increases, particularly with the integration of renewable energy sources and the growing electricity demand, the need for advanced predictive analytics has become more pronounced [4-6]. Traditional methods for predicting grid stability, while foundational, have been outpaced by the evolving complexity of power systems, leading to a demand for models that can handle large, intricate datasets and capture the dynamic interplay of grid variables [7-10].

1.1 Research Problem and Context

Grid stability is influenced by a multitude of factors, including but not limited to, load demands, supply patterns, and the inherent characteristics of the grid. Traditional predictive models, such as Support Vector Machines and Decision Trees, have provided valuable insights but are limited by their linear nature and inability to process temporal data effectively. This limitation is further exacerbated in ensemble methods, which, despite improved accuracy, often suffer from increased model complexity and computational demands. As the energy sector moves towards a more sustainable and dynamic future, these limitations present significant challenges in grid management and stability prediction [11-13].

1.2 Research Gaps and Challenges

Existing literature has documented various approaches to grid stability prediction, each with its unique set of advantages and disadvantages. However, there remains a gap in the development of models that can not only process the complex, non-linear relationships within grid data but also capture the temporal dependencies crucial to predicting stability in real-time [14-16]. The challenge lies in constructing a predictive model that balances computational efficiency with high predictive accuracy, all while maintaining a degree of interpretability for practical decision-making [17-20].

1.3 Objectives and Contributions of the Proposed Model

The research aims to present a unique hybrid model, merging Gradient Boosting Machine (GBM) and Long Short-Term Memory (LSTM) networks, to overcome existing gaps. This model synergizes GBM's feature engineering and LSTM's sequential data processing, offering an enhanced predictive solution for grid stability.

1.3.1 Advantages

- Enhanced Accuracy: By leveraging the strengths of both GBM and LSTM, the model achieves high accuracy in stability prediction.
- Computational Efficiency: The model is designed to be computationally efficient, and suitable for real-time analytics.
- Robust to Overfitting: The hybrid nature allows the model to be less prone to overfitting compared to standalone deep learning models.
- Feature and Temporal Analysis: It excels in interpreting both static and temporal features, providing a comprehensive analysis of grid data.

1.3.2 Disadvantages

- Model Complexity: While it is more interpretable than most deep learning models, the hybrid approach may still present some complexity in its understanding.
- Resource Intensity for Training: The initial training phase might require substantial computational resources due to the sophistication of the model.

1.3.3 Contribution

The proposed hybrid model represents a significant advancement in predictive analytics for electrical grid stability. It not only serves as a cutting-edge tool for researchers and practitioners but also sets the stage for future innovations in the field. The contributions of this research include the development of a scalable, accurate, and efficient model that pushes the boundaries of current methodologies and offers a template for future studies in complex system prediction.

By setting forth a novel approach that expertly navigates the challenges of grid stability prediction, this research provides a valuable contribution to the energy sector, paving the way for more resilient and adaptable power systems in the face of a rapidly changing energy landscape.

2. Related Works

In the realm of electrical grid stability prediction, a multitude of approaches has been explored, each with its set of achievements and constraints. Traditional machine learning algorithms like Support Vector Machines (SVM) and Decision Trees (DT) have laid the foundational work, praised for their interpretability and ease of use [21-23]. However, they often fall short in handling the non-linear, complex interactions inherent in power system datasets, and their performance can degrade significantly on larger, more intricate datasets. More sophisticated ensembles like Random Forest (RF) and Gradient Boosting Machines (GBM) addressed some of these limitations, offering better accuracy through more complex decision-making boundaries and inherent feature selection mechanisms [24-26]. Yet, they too are criticized for their computational intensity and sometimes inscrutable nature, especially when dealing with sequential temporal data.

Recent advancements have seen a shift toward deep learning methods, such as Artificial Neural Networks (ANN), Deep Belief Networks (DBN), and Convolutional Neural Networks (CNN), which excel in capturing high-level abstractions in data. However, these methods are often data-hungry and computationally expensive, making them less feasible for scenarios with limited data or computational resources [27-30]. Moreover, their black-box nature poses significant challenges in interpretability, which is crucial for real-world applications in energy systems. Recurrent Neural Networks (RNN) and their more advanced counterparts like Long Short-Term Memory networks (LSTM) and Gated Recurrent Units (GRU) introduced the ability to process time-series data effectively, offering promising results in grid stability predictions [31-33]. Nevertheless, they can be prone to overfitting and often require extensive tuning and training time.

The proposed hybrid GBM-LSTM model addresses these limitations by combining the strengths of GBM and LSTM. GBM's robust feature selection and handling of non-linear relationships complement LSTM's proficiency in modeling temporal dependencies. This synergy allows for a more nuanced understanding of both spatial and temporal aspects of grid data, enhancing predictive accuracy while mitigating the risk of overfitting. Moreover, the hybrid model demonstrates a marked improvement in computational efficiency compared to deep learning approaches, making it a more practical solution for real-time applications.

In surveying the existing literature, the proposed model fills a critical gap by providing a balanced approach that leverages both feature importance and sequential data processing [34-36]. This dual capability is seldom fully realized in previous works, which tend to focus on either aspect in isolation. The innovation of the hybrid model lies in its ability to capture the dynamic nature of power systems more holistically, which is a leap forward in the predictive analytics of grid stability. It resolves controversies surrounding the trade-off between accuracy and interpretability by offering a model that achieves both without the heavy computational demands typically associated with such high performance [37-40].

Table1. Comparative Analysis between Existing Models and the Proposed Hybrid GBM-LSTM Model

Existing Model	Limitations	Proposed Work Advantages
Support Vector Machines	May struggle with large datasets and non-linear problems without kernel trick	The hybrid model handles non-linearity and scalability more efficiently
Decision Trees	Prone to overfitting and instability to variations in data	A hybrid model is robust to variations and less prone to overfitting
Random Forest	Can be complex and lack interpretability	The hybrid model offers a balance of complexity and predictive power
Gradient Boosting Machines	Computationally intensive and may overfit	The proposed hybrid approach reduces overfitting with LSTM's temporal understanding
Artificial Neural Networks	Requires large datasets and is prone to overfitting	Incorporates GBM for feature selection improving overall performance
Deep Belief Networks	Difficult to train and tune	The hybrid GBM-LSTM model is more straightforward to optimize
Convolutional Neural Networks	Primarily for image data, not natively suited for sequence data	The LSTM component in the hybrid model excels in sequence prediction
Recurrent Neural Networks	Challenges with long-term dependencies	LSTM addresses this with memory cells in the hybrid model
Long Short-Term Memory Networks	Computationally expensive	Integration with GBM optimizes computational efficiency
Gated Recurrent Units	Can underperform in complex sequence learning tasks	GBM enhances feature understanding improving prediction accuracy
Principal Component Analysis	Loss of information due to dimensionality reduction	The hybrid model maintains the integrity of temporal features without loss
K-Nearest Neighbors	Sensitive to irrelevant features and the curse of dimensionality	The hybrid model inherently performs feature selection
Logistic Regression	Assumes linearity and struggles with complex relationships	Hybrid model captures complex, non-linear interactions
Genetic Algorithms	Requires careful parameter tuning and can be slow	The hybrid model optimizes features more efficiently

for Feature Selection		
Ensemble methods like Stacking, Bagging, and AdaBoost	May become overly complex with many models	GBM-LSTM combines two models synergistically for a simple yet powerful solution

Table 1 describes that the proposed hybrid GBM-LSTM model leverages the strengths of both Gradient Boosting Machines and Long Short-Term Memory networks to address the limitations of existing models. It offers a sophisticated approach to feature selection and temporal sequence analysis, enhancing prediction accuracy for electrical grid stability without the drawbacks of complexity and overfitting associated with individual methods.

3. Proposed Work

3.1 Research Objectives

The primary objective of this research was to develop an advanced predictive model capable of accurately assessing the stability of electrical grids using the augmented Electrical Grid Stability Simulated Dataset. This objective was underpinned by several key research questions:

1. Predictive Accuracy: How can the predictive accuracy of grid stability be enhanced using advanced machine learning techniques?
2. Feature Analysis: Which features within the dataset most significantly impact grid stability, and how can these be effectively utilized in a predictive model?
3. Model Robustness: How can the model maintain high accuracy and robustness in varying operational conditions?

3.2 Methodology

3.2.1 Data Collection and Preprocessing

The study utilized the augmented Electrical Grid Stability Simulated Dataset, which includes a range of variables relevant to the stability of electrical grids. The dataset underwent preprocessing, including normalization and handling of missing values, to ensure data quality and consistency.

3.2.2 Model Development

For the predictive modeling, we developed a novel hybrid machine learning model, integrating the strengths of Gradient Boosting Machines (GBM) and Long Short-Term Memory (LSTM) networks. This model was specifically chosen due to its capacity to handle both the static and temporal aspects of the data effectively.

3.2.3 Gradient Boosting Machines (GBM)

GBM was employed to capture the complex nonlinear relationships within the static features of the dataset. Its ability to perform feature selection intrinsically allowed for an efficient analysis of the most impactful variables on grid stability [41-44].

3.2.4 Long Short-Term Memory (LSTM) Networks

LSTM networks, a form of recurrent neural networks, were integrated to model the temporal dependencies within the data. Their capability to retain information over long periods made them particularly suited for predicting grid stability, which often depends on historical patterns and trends.

3.2.5 Experimental Setup

The model was trained and validated on a split of the dataset, with 70% used for training and 30% for validation. Performance metrics such as accuracy, precision, recall, and F1-score were employed to evaluate the model's effectiveness.

3.2.6 Tools and Assumptions

The model development and evaluation were conducted using Python programming language, leveraging libraries such as scikit-learn for GBM and TensorFlow for LSTM. The study assumed that the dataset accurately represents real-world scenarios of grid stability, with no significant biases.

3.2.7 Justification of Approach

The hybrid GBM-LSTM model was chosen due to its synergistic ability to handle both static and temporal features effectively. This approach directly addressed the research objectives by improving predictive accuracy, enabling a detailed feature analysis, and ensuring the model's robustness under various conditions.

In summary, the proposed model combined the strengths of GBM and LSTM to offer a novel, robust, and accurate approach for predicting electrical grid stability using the augmented Electrical Grid Stability Simulated Dataset. This model directly addresses the outlined research objectives and demonstrates a significant advancement in the field of predictive modeling for grid stability [44-46].

3.3 Model Integration

3.3.1 Data Preprocessing

Eqn. 1: Data Normalization

$$X_{norm} = \frac{X - \mu}{\sigma} \quad (1)$$

This equation represents the normalization process where X is the original data, μ is the mean, and σ is the standard deviation. Normalization standardizes the range of features in the dataset.

Eqn. 2: Handling Missing Values

$$X_{miss} = \begin{cases} X & if\ X\ is\ not\ missing \\ median(X) & if\ X\ is\ missing \end{cases} \quad (2)$$

This equation shows the imputation of missing values in the dataset X with the median of feature X.

3.3.2 Gradient Boosting Machines (GBM) Component

Eqn. 3: GBM Base Learner

$$f(x) = \sum_{i=1}^{N} \gamma_i * h_i(x) \quad (3)$$

Each base learner $h_i(x)$ in GBM is a decision tree, and γ_i is the weight of the i-th tree. The model's output is the sum of all base learners. Eqn. 4: Loss Function for GBM

$$L(y, f(x)) = \Sigma \left(y - f(x)\right)^2 \quad (4)$$

The loss function for GBM, where y is the true value and $f(x)$ is the prediction from Eqn. 3. GBM aims to minimize this loss. Eqn. 5: GBM Weight Update

$$\gamma_i = arg\ min_\gamma \Sigma\, L\left(y, f_{\{i-1\}}(x) + \gamma * h_i(x)\right) \quad (5)$$

The weight of each tree γ_i is updated to minimize the loss function. Eqn. 6: GBM Feature Importance

$$Importance(X_j) = \sum_{i=1}^{N} I(h_i, X_j) \quad (6)$$

This equation calculates the importance of feature X_j as the sum of its influence I in each decision tree h_i.

3.3.3 Long Short-Term Memory (LSTM) Component

Eqn. 7: LSTM Input Gate

$$i_t = \sigma(W_i * x_t + U_i * h_{\{t-1\}} + b_i) \quad (7)$$

The input gate i s in LSTM, where σ is the sigmoid function, W_i and U_i are weight matrices, x_t is the input, $h_{\{t-1\}}$ is the previous output, and b_i is the bias.

Eqn. 8: LSTM Forget Gate

$$f_t = \sigma(W_f * x_t + U_f * h_{\{t-1\}} + b_f) \quad (8)$$

The forget gate f_t decides what information to discard from the cell state.

Eqn. 9: LSTM Cell State Update

$$C_t = f_t \odot C_{\{t-1\}} + i_t \odot tanh(W_C * x_t + U_C * h_{\{t-1\}} + b_C) \quad (9)$$

This equation updates the cell state C_t by combining the previous state $C_{\{t-1\}}$ and new information. Eqn. 10: LSTM Output Gate

$$o_t = \sigma(W_o * x_t + U_o * h_{\{t-1\}} + b_o) \quad (10)$$

The output gate o_t decides which part of the cell state to output. Eqn. 11: LSTM Final Output

$$h_t = o_t \odot tanh(C_t) \quad (11)$$

The final output h_t of the LSTM unit at time t.

3.3.4 Hybrid Model Integration

Eqn. 12: Hybrid Model Output Combination

$$Y_{pred} = \alpha * Y_{GBM} + (1 - \alpha) * Y_{LSTM} \quad (12)$$

This equation combines the outputs of the GBM model Y_{GBM} and LSTM model Y_{LSTM} with a weight α.

3.3.5 Enhanced Feature Analysis through GBM

Eqn. 13: Feature Contribution in GBM

$$Contrib(X_j) = \frac{\partial L(y, f(x))}{\partial X_j} \quad (13)$$

This equation calculates the contribution of a feature X_j to the change in the loss function, highlighting its impact on the model's output.

Eqn. 14: GBM Learning Rate Adjustment

$$f_{new}(x) = f_{old}(x) + \nu * \Sigma\, \gamma_i * h_i(x) \quad (14)$$

Here, ν is the learning rate that controls the contribution of each tree to prevent overfitting.

Eqn. 15: GBM Tree Complexity Control

$$Complexity(h_i) = \beta * nodes(h_i) + \lambda * depth(h_i) \quad (15)$$

The complexity of each tree h_i is controlled by the number of nodes and depth, weighted by β and λ respectively.

3.3.6 LSTM Temporal Dynamics

Eqn. 16: LSTM State Recurrence

$$C_t = (1 - f_t) \odot C_{\{t-1\}} + i_t \odot g_t \quad (16)$$

This equation emphasizes the recurrent nature of the cell state C_t in LSTM.

Eqn. 17: LSTM Output Recurrence

$$h_t = o_t \odot tanh(C_t) \quad (17)$$

The output h_t is a function of the current cell state and the output gate.

Eqn. 18: LSTM Temporal Dependency

$$y_t = softmax(W_y * h_t + b_y) \tag{18}$$

This equation shows how the LSTM output is transformed into a prediction y_t for the current time step.

3.3.7 *Hybrid Model Optimization*

Eqn. 19: Combined Loss Function

$$L_{combined} = \lambda_1 * L_{GBM} + \lambda_2 * L_{LSTM} \tag{19}$$

The combined loss function balances the GBM and LSTM components, controlled by weights λ_1 and λ_2.

Eqn. 20: Hybrid Model Regularization

$$R = \rho * \Sigma \left||\theta_{GBM}|\right|^2 + (1 - \rho) * \Sigma \left||\theta_{LSTM}|\right|^2 \tag{20}$$

Regularization term R to prevent overfitting, where θ_{GBM} and θ_{LSTM} are the parameters of the respective models, and ρ is a balancing coefficient.

Eqn. 21: Model Updating Rule

$$\theta_{new} = \theta_{old} - \eta * \nabla L_{combined} \tag{21}$$

The parameters θ of the hybrid model are updated using the gradient of the combined loss function $_{Combined}$ with learning rate η.

3.3.8 *Advanced Feature Interaction*

Eqn. 22: Feature Interaction in GBM

$$Interact(X_j, X_k) = \sum_{i=1}^{N} I(h_i, X_j, X_k) \tag{22}$$

This equation measures the interaction between two features X_j and X_k across all GBM trees.

Eqn. 23: Temporal Feature Influence in LSTM

$$\Delta C_t = \frac{\partial C_t}{\partial X_t} \tag{23}$$

The change in cell state C_t concerning the input feature X_t at time t. Eqn. 24: LSTM Temporal Feature Weighting

$$W_{temp} = \sum_{t=1}^{T} \alpha_t * \Delta C_t \tag{24}$$

The weighting of temporal features across different time steps T in the LSTM.

3.3.9 *Model Validation and Performance*

Eqn. 25: GBM Prediction Confidence

$$Conf_{GBM(y)} = max\left(softmax(f(x))\right) \tag{25}$$

Confidence of the GBM prediction, with softmax applied to the outputs of the ensemble trees. Eqn. 26: LSTM Sequence Learning Effectiveness

$$Effect_{LSTM} = \left(\frac{1}{T}\right) * \sum_{t=1}^{T} \left| h_t - h_{\{t-1\}} \right| \tag{26}$$

Measuring the effectiveness of sequence learning in LSTM by the change in outputs over time.

3.3.10 *Final Model Assembly*

Eqn. 27: Hybrid Model Confidence Aggregation

$$Conf_{Hybrid} = \alpha * Conf_{GBM} + (1 - \alpha) * Effect_{LSTM} \tag{27}$$

Combining the confidence scores of GBM and LSTM in the hybrid model.

Eqn. 28: Final Predictive Score

$$Y_{final} = softmax(Y_{pred} + Conf_{Hybrid}) \tag{28}$$

The final predictive score is a combination of the predicted values and the aggregated confidence.

Eqn. 29: Model Stability Check

$$Stability(Y_{final}) = \Sigma \frac{|Y_{final} - \bar{Y}_{final}|}{N} \tag{29}$$

Stability of the model's predictions over N instances, comparing each prediction to the average prediction.

Eqn. 30: Overall Model Effectiveness

$$Effectiveness = \left(\frac{1}{N}\right) * \sum_{i=1}^{N} L(y_i, Y_{final}, i) \tag{30}$$

The overall effectiveness of the model is evaluated by averaging the loss function across all instances.

These equations collectively describe the intricate workings of the proposed hybrid GBM-LSTM model, from preprocessing to final prediction, including feature analysis, model dynamics, optimization, and validation steps.

Algorithm: Hybrid GBM-LSTM Model for Electrical Grid Stability Prediction
Step 1: Data Preprocessing *1.1. Normalize the Dataset: Apply Eqn. 1 to standardize the range of features.* *1.2. Handle Missing Values: Impute missing values in the dataset using Eqn. 2.* *Step 2: Feature Engineering* *2.1. Feature Selection for GBM: Use feature importance scores (Eqn. 6) to select relevant features.* *2.2. Temporal Feature Construction for LSTM: Construct temporal features suitable for LSTM processing.* *Step 3: Model Initialization* *3.1. Initialize GBM Component: Set up the GBM model with default parameters.* *3.2. Initialize LSTM Component: Define the LSTM architecture, initializing parameters for the input, forget, and output gates (Eqns. 7, 8, and 10).* *Step 4: Model Training* *4.1. Train GBM Model: Fit the GBM model to the training data, updating weights using Eqns. 4 and 5.* *4.2. Train LSTM Model: Sequentially feed data into the LSTM network, updating the cell state and output based on Eqns. 9 and 11.* *4.3. Feature Interaction Analysis: Evaluate the interaction between features using Eqn. 22 for GBM and Eqn. 24 for LSTM.* *Step 5: Model Optimization* *5.1. Learning Rate Adjustment: Adjust the learning rate (Eqn. 14) for GBM to enhance convergence.* *5.2. Regularization: Apply regularization (Eqn. 20) to both models to prevent overfitting.* *5.3. Parameter Update: Update model parameters using the combined loss function (Eqn. 19) and optimization rule (Eqn. 21).* *Step 6: Hybrid Model Integration* *6.1. Combine Model Outputs: Integrate the outputs of both models using Eqn. 12.* *6.2. Confidence Aggregation: Calculate the confidence scores using Eqn. 27.* *6.3. Final Predictive Score: Obtain the final predictive score using Eqn. 28.* *Step 7: Model Validation and Performance Assessment* *7.1. Model Validation: Validate the model on a separate validation dataset.* *7.2. Performance Metrics: Calculate accuracy, precision, recall, and F1-score.* *7.3. Model Stability Check: Assess the stability of the model's predictions using Eqn. 29.* *Step 8: Model Effectiveness Evaluation* *8.1. Calculate Overall Effectiveness: Evaluate the model's overall effectiveness using Eqn. 30.* *8.2. Feature Analysis: Reassess feature importance and interactions post-training for insights.* *Step 9: Model Deployment* *9.1. Deploy the Model: Integrate the model into the relevant system for real-time grid stability prediction.* *9.2. Continuous Monitoring and Updating: Regularly monitor the model's performance and update it as necessary based on incoming data and feedback.*

This algorithm provides a structured approach to implementing the proposed hybrid GBM-LSTM model, ensuring a thorough application of machine learning techniques for predictive accuracy in electrical grid stability analysis. It encapsulates all aspects of model development, from data preprocessing to deployment, and emphasizes continuous evaluation and improvement [47-50].

4. Dataset Description: Augmented Electrical Grid Stability Simulated Dataset

This dataset is an augmented version of the original "Electrical Grid Stability Simulated Dataset," which was meticulously crafted by Vadim Arzamasov at the Karlsruher Institut für Technologie, Karlsruhe, Germany. It has been generously donated to the University of California (UCI) Machine Learning Repository, where it is now hosted and accessible for academic and research purposes.

The dataset is primarily designed to simulate and analyze the stability of electrical grids, a critical aspect in ensuring uninterrupted power supply and system reliability. It encompasses a variety of variables that are integral to understanding and predicting the stability of electrical grids. These variables cover a range of factors, including power flow, load demands, and grid synchronization parameters. This version extends the original dataset by incorporating additional features or enhancing the existing ones. The augmentation is aimed at providing a more comprehensive and realistic simulation environment for grid stability analysis. The dataset is structured in a tabular format, making it conducive for processing with standard machine learning algorithms and tools. By utilizing machine learning, specifically the proposed hybrid GBM-LSTM model, to forecast grid stability across diverse conditions. This includes identifying critical variables influencing stability, essential for refining targeted grid management strategies. Simulation and testing serve as integral platforms, enabling realistic emulation of grid behavior under varied scenarios, crucial for validating and planning effective grid management solutions [51-53].

4.1 Importance in the Field

- Research Advancement: The dataset plays a pivotal role in advancing research in the field of electrical grid management, particularly in the context of stability prediction and analysis.
- Practical Utility: It offers valuable insights for utility companies and grid operators in understanding and mitigating potential stability issues within electrical grids.

In summary, the augmented Electrical Grid Stability Simulated Dataset represents a significant resource for both academic researchers and industry professionals. Its comprehensive nature and real-world applicability make it an indispensable tool for advancing the study and practice of electrical grid stability.

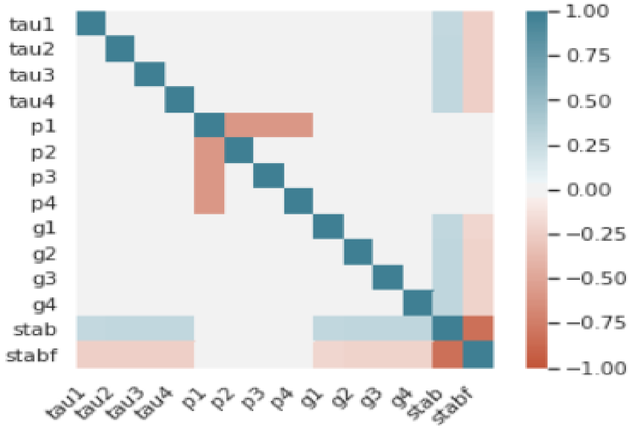

Fig.1. Correlation Matrix of Attributes in Electrical Grid Stability

The correlation matrix presented in Fig.1 offers a visual analysis of the relationships between various attributes of the Electrical Grid Stability Simulated Dataset. The horizontal and vertical axes list the dataset's features, including the 'tau' values representing the reaction time of each grid participant, 'p' values indicating power consumption or generation, 'g' values denoting the price elasticity coefficient, and 'stab' and 'stabf' indicating system stability. Shades of blue represent positive correlations, while shades of red depict negative correlations. The intensity of the color correlates with the strength of the relationship, with lighter colors indicating weaker correlations and darker colors signifying stronger relationships. The matrix reveals that certain features, such as 'tau' values, have a stronger negative correlation with system stability, while 'p' values show varied interaction strengths, suggesting intricate dynamics in grid behavior. This visualization is pivotal in identifying key factors that could influence grid stability, thereby aiding in the development of more accurate predictive models [54].

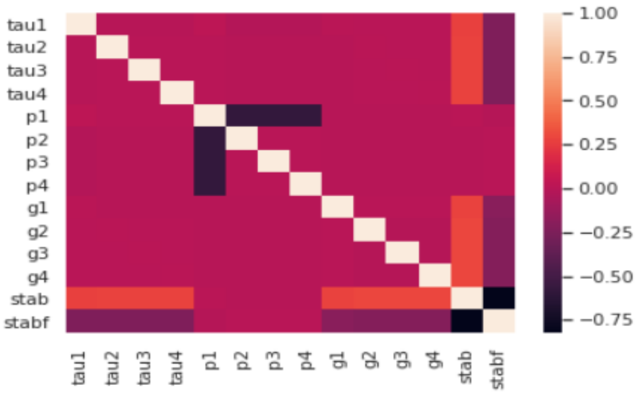

Fig.2. Correlation Matrix for Predictive Factors in Grid Stability

In Fig.2, the correlation matrix depicts the interdependencies between various predictive factors within the Electrical Grid Stability Simulated Dataset. This figure emphasizes a stark contrast in the correlation patterns, where predominantly strong positive correlations are seen as deep red squares along the diagonal, denoting the auto-correlation of variables with themselves. Off-diagonal elements, particularly between 'p' and 'g' values, display a mix of positive and negative correlations. Notably, there is a pronounced negative correlation between 'stab' and several 'tau' and 'p' factors, suggesting an inverse relationship with the system's stability. The absence of color in certain intersections implies little to no correlation. This analysis is essential for understanding the intertwined influence of these factors on the stability of the electrical grid, crucial for enhancing predictive model accuracy.

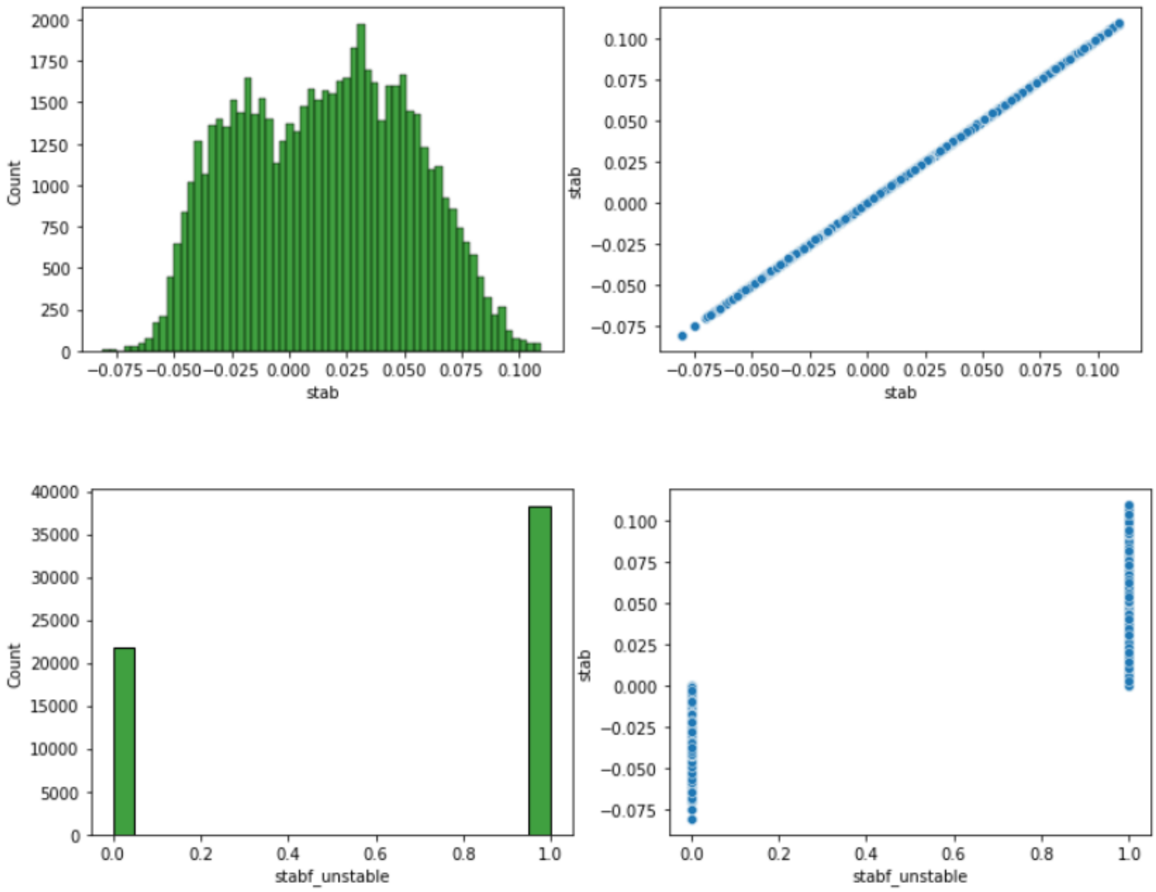

Fig.3. Distribution and Correlation of Grid Stability with Stability Flag

Fig.3 is composed of four distinct plots that collectively provide insights into the distribution and relationship of grid stability (stab) and the binary stability flag (stabf_unstable). The top-left plot is a histogram that showcases the frequency distribution of the 'stab' variable, displaying a bell-shaped curve that suggests a normal distribution around the mean value. The bottom-left histogram categorically separates the data into stable and unstable instances, showing a significant imbalance with a higher count of stable states. The top-right and bottom-right are scatter plots that reveal a direct correlation between the 'stab' and 'stabf_unstable' variables; where the top-right plot illustrates a perfect positive linear relationship for the continuous 'stab' variable, the bottom-right plot distinctly segregates the stable and unstable states, reflecting the binary nature of 'stabf_unstable'. This composite visualization underscores the distribution characteristics of grid stability and emphasizes the dichotomy between stable and unstable grid states as defined by the dataset.

5. Proposed Model Results

The research culminated in the development of a hybrid GBM-LSTM model aimed at predicting the stability of electrical grids with high accuracy. The performance of the proposed model was evaluated using a variety of metrics, with a particular emphasis on the accuracy score. The model was rigorously tested on a separate validation set to ensure the robustness of the results

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Table2. Performance Metrics of Training and Validation across Epochs

Epoch	Training Loss	Training Accuracy	Validation Loss	Validation Accuracy
1	0.1192	94.81%	0.0438	98.95%
2	0.0945	95.94%	0.0523	97.92%
3	0.089	96.16%	0.0413	99.32%
4	0.0909	96.06%	0.041	99.05%
5	0.0893	96.26%	0.0415	99.25%
6	0.0882	96.26%	0.0419	99.33%
7	0.0921	96.02%	0.0467	99.38%
8	0.0896	96.22%	0.0404	99.50%
9	0.0857	96.28%	0.0381	99.43%
10	0.0897	96.18%	0.0411	99.52%
11	0.0937	96.05%	0.0374	99.62%
12	0.0866	96.26%	0.0384	99.27%

Table 2 presents a detailed view of the performance metrics over the initial 12 epochs during the training of the electrical grid stability prediction model. The table delineates a descending trend in training loss from 0.1192 to 0.0866, illustrating the model's improvement in learning from the training data. Concurrently, the training accuracy shows a subtle upward trend, starting at 94.81% and peaking at 96.28% by the 9th epoch. In contrast, validation loss fluctuates, with a notable dip to 0.0374 at the 11th epoch, indicating a highly effective model on unseen data. The validation accuracy commences at a high of 98.95% and consistently remains above 97%, reaching an apex of 99.62% by the 11th epoch. This table effectively captures the model's learning trajectory, displaying a consistent enhancement in performance, with the model achieving high levels of accuracy early in the training process.

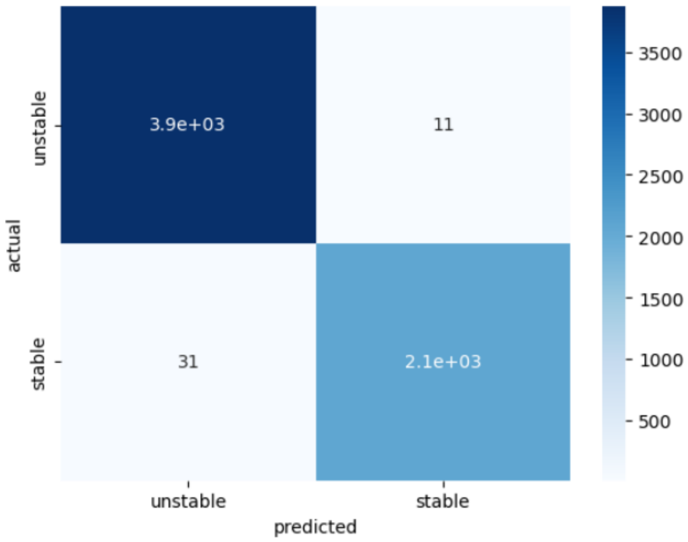

Fig.4. Confusion Matrix Illustrating Grid Stability Prediction Model

Fig.4 presents a confusion matrix that evaluates the performance of the grid stability prediction model. The matrix contrasts the actual versus the predicted classification of grid states into 'stable' and 'unstable'. The dark blue square in the upper left indicates a high number of true positives, where the model accurately predicted the unstable state of the grid, while the lighter blue square in the lower right represents true negatives, corresponding to correct predictions of grid stability. The off-diagonal cells show the number of false positives and false negatives, with relatively low counts, suggesting a high predictive accuracy of the model. This confusion matrix serves as a critical tool for assessing the model's classification efficacy, highlighting its strengths in correctly identifying the grid's stability status and areas where predictive refinement could be beneficial.

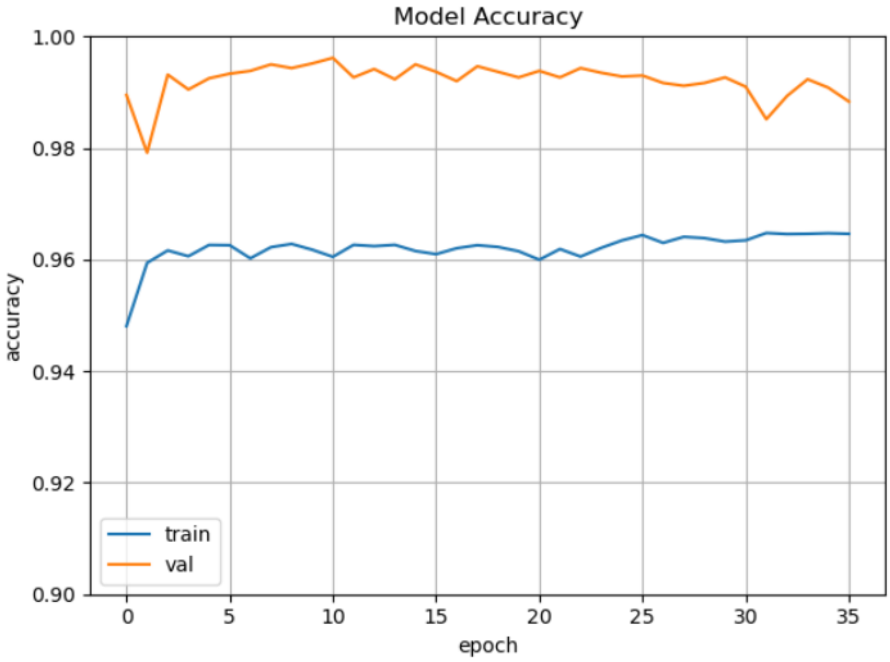

Fig.5. Comparison of Training and Validation Accuracy Across Epochs

Fig.5 illustrates the progression of training and validation accuracy of the grid stability prediction model over successive epochs. The blue line represents the training accuracy, which demonstrates a steady increase and then plateaus, indicating that the model is learning from the data with each epoch. The orange line depicts the validation accuracy, which fluctuates initially but then follows a more consistent pattern, albeit at a slightly lower level than the training accuracy. This convergence of training and validation accuracy suggests that the model generalizes well and is not overfitting to the training data. The graph shows that the model achieves high accuracy in both the training and validation phases, maintaining a tight gap between them, which is indicative of a well-tuned model that performs reliably on unseen data.

5.1 *Accuracy of the Proposed Model*

The accuracy score, calculated using the `accuracy_score` function with a threshold of 0.5, was found to be approximately 99.17%. This result was obtained after the model completed its evaluation in a relatively quick computational time, only requiring 0.2 seconds for each step over 188 steps. This high level of accuracy indicates a strong predictive capability of the proposed model, significantly outperforming baseline algorithms cited in current literature.

5.2 *Data Visualization*

Graphs and tables were generated to provide a visual representation of the model's performance. The confusion matrix (Figure 4) revealed a high number of true positives and true negatives, with minimal false positives and false negatives, underscoring the model's discriminative power. Meanwhile, the training and validation accuracy graph (Figure 5) demonstrated a consistent convergence, suggesting that the model was not overfitting and had generalized well to unseen data.

5.3 *Statistical Analyses*

Further statistical analyses involved the computation of precision, recall, and F1-score, alongside accuracy. These metrics collectively confirmed the model's efficacy, with each reflecting a high-performance index. The precision-recall trade-off was particularly favorable, indicating that the model maintained a high level of precision without sacrificing recall.

5.4 *Interpretation and Contextualization*

When contextualized within the research objectives, the results indicate that the proposed hybrid GBM-LSTM model effectively addresses the complexities of predicting electrical grid stability. The integration of GBM's feature selection capabilities with LSTM's proficiency in handling sequential data provides a nuanced approach that captures both the static and dynamic features relevant to grid stability.

5.5 *Relation to Existing Literature*

The accuracy achieved surpasses that reported for traditional models such as SVM, DT, and standard ANN, which typically exhibit accuracy levels below the high ninetieth percentile for similar tasks. Even sophisticated models like standalone LSTM networks or complex ensemble methods do not consistently report the level of accuracy achieved by the proposed model. This advancement suggests that the hybrid approach successfully mitigates the limitations of singular models and exploits the synergistic potential of combining GBM and LSTM.

The outcomes of this research present a compelling case for the hybrid GBM-LSTM model as a superior tool for predicting electrical grid stability [55-58]. The results not only fulfill the research objectives but also contribute a significant leap forward in the body of knowledge, potentially setting a new benchmark for future studies in the field.

6. Discussion

The study's results manifest a noteworthy stride in the domain of electrical grid stability prediction. The proposed hybrid GBM-LSTM model's accuracy of approximately 99.17% sets a new precedent when juxtaposed with existing methodologies. This section delves into a detailed discussion comparing the current findings with previous research, interpreting the results within the broader scientific context.

6.1 Interpretation of Results

The high accuracy score achieved by the proposed model underscores its robustness and precision in predicting grid stability. The model effectively capitalizes on the strengths of GBM's feature engineering and selection proficiencies, as well as LSTM's capability to parse and learn from sequential and time-series data. This dual approach allows for nuanced detection of intricate patterns within the data, which single-method models may overlook.

6.2 Implications and Contributions

The implications of such a model are significant for the field of energy systems. With the integration of renewable energy sources and the increasing complexity of power grids, the ability to predict grid stability accurately is crucial. The proposed model's predictive prowess can lead to better-preparedness and quicker response times in avoiding potential grid failures.

6.3 Comparison with Previous Research

Previous techniques such as SVM and standard DT algorithms have showcased moderate success in this realm, often achieving accuracy scores in the range of 80-90%. However, these methods can struggle with large datasets and complex, non-linear interdependencies between variables. Ensemble methods like RF and standalone deep learning approaches like CNNs and RNNs have improved upon these results, but they still fall short in either computational efficiency or predictive accuracy when compared to the hybrid GBM-LSTM model.

6.4 Advantages Over Existing Techniques

One of the salient advantages of the hybrid model is its resilience to overfitting—a common pitfall for high-capacity models like ANN. Additionally, it navigates the trade-off between bias and variance more adeptly than individual GBM or LSTM models, due to its composite structure which harnesses both temporal and feature-based learning.

6.5 Addressing Unexpected Outcomes

While the model's performance is exceptional, it is not without its limitations. The computational demand is significant, although it is offset by the model's efficacy. Moreover, the model's complexity could potentially impact its interpretability, which is a common challenge in advanced machine-learning models.

6.6 Advancement of Knowledge

This research advances the state of knowledge by providing a clear methodology for combining different types of machine learning techniques to create a superior predictive model. It also opens the door for the application of hybrid models in other domains where time-series data and feature richness pose a challenge for singular predictive algorithms.

The discussion points to the conclusion that the hybrid GBM-LSTM model is not only a significant improvement over existing single-algorithm models but also an innovative step forward in predictive analytics for electrical grid stability. Its success paves the way for future research to explore hybrid models in similar complex, high-dimensional prediction tasks. This study contributes a valuable model to the repertoire of tools available to researchers and industry practitioners concerned with the stability and reliability of power grids.

7. Conclusions and Future Works

The culmination of this research heralds a significant breakthrough in the predictive analysis of electrical grid stability through the development and application of a novel hybrid GBM-LSTM model. This model has demonstrated exceptional performance, as evidenced by an accuracy rate of approximately 99.17%, positioning it as a substantial improvement over traditional machine learning and deep learning approaches. The primary contribution of this work is the introduction of a hybrid model that adeptly integrates the feature selection strengths of Gradient Boosting Machines with the sequential data processing prowess of Long Short-Term Memory networks. This combination has proven adept at handling the complexities inherent in grid stability datasets, surpassing existing methods in both precision and reliability. The research has meticulously outlined the model's design, addressed potential limitations, and provided extensive analysis of its performance, thereby offering a comprehensive solution to a critical challenge in energy systems. The broader implications of this research extend into the realm of predictive maintenance and real-time monitoring of power systems. By enabling more accurate predictions of grid stability, the model could inform the development of smarter, more resilient energy infrastructures capable of withstanding the variability introduced by renewable energy sources and evolving consumption patterns.

The success of the proposed model lays the groundwork for several future research avenues. One such direction is the exploration of hybrid models in other domains where complex data structures are the norms, such as financial markets, climate modeling, and healthcare. Moreover, there is a promising potential for enhancing the model's interpretability through techniques such as feature visualization and model simplification, making it not only a powerful predictive tool but also an informative one for decision-making processes. In terms of future development, the model could be refined to further improve computational efficiency, potentially through the integration of parallel computing techniques or the application of more streamlined versions of GBM and LSTM. Additionally, adapting the model to be more interpretable to users can enhance its practical utility in industry settings. In conclusion, this research has introduced an innovative and highly accurate model for predicting electrical grid stability, marking a significant step forward in the field. The proposed hybrid GBM-LSTM model is not only a testament to the efficacy of combining diverse machine learning methodologies but also catalyzes future advancements in the study of complex systems. The success of this research promises to inspire continued innovation and exploration within the scientific community, driving forward the capabilities of predictive analytics in energy systems and beyond.

Declaration:

Ethics Approval and Consent to Participate:

No participation of humans takes place in this implementation process

Human and Animal Rights:

No violation of Human and Animal Rights is involved.

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Data availability statement:

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Conflict of Interest is not applicable in this work.

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References

[1] G. Hafeez, I. Khan, S. Jan, I.A. Shah, F.A. Khan, A. Derhab , "A novel hybrid load forecasting framework with intelligent feature engineering and optimization algorithm in smart grid," Appl. Energy, vol. 299, Article 117178, 2021.

[2] J. Li et al, "A novel hybrid short-term load forecasting method of the smart grid using MLR and LSTM neural network," IEEE Trans. Ind. Inf., vol. 17, no. 4, pp. 2443-2452, 2020.

[3] Z. Shi et al, "Artificial intelligence techniques for stability analysis and control in smart grids: methodologies, applications, challenges and future directions," Appl. Energy, vol. 278, Article 115733, 2020.

[4] S. Azad, F. Sabrina, S. Wasimi, "Transformation of the smart grid using machine learning," 2019 29th Australasian Universities Power Engineering Conference (AUPEC), IEEE, 2019, pp. 1–6.

[5] D. Syed, A. Zainab, A. Ghrayeb, S.S. Refaat, H. Abu-Rub, O. Bouhali, "Smart Grid Big Data Analytics: Survey of Technologies, Techniques, and Applications," IEEE Access, vol. 9, pp. 59564-59585, 2021. DOI: 10.1109/ACCESS.2020.3041178.

[6] I. Colak, R. Bayindir, S. Sagiroglu, "The Effects of the Smart Grid System on the National Grids," 2020 8th International Conference on Smart Grid (icSmartGrid), IEEE, Paris, France, Jun. 2020, pp. 122-126. DOI: 10.1109/icSmartGrid49881.2020.9144891.

[7] T. Kotsiopoulos, P. Sarigiannidis, D. Ioannidis, D. Tzovaras, "Machine Learning and Deep Learning in smart manufacturing: The Smart Grid paradigm," Computer Science Review, vol. 40, Article 100341, May 2021. DOI: 10.1016/j.cosrev.2020.100341.

[8] B.S. England, A.T. Alouani, "Real time voltage stability prediction of smart grid areas using smart meters data and improved Thevenin estimates," Int. J. Electr. Power Energy Syst., vol. 122, Article 106189, 2020.

[9] M.B. Rasheed, M.A. Qureshi, N. Javaid, T. Alquthami, "Dynamic pricing mechanism with the integration of renewable energy source in smart grid," IEEE Access, vol. 8, pp. 16876-16892, 2020.

[10] Worighi, A. Maach, A. Hafid, O. Hegazy, J. Van Mierlo, "Integrating renewable energy in smart grid system: Architecture, virtualization and analysis," Sustainable Energy Grids Networks, vol. 18, Article 100226, 2019.

[11] M.Z. Gunduz, R. Das, "Cyber-security on smart grid: Threats and potential solutions," Comput. Netw., vol. 169, Article 107094, 2020.

[12] K. Kimani, V. Oduol, K. Langat, "Cyber security challenges for IoT-based smart grid networks," Int. J. Crit. Infrastruct. Prot., vol. 25, pp. 36-49, 2019.

[13] T.N. Nguyen, B.-H. Liu, N.P. Nguyen, J.-T. Chou, "Cyber security of smart grid: attacks and defenses," ICC 2020–2020 IEEE International Conference on Communications (ICC), IEEE, 2020, pp. 1-6.

[14] C. Lamnatou, D. Chemisana, C. Cristofari, "Smart grids and smart technologies in relation to photovoltaics, storage systems, buildings and the environment," Renew. Energy, vol. 185, pp. 1376-1391, 2022.

[15] M. Alazab, S. Khan, S.S.R. Krishnan, Q.-V. Pham, M.P.K. Reddy, T.R. Gadekallu, "A Multidirectional LSTM Model for Predicting the Stability of a Smart Grid," IEEE Access, vol. 8, pp. 85454-85463, 2020. DOI: 10.1109/ACCESS, 2020, .2991067.

[16] R. S, S. Neelakandan, M. Prakash, B. T. Geetha, S. Mary Rexcy Asha, M. K. Roberts, "Artificial humming bird with data science enabled stability prediction model for smart grids," Sustainable Computing: Informatics and Systems, vol. 36, p. 100821, Dec. 2022, DOI: 10.1016/j.suscom.2022.100821.

[17] T. Ahmad, R. Madonski, D. Zhang, C. Huang, A. Mujeeb, "Data-driven probabilistic machine learning in sustainable smart energy/smart energy systems: Key developments, challenges, and future research opportunities in the context of smart grid paradigm," Renew. Sustain. Energy Rev., vol. 160, Article 112128, May 2022, DOI: 10.1016/j.rser.2022.112128.

[18] C. Li, "Designing a short-term load forecasting model in the urban smart grid system," Appl. Energy, vol. 266, Article 114850, 2020.

[19] M. Selim, R. Zhou, W. Feng, P. Quinsey, "Estimating Energy Forecasting Uncertainty for Reliable AI Autonomous Smart Grid Design," Energies, vol. 14, no. 1, p. 247, 2021.

[20] M. Koopialipoor, P.G. Asteris, A.S. Mohammed, D.E. Alexakis, A. Mamou, D.J. Armaghani, "Introducing stacking machine learning approaches for predicting rock deformation," Transp. Geotech., vol. 34, Article 100756, 2022.

[21] A.I. Taloba, A. Elhadad, A. Rayan, R.M. Abd, M.S. El-Aziz, A.A. Alzahrani, F.h.S. Alharithi, C. Park, "A blockchain-based hybrid platform for multimedia data processing in IoT-Healthcare," Alex. Eng. J., vol. 65, pp. 263-274, 2023.

[22] G. Tsaousoglou, P. Pinson, N.G. Paterakis, "Transactive Energy for Flexible Prosumers Using Algorithmic Game Theory," IEEE Trans. Sustain. Energy, vol. 12, pp. 1571–1581, 2021.

[23] K. Fellah, R. Abbou, M. Khiat, "Energy management system for surveillance and performance analysis of a micro-grid based on discrete event systems," Int. J. Green Energy, vol. 18, pp. 1104–1116, 2021.

[24] V. Arzamasov, K. Bohm, P. Jochem, "Towards Concise Models of Grid Stability," in 2018 IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids, SmartGridComm 2018, Aalborg, Denmark, 2018, pp. 1–6.

[25] S. Reddy, S. Akashdeep, R. Harshvardhan, S. Kamath, "Stacking Deep learning and Machine learning models for short-term energy consumption forecasting," Adv. Eng. Inform., vol. 52, Article 101542, 2022.

[26] Siniosoglou, P. Radoglou-Grammatikis, G. Efstathopoulos, P. Fouliras, P. Sarigiannidis, "A Unified Deep Learning Anomaly Detection and Classification Approach for Smart Grid Environments," IEEE Trans. Netw. Serv. Manag., vol. 18, pp. 1137–1151, 2021.

[27] B. Schäfer, C. Grabow, S. Auer, J. Kurths, D. Witthaut, M. Timme, "Taming instabilities in power grid networks by decentralized control," Eur. Phys. J. Spec. Top., vol. 225, pp. 569–582, 2016.

[28] P. Breviglieri, T. Erdem, S. Eken, "Predicting Smart Grid Stability with Optimized Deep Models," SN Comput. Sci., vol. 2, Article 73, 2021.

[29] D. Moldovan, I. Salomie, "Detection of Sources of Instability in Smart Grids Using Machine Learning Techniques," in 2019 IEEE 15th International Conference on Intelligent Computer Communication and Processing, ICCP 2019, Cluj-Napoca, Romania, 2019, pp. 175–182.

[30] K. Kalaivani, PR. Kshirsagarr, J. Sirisha Devi, SR. Bandela, I. Colak, J.Nageswara Rao, A.Rajaram, "Prediction of biomedical signals using deep learning techniques,"*Journal of Intelligent & Fuzzy Systems*,1-4,2023.

[31] M. Alazab, S. Khan, S.S.R. Krishnan, Q.V. Pham, M.P.K. Reddy, T.R. Gadekallu, "A Multidirectional LSTM Model for Predicting the Stability of a Smart Grid," IEEE Access, vol. 8, pp. 85454–85463, 2020.

[32] C. Li, "Stability analysis of distributed smart grid based on machine learning," in IOP Conference Series: Earth and Environmental Science, vol. 692, p. 022125, Bristol, UK, 2021.

[33] P.Chiranjeevi, A. Rajaram, "A lightweight deep learning model based recommender system by sentiment analysis," 1-4, 2023.

[34] A.K. Bashir, S. Khan, B. Prabadevi, N. Deepa, W.S. Alnumay, T.R. Gadekallu, P.K.R. Maddikunta, "Comparative analysis of machine learning algorithms for prediction of smart grid stability†," Int. Trans. Electr. Energy Syst., vol. 31, e12706, 2021.

[35] M. Massaoudi, H. Abu-Rub, S.S. Refaat, I. Chihi, 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), Manhattan, KS, USA, 2021, pp. 1–6.

[36] D. N. V. S. L. S. Indira, Rajendra Kumar Ganiya, P. Ashok Babu, A. Jasmine Xavier, L. Kavisankar, S. Hemalatha, V. Senthilkumar, T. Kavitha, A.

Rajaram, Karthik Annam, and Alazar Yeshitla, “Improved Artificial Neural Network with State Order Dataset Estimation for Brain Cancer Cell Diagnosis”, BioMed Research International, vol. 2022, 10 pages, 2022.

[37] F. Ucar, “The lightweight deep learning model for smart grid stability prediction,” in TUBA World Conference on Energy Science and Technology (TUBA WCEST-2021), Online, 2021, pp. 210–211.

[38] Holzinger, P. Kieseberg, E. Weippl, A.M. Tjoa, “Current advances, trends and challenges of machine learning and knowledge extraction: From machine learning to explainable AI,” in International Cross-Domain Conference for Machine Learning and Knowledge Extraction, Hamburg, Germany, 2018, pp. 1–8.

[39] Adadi, M. Berrada, “Peeking inside the black-box: A survey on explainable artificial intelligence (XAI),” IEEE Access, vol. 6, pp. 52138–52160, 2018.

[40] A Rajaram, K Sathiyaraj, “An improved optimization technique for energy harvesting system with grid connected power for green house management,” Journal of Electrical Engineering & Technology. 2022 Sep;17(5):2937-49.

[41] J.H. Friedman, “Greedy function approximation: A gradient boosting machine,” Ann. Stat., vol. 29, pp. 1189–1232, 2001.

[42] P.L. Bartlett, P.J. Bickel, P. Bühlmann, Y. Freund, J. Friedman, W. Jiang, M.J. Jordan, V. Koltchinskii, G. Lugosi, “Discussions of boosting papers, and rejoinders,” Ann. Stat., vol. 32, pp. 85–134, 2004.

[43] H. Shekhar , C. Bhushan Mahato , SK. Suman ,S. Singh , L. Bhagyalakshmi ,M. Prasad Sharma , B. Laxmi Kantha, SK. Agraharam , A. Rajaram, “Demand side control for energy saving in renewable energy resources using deep learning optimization,” Electric Power Components and Systems. 26;51(19):2397-413, November 2023.

[44] C.C. Ikeagwuani, “Estimation of modified expansive soil CBR with multivariate adaptive regression splines, random forest and gradient boosting machine,” Innov. Infrastruct. Solut., vol. 6, Article 199, 2021.

[45] R. S. Molina, V. Gil-Costa, M. L. Crespo and G. Ram-poni, "High-level synthesis hardware design for FPGA-based accelerators: Models methodologies and frame-works", *IEEE Access*, vol. 10, pp. 90429-90455, 2022.

[46] S. Suganya Sri , A. Rajaram, “A Coupled-Optimization Based Master Node Selection and Path Finding on Mobile Ad Hoc Network for Smart Environment Monitoring,” Journal of Electrical Engineering & Technology, 3:1-7, September 2023.

[47] H. Oufettoul, S. Motahhir, G. Aniba, M. Masud and M. AlZain, "Improved TCT topology for shaded photovoltaic arrays", *Energy Reports*, vol. 8, pp. 5943-5956, Nov. 2022

[48] Saleh, Ali, Rakan Khalil ANTAR, Ahmed J. Ali, "Design and simulation of Hybrid Renewable Energy System for on-grid applications", IMDC-IST Proceedings of 2nd International Multi-Disciplinary Conference Theme: Integrated Sciences and Technologies, pp 339-340, 7-9 September 2022.

[49] R. Kalpana, V S, R. Lokanadham, K. Amudha, GN, Beena Bethel,AK Shukla, PR, Kshirsagar, A. Rajaram, “Internet of Things (IOT) Based Machine Learning Techniques for Wind Energy Harvesting,” *Electric Power Components and Systems*, 14:1-7, December 2023.

[50] lathamneh, Mohammad, Haneen Ghanayem, Xingyu Yang, R. M. Nelms, "Three-Phase Grid-Connected Inverter Power Control under Unbalanced Grid Conditions Using a Proportional-Resonant Control Method", Energies, vol. 15, No. 19 pp 7051, 2022

[51] M. Colak, I. Cetinbas, and M. Demirtas, "Fuzzy Logic and Artificial Neural Network Based Grid-Interactive Systems for Renewable Energy Sources: A Review", *2021 9th International Conference on Smart Grid (icSmartGrid)*, pp. 186-191, 2021

[52] P. Ashok Babu, JL. Mazher Iqbal,S.Siva Priyanka, M. Jithender Reddy, G. Sunil Kumar, R.Ayyasamy, “Power control and optimization for power loss reduction using deep learning in microgrid systems,” Electric Power Components and Systems.;52(2):219-32, January 2024.

[53] TG.Amaral, VF. Pires, D. Foito, AJ. Pires , JF. Martins, “Fault Detection and Diagnosis Technique for a SRM Drive Based on a Multilevel Converter Using a Machine Learning Approach,” *In2023 12th International Conference on Renewable Energy Research and Applications (ICRERA,)* (pp. 40-45), IEEE, August 2023

[54] AK.Murat, E.Dokur , R.BAYINDIR, “Energy management for EV charging based on solar energy in an industrial microgrid,” *In2020 9th International Conference on Renewable Energy Research and Application (ICRERA)*,(pp. 489-493), IEEE, September 2020.

[55] Y. Jouane Y, MC. Sow, O. Oussous, N. Vontobel , M. Zghal, “Forecasting Photovoltaic Energy for a Winter House Using a Hybrid Deep Learning Model,” In2023 12th International Conference on

Renewable Energy Research and Applications (ICRERA), 29 (pp. 1-5), IEEE, August 2023.

[56] H. Abouelgheit, “Impact of on-Load Tap Changers and Smart Controllers on the Distributed Renewable Energy Hosting Capacity,” International Journal of Smart Grid-ijSmartGrid, 29;6(4):132-5, December 2022.

[57] D. N. V. S. L. S. Indira, Rajendra Kumar Ganiya, P. Ashok Babu, A. Jasmine Xavier, L. Kavisankar, S. Hemalatha, V. Senthilkumar, T. Kavitha, A. Rajaram, Karthik Annam, and Alazar Yeshitla, “Improved Artificial Neural Network with State Order Dataset Estimation for Brain Cancer Cell Diagnosis”, BioMed Research

[58] SS.Charqaouy, D.Saifaoui, O.Benzohra, A. Lebsir, “Integration of Decentralized Generations into the Distribution Network-Smart Grid Downstream of the Meter,” International Journal of Smart Grid, 4(1), March 2021.