International Journal on Science and Technology (IJSAT)

E-ISSN: 2229-7677 ● Website: www.ijsat.org ● Email: editor@ijsat.org

Optimizing Smart Grid Performance with Deep Learning Models

Ashok Gajapathi Raju.V [1], Rohit Kumar.B [2], Sai Kumar.S [3] , Sravya.P [4], Bhanuprakash.I [5]

[1]Teacher, Information Technology Department, Aditya Institute of Technology and Management, 532201, Tekkali, India

[2,3,4,5]Student, Information Technology Department, Aditya Institute of Technology and Management, 532201, Tekkali, India

Abstract

The smart grid is a cutting-edge power system idea that balances communication and electricity in system networks. It gives producers, operators, and consumers access to real-time information. The need to effectively manage electricity distribution to different consuming domains, including homes, businesses, industries, and smart cities, is growing. In this regard, dynamic power demand must be met by a stable smart grid system. Because there are so many affecting factors, predicting the stability of the smart grid is still difficult. Participation from producers and consumers is crucial since determining their level of involvement can help maintain grid stability. In this study, we suggest a deep learning model for smart grid stability prediction that is based on Gated Recurrent Units (GRU). Other conventional machine learning and deep learning classifiers. Such as Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), and Artificial Neural Networks (ANN), are contrasted with the outcomes of the suggested GRU model. With a 97.45% accuracy rate, our suggested GRU model outperforms previous models in predicting the stability of the smart grid.

Keywords: Smart Grid Dataset, Decision tree Classifier, Logistic regression, Artificial Neural Networks, recurrent Neural Networks, Recurrent Neural Networks, Long Short-Term Memory, Gated Recurrent Units.

1. Introduction

The term of the electrical grid is a large and interconnected network that delivers electricity from renewable energy resources such as power plants, thermal power, solar plants etc., to homes and industries. It includes components such as power stations, transmission lines and distribution networks. Traditional grids have been vital for supporting global development. but they face different challenges like limited scalability, reliability issues and inefficiency. Furthermore, because conventional grids rely on centralized power generation, integrating renewable energy sources like wind and solar power is more difficult. Due to these limitations and the demand for sustainable alternatives, smart grids more sophisticated and intelligent systems have been developed.

International Journal on Science and Technology (IJSAT)
E-ISSN: 2229-7677 ● Website: www.ijsat.org ● Email: editor@ijsat.org

Smart grids are an advanced version of traditional grids, enhanced with digital technologies, communication systems and advanced controls. These characteristics make it possible to monitor and optimize energy flows in real time. Smart grids, as opposed to conventional grids, are able to incorporate a variety of energy sources, including renewable ones. Technologies like Advanced Metering Infrastructure (AMI) and Wide Area Measurements Systems (WAMS) improve energy distribution, making it more reliable and efficient. Smart grids also allow two-way energy flows and decentralized energy production. Smart grids monitor and control energy in real time using cutting-edge technologies. By solving problems like peak energy demand and the inconsistent availability of renewable energy, smart grids are transforming how we produce, distribute and use electricity. However, there are challenges, for example, smart grids rely heavily on digital systems. Additionally, Implementing and maintaining smart grids is expensive, making it harder for some regions to adopt this technology.

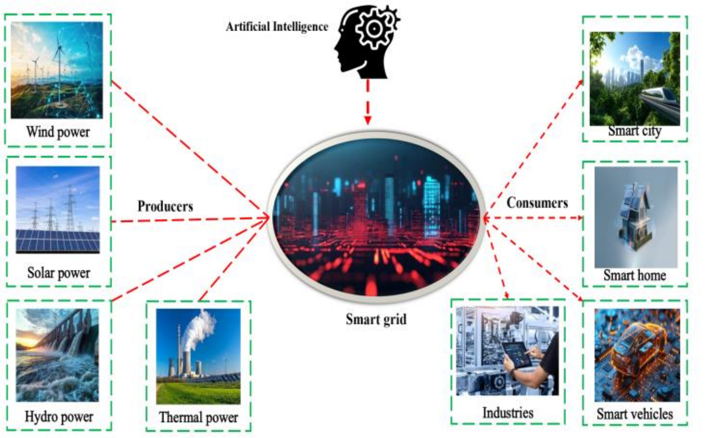

Figure 1: Smart grid workflow

To address such challenges, deep learning is type of artificial intelligence is being employed in enhancing smart grid operations. Deep learning models scrutinize the information from the real-time data or sources to predict potential faults and enhance grid performance in real-time. These models assist with activities such as predicting maintenance requirements ,detecting faults, forecasting energy, Early outcomes indicate that smart grids with support from deep learning can conserve energy, enhance reliability and promote the utilization of renewable energy [1], [2].

The significance of smart grid stability is that it can satisfy the dynamic power requirements of different users with minimal interruptions in energy supply. A reliable smart grid can minimize energy losses, optimize the use of renewable energy sources, and manage varying levels of electrical demand. We can have a more dependable and sustainable electricity system with accurate grid stability predictions. This can greatly increase the energy distribution efficiency, lower operational expenses and better overall user experience for industries and consumers [3], [4].

Smart grid stability prediction is a universal application applicable in numerous fields. For consumers and homes, it allows effective power management, minimizing cost and ensuring sustainability. On the industrial and commercial front, stable grids are vital for enterprises that require a consistent flow of power. Predictive models provide low downtime and optimize energy usage, facilitating industrial efficiency. Moreover in integration of renewable energy, precise predictions of stability are most importance. They allow for the smooth integration of intermittent energy sources such as wind and solar into the grid, overcoming issues related to their unpredictable availability [5], [6].

Machine & Deep Learning models provide a number of major advantage for forecasting smart grid stability. First of all, these models are very effective in dealing with complicated data since they can manage large amount of data and detect patterns. Secondly, Deep learning models make predictions in real-time, which is important to grid operators to make instant adjustments and ensure the stability of the grid. These models are very adaptable, with architectures such as RNNs and GRUs specifically designed to cope with sequential data, making them ideal for predicting time-based events such as grid stability. Moreover, models like LSTM and ANNs have proven high accuracy in tasks that involve learning from large datasets, providing better predictions than the use of traditional machine learning algorithms. we plan to deliver more accurate, real-time predictions, assisting in enhancing the reliability and efficiency of smart grids [7].

In our project, we have imported the UCI Machine Learning Repository dataset. The dataset adheres to the local stability study of the Decentral Smart Grid Control concept in a 4-node star system. The dataset consists of 14 features and 10,000 instances with associated tasks of binary classification.

- After importing the dataset, perform data preprocessing, i.e., check for NaN values in the dataset. Apply Min-Max Scaling for independent variables and Label Encoding for the target variable to convert categorical data into numerical.
- Train the traditional machine learning models using Scikit-learn and deep learning models using the Keras module. Compare them with the proposed GRU model.
- After that, perform evaluation metrics to find out the accuracy, recall, F1-score, and ROC.
- To visualize the results, plot the confusion matrix, training and validation accuracy, and loss.

Literature Survey

Daniel [8] sought to determine the most effective machine learning method for forecasting the reliability of the smart grid utilizing a dataset of 60,000 observations with 12 features. They optimized hyperparameters for improved performance while training and testing a variety of models, such as Decision Tree, K-NN, Logistic Regression, SVM, Naïve Bayes, Random Forests and Ann-MLP. Metrics like accuracy, F1-Score, and specifically were used to evaluate performance, with an emphasis on negative case identification and prediction accuracy. With a 94.8% F1-score and 93.5% accuracy, the Random Forest are the best method for predicting the reliability of smart grids and suggested using these methods for other power grid activities.

MUHAMMAD et al.,[9] inorder to anticipate voltage stability in the IEEE 4-bus system, they tested four models and created an ensemble model for increased accuracy using an Artificial Neural Network (ANN). They evaluated the models performance using accuracy, MSE, and MAE after training them on 80% of the dataset, which included transmission characterstics and power usage. Despite requiring more training and inference time, the ensemble model yielded the maximum accuracy of 98.73% with the lowest MSE (0.0095) and MAE (0.0141). They found that the ensemble model is a very good way to forecast voltage stability. The model will be optimized in the future to reduce processing time without sacrificing accuracy.

Pranobjyothi Lahon et al.,[10] examined a number of machine learning classifiers, including deep neural networks(DNN), XGBoost, SVM with Radial Basis Function(SVM-RBF), and Linear SVM. The models were assessed using F1 scores, recall, accuracy and precision. The DNN model achieved the greatest accuracy of 96.5%, followed by Logistic Regression and Linear SVM at 95.9% and XGBoost at 94.8%. It came to the conclusion that DNN perform best, understanding the potential of deep learning and machine learning to improve smart grid control.

LEPOLESA et al.,[11] explains how to identify electricity theft using a classification algorithm based on deep neural networks. It makes use of data from the State Grid Corporation of China (SGCC), which comprises 42,372 customers electricity usage records collected from January 1, 2014 to October 31,2016.Data interpolation and synthetic data generation techniques were used to address missing data and class imbalance (91% normal users, 9% fraudulent users). The model integrates the characterstics of the frequency and time domains and its performance is maximized through the use of Bayesian Hyperparameter tuning, PCA and Minimum Redundancy Maximum relevance (MRMR). The proposed method ranked second on the benchmark dataset with an accuracy of 91.8% and an area under the curve of 97%, which is 1% better than prior works.

Amjad et al.,[12] focuses on forecasting smart grid stability using a Multi-Layer perceptron-Extreme Learning Machine(MLP_ELM) approach. It utilizes a smart grid dataset containing stability-related data, through the exact number of instances is not specified. Principal Component Analysis(PCA) is applied for feature extraction, and the models performance is evaluated through empirical assessments and comparisons with traditional machine learning techniques. The proposed MLP-ELM method outperforms conventional approaches, achieving an accuracy an accuracy of 95.8%.

2. Materials and Methods

The deep learning model, the assessment metrics, and the electrical smart grid stability dataset are described in depth in this section. These components plays a crucial role in building an optimized smart grid stability system, leveraging deep learning predictions for enhanced performance.

2.1 Smart grid Stability Dataset

The dataset used in this study is the Smart Grid Stability Dataset, firstly contributed by Vadim Arzamasov and made available through the University of California(UCI). This dataset which is also accessible on Kaggle, consists of 12 features, 2 dependent variables and an aggregate of 10,000 data points. The primary ideal of the dataset is to assess grid stability grounded on these features and classify the grid as either stable or unstable. Below is a breakdown of features. Duration of response (tau1, tau2, tau3, tau4) Each component of the power metwork’s response time is represented by these four characteristics. These attributes have values ranging from 0.5 to 10. The provider knot is represented by the tau1 point, while the consumer bumps are represented by the tau2, tau3, tau4 points. Power generation and use (p1, p2, p3, p4) These characteristic show how much electricity each system participant generates and uses. Power product is represented by a positive value, whereas power consumption is represented by a negative value. The supplier is represented by point p1, while the customers are represented by points p2, p3, and p4. These traits have values in the range of -0.2 to -0.5. Additionally, the negative sum of p2, p3, and p4 is considered p1. Price-elasticity Measure (g1, g2, g3, g4) These four attributes denote the price--elasticity measure for each party, with values falling between 0.05 and 1.00. The point g1 corresponds to the supplier, while g2, g3, and g4 correspond to the consumers. The letter" g" in these features stands for gamma. Stability (stab, stabf) While the first 12 features serve as prophetic inputs, the final two attributes, stab and stabf, act as dependent variables. The stab point calculates a stability value, and its sign determines the stabf classification. However, the grid is considered unstable, whereas a negative stab signifies a stable grid, If stab is positive.

2.2 Steps Involved in Working with Datasets for Deep Learning

- Cleaning and converting unprocessed data into a format that may be used is known as data pre-processing.
- Feature scaling uses a variety of methods, including standardization, Min-Max scaling, and robust scaling to guarantee that all numerical features are on the same scale.
- Label Encoding, often known as one-hot encoding, is the process of converting category data into numerical notation.
- Dividing the dataset into testing and training sets in order to assess model performance.
- Using X and Y to update data divides the dataset into target labels (Y) and features (X).
- Using preprocessed data to apply machine learning and deep learning models through a variety of processes, including model selection, compilation, training, and evaluation.
- Data distribution and model performance can be better understood by displaying data patterns.

These procedures enable us to deploy machine learning and deep learning models, preprocess data effectively, and visualize the results, which improves model performance and produces more accurate predictions.

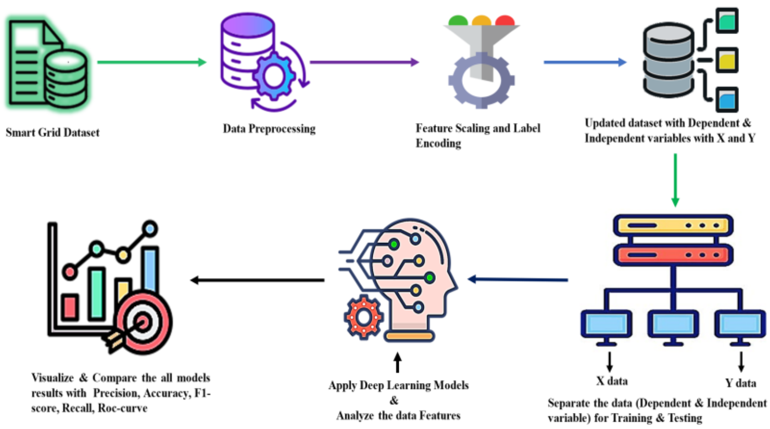

Figure 2: ML and DL model workflow

2.3 Machine Learning

Within the field of artificial intelligence (AI), machine learning focuses on creating models and algorithms that let computers learn from data and perform better without explicit programming. It entails sending vast volumes of data into algorithms, which use the data to find patterns, decide what to do, and forecast results. Machine learning can be roughly divided into three categories: supervised learning, which involves training models on labeled data; unsupervised learning, which uses unlabeled data to cover hidden patterns; and reinforcement learning, which involves rewarding or punishing models as they learn. This technology powers many modern applications, such as recommendation systems, image and speech recognition, autonomous vehicles, and fraud detection, making it a critical component in the advancement of AI and data-driven decision-making.

In this Traditional Machine Learning Models We used Decision Tree Classifier, Logistic Regression models for Smart grid Dataset.

2.3.1 Decision Tree Classifier

A decision tree is a popular supervised machine learning approach that uses a tree-like structure to divide a dataset into smaller groups for both classification and regression problems. The core nodes in this structure stand for feature tests, the branches display the results of these tests and the leaf nodes provide the final output or conclusion. The best feature is selected at the root node to divide the data according to criteria like information gain or gini impurity. The decision path from root to leaf is followed to make predictions as this splitting proceeds recursively until the stopping condition is satisfied [13].

2.3.2 Logistic Regression

Another supervised machine learning approach is logistic regression, which is primarily used for binary classification tasks like making yes/no or 1/0 predictions. Contrary to what its name suggests, It is used for classification rather than regression and calculates the likelihood that a given class of data points will belong to it. It first calculates the weighted sum of the input features, then squeezes the result between 0 and 1 using a sigmoid activation function, and then classifies the output according to a threshold(usually 0.5). Based on study hours, for instance, it forecasts an 85% likelihood of passing an exam, resulting in a “pass” classification. For data that is linearly seperable, logistic regression is easy quick and efficient [14].

2.4 Deep Learning

Deep Learning is a kind of machine learning that uses multi-layered artificial neural networks to simulate how the human brain processes information. Through a process known as training, it learns patterns from massive datasets and uses optimization methods to minimize errors by adjusting the networks weight and biases. Each neuron uses activation function like ReLu, sigmoid, or softmax to process and transfer information in the architecture, which normally consists of an input layer, many hidden layers and an output layer. Without requiring human feature engineering, deep learning models such as Recurrent neural networks and Gated recurrent Units for sequential data automatically extract and learn hierarchical features. Large volumes of data and processing power are used by these models, which frequently make use of GPUs for quicker processing. Deep learning is a potent tool for resolving challenging real-world issues since it is extensively used in fields including image identification, natural language processing, and smart grid stability prediction. In order to anticipate the stability of the smart grid , we proposed Artificial Neural Networks, Recurrent Neural Networks, Long Short-Term Memory and Gated Recurrent Unit models.

2.4.1 Artificial Neural Networks

A computational model that is modeled after the structure and operation of a biological neural network is called an artificial neural network. Each neuron processes information using weighted sums and activation functions in its input, hidden and output layers. Data travels through the network during forward propagation and the loss function determines the discrepancy between expected and actual outputs. Weights are updated and the loss is decreased across several training iterations using gradient descent and back propagation. This model can capture non-linear patterns and handle high-dimensional data, making them powerful tools in deep learning. However, they require large datasets are computationally intensive and can be difficult to interpret [15].

2.4.2 Recurrent Neural Networks

A recurrent neural network is a kind of neural network that is intended for sequential data, such as speech, text, time series and in which the output is influenced by information from the past. Because RNNs contain memory, unlike standard neural networks, they can use loops in their architecture to remember information from earlier steps. They are ideal for jobs like language translation and text production because they update the current state and generate an output at each time step by combining the input with prior concealed state. Based on context, like the next word in a sentence, these models are able to forecast results. They perform well on sequence based tasks, but because of delayed training and disappearing gradients, they may have trouble with lengthy sequences. They are also prone to forgetting long-term dependencies without enhancements like LSTM or GRU [16].

2.4.3 Long Short-term Memory

A particular kind of recurrent neural network called Long Short-Term Memory was created to tackle the vanishing gradient issue that ordinary RNNs frequently face and retain information over extended periods of time. For tasks where context from far back in the sequence is crucial such as language modelling, machine translation, and speech recognition, LSTM are very useful. They employ a memory cell layout with input, forget, and output gates that regulate which data should be retained, discarded, or output. This enables the model to exclude unnecessary input while preserving significant data over a wide range of time steps. During training, LSTM adjust their gates using backpropagation through time to better capture long-range dependencies. Although they are more complex and computationally intensive than basic RNN, they offer better performance in handling long-term context in sequential data [17].

2.4.4 Proposed Gated Recurrent Unit

One kind of recurrent neural network (RNN) that may effectively handle sequential input and resolve the vanishing gradient problem is the Gated Recurrent Unit (GRU). Because it uses fewer gates and parameters, it is computationally less expensive than Long Short-Term Memory (LSTM) networks. GRU's ability to manage long-term dependencies without requiring a significant amount of computing power has led to its widespread use in time-series prediction, speech recognition, and Natural Language Processing (NLP). Using gating methods to selectively update the concealed state at each time step is the fundamental concept of a Gated Recurrent Unit (GRU). The network's information flow is managed by these techniques. The reset gate and the update gate are the two gates used by the GRU. While the update gate decides how much of the new input goes toward updating the hidden state, the reset gate governs how much of the prior hidden state should be deleted. This updated concealed state is the source of the GRU's final output.

The following formulas are used to determine a GRU's reset gate, candidate hidden state, update gate, and final hidden state:

Reset gate (r_t) = $\sigma(W_r * [h_{t-1}, x_t] + b_r)$ (1)

Candidate Hidden state ($\tilde{h}_t$) = $tanh(W_h * [r_t \odot h_{t-1}, x_t] + b_h)$ (2)

Update gate (z_t) = $\sigma(W_z * [h_{t-1}, x_t] + b_z)$ (3)

Final hidden state (h_t) = $Z_t \odot h_{t-1} + (1 - Z_t) \odot \tilde{h}_t$ (4)

Where x_t is the input, h_{t-1} is the previous hidden state, W and b are the weight and bias , tanh ensures non-linearity, ⊙ denotes element-wise multiplication, $\tilde{h}_t$ is new candidate state.

Fig.3, represents the workflow of GRU model. It represents the how works the reset gate, candidate hidden gate and update gate

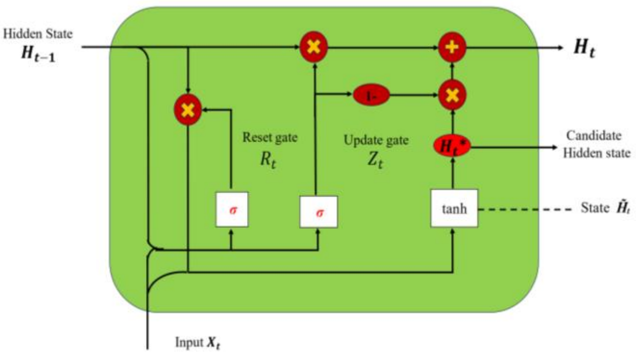

Figure 3: GRU model workflow

2.5 Evaluation metrics

In order to evaluate the effectiveness of machine learning and deep learning models and make sure they produce accurate and trustworthy predictions, evaluation metrics are quantifiable measurements. Depending on whether a model is used for ranking, regression, or classification tasks, various models need different evaluation metrics.

A typical evaluation statistic for classification models is accuracy, which quantifies the proportion of examples that are properly classified:

$$ACCURACY = \frac{TP+TN}{TP+TN+FP+FN} \quad (5)$$

Precision (Positive Predictive Value) measures how many predicted

$$PRECISION = \frac{TP}{TP+FP} \quad (6)$$

Recall (Sensitivity) indicates how many actual positives were correctly identified:

$$RECALL = \frac{TP}{TP+FN} \tag{7}$$

F1-score is the harmonic mean of precision and recall, balancing both metrics:

$$F1 - SCORE = \frac{2.Precision.Recall}{Precision+Recall} \tag{8}$$

Plotting the true positive rate (TPR) against the false positive rate (FPR) allows AUC-ROC (Area Under the Receiver Operating Characteristic Curve) to assess a model's capacity to discriminate between classes.

3. Results and Discussions

The data includes 12 features, such as price elasticity coefficient, power balance, and producer and consumer reaction times, in order to maximize grid stability. 20% of the dataset is used for testing, and the remaining 80% is used for training. Lastly, the GRU model performed noticeably better than the other models, including the Artificial Neural Network, Recurrent Neural Network, Long Short-Term Memory, Decision Tree, and Logistic Regression. The benchmark results for the GRU and other models are shown in Table 1.

Table 1 : Findings from the Learning Models

Models	**Accuracy**	**Precision**	**Recall**	**F1 score**	**ROC**
Decision Tree	0.8435	0.85	0.84	0.84	0.832
Logistic Regression	0.8160	0.81	0.82	0.80	0.792
ANN	0.9639	0.96	0.96	0.96	0.995
RNN	0.9325	0.93	0.93	0.93	0.986
LSTM	0.9639	0.97	0.96	0.96	0.941
GRU	0.9745	0.97	0.97	0.97	0.996

We present the prediction performance of the GRU model over a period of fifty epochs. The model showed little overfitting, despite the fact that overfitting is a frequent problem during training, as seen in Fig.4 and Fig.5. Over the course of the training procedure, the accuracy increased steadily, reaching 97.45% in the final five epochs.

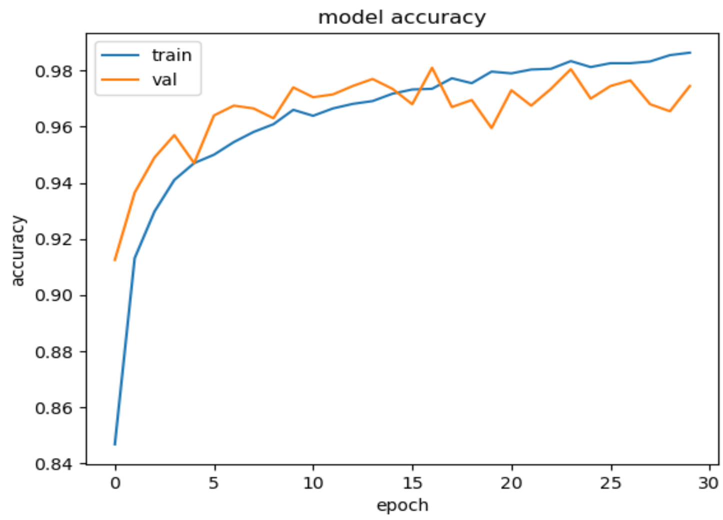

Figure 4: The GRU Model's Accuracy

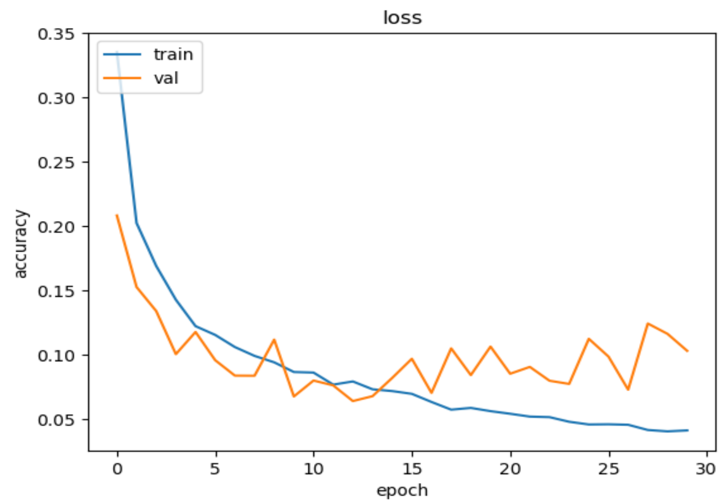

Figure 5: GRU Model Loss

The confusion matrix for the GRU model for actual over-predicted outcomes is shown in Fig.6, This chart shows that the model produces 701 true negatives, 1248 true positives, 23 false positives, and 28 false negatives. The GRU model's testing classification results for class 0 and class 1 accuracies are displayed in Table 2 along with the accuracy, weighted average, and macro average.

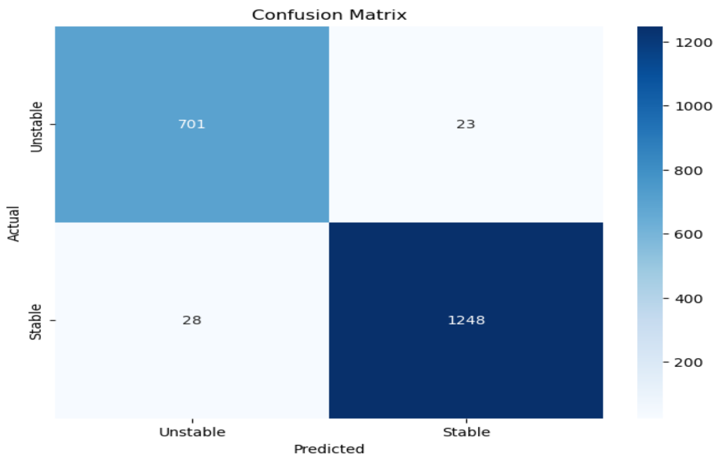

Figure 6: Matrix of Confusion for the GRU Model

Table 2: GRU Model Testing Classification Outcomes

Evaluation Metric	Precision	Recall	F1-score	Support
Accuracy of class 0	0.96	0.97	0.96	724
Accuracy of class 1	0.98	0.98	0.98	1276
Accuracy			0.97	2000
Macro Avg	0.97	0.97	0.97	2000
Weighted Avg	0.97	0.97	0.97	2000

During the testing phase, the total accuracy was measured at 97.45%, with class 0 accuracy of 96% and class 1 accuracy of 98%. The metric value 2000 in the performance report often indicates the number of real instances the number of real instances of a specific class that are involved in the model evaluation process. Nevertheless, this metric also aids in comprehending the data that is accessible to evaluate the model performance and reliability of a specific issue.

The GRU model retains the statistical significance and depth of performance indicators, including precision, recall, and F1-Score , during the validation phase, closely matching the outcomes of training and testing.

4. Conclusion

The capacity of GRU, LSTM, RNN, ANN, Decision Tree, Logistic Regression to categorize data extracted from a smart grid dataset in order to forecast grid stability was investigated in this study. In order to improve the forecast of smart power grid stability, we then suggest a GRU model. Both user-consumed energy and smart grid-generated energy were included in the test simulation data. The accuracy of the GRU model is 97.45%, while its loss is only 10.33%. Additionally, 97% precision, 97% recall, and 97% F1-Score are attained with the GRU model. However, the accuracy of the LSTM, RNN, ANN, Decision Tree classifier, and Logistic Regression models is 96.39%, 93.25%, 96.39%, 84.35%, and 81.60%, respectively. The model with the highest accuracy among the examined models was determined to be the most appropriate for predicting the stability of smart grids. The findings demonstrate how deep learning approaches can enhance grid stability evaluation, which is crucial for effective power distribution in contemporary energy systems. To improve real-time prediction ability, future research can concentrate on refining these models even more and adding more affecting variables.

5. Acknowledgement

We are appreciative of the chance to investigate smart grid stability prediction using cutting-edge deep learning methods. This study demonstrates the efficacy of the suggested GRU model, which outperformed traditional models like Decision Tree Classifier, Logistic Regression Classifier, RNN, LSTM, and ANN with an accuracy of 97.45%. We value the important roles that all producers and consumers play in preserving grid stability.

References

1. M. Alazab, S. Khan, S. S. R. Krishnan, Q.-V. Pham, M. P. K. Reddy, and 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.
2. M. Nakıp, O. Çopur, E. Biyik, and C. Güzeliş, "Renewable energy management in smart home environment via forecast embedded scheduling based on Recurrent Trend Predictive Neural Network," 2023, doi: 10.48550/ARXIV.2307.01622.
3. M. H. Zafar *et al.*, "Step towards secure and reliable smart grids in Industry 5.0: A federated learning assisted hybrid deep learning model for electricity theft detection using smart meters," *Energy Rep.*, vol. 10, pp. 3001–3019, Nov. 2023, doi: 10.1016/j.egyr.2023.09.100.
4. B. Biswal, S. Deb, S. Datta, T. S. Ustun, and U. Cali, "Review on smart grid load forecasting for smart energy management using machine learning and deep learning techniques," *Energy Rep.*, vol. 12, pp. 3654–3670, Dec. 2024, doi: 10.1016/j.egyr.2024.09.056.
5. S. Oyucu, Ş. Sağıroğlu, A. Aksöz, and E. Biçer, "Estimating Smart Grid Stability with Hybrid RNN+LSTM Deep Learning Approach," in *2024 12th International Conference on Smart Grid (icSmartGrid)*, Setubal, Portugal: IEEE, May 2024, pp. 738–741. doi: 10.1109/icSmartGrid61824.2024.10578179.
6. I. H. Sarker, "Deep Learning: A Comprehensive Overview on Techniques, Taxonomy, Applications and Research Directions," *SN Comput. Sci.*, vol. 2, no. 6, p. 420, Nov. 2021, doi: 10.1007/s42979-021-00815-1.
7. S. Raissi and T. G. Reames, "'If we had a little more flexibility.' perceptions of programmatic challenges and opportunities implementing government-funded low-income energy efficiency programs," *Energy Policy*, vol. 147, p. 111880, Dec. 2020, doi: 10.1016/j.enpol.2020.111880.
8. G.-V. V. Daniel, "Smart Grid Stability Prediction with Machine Learning," *WSEAS Trans. POWER Syst.*, vol. 17, pp. 297–305, Oct. 2022, doi: 10.37394/232016.2022.17.30.

9. M. J. Abbass, R. Lis, and Z. Mushtaq, "Artificial Neural Network (ANN)-Based Voltage Stability Prediction of Test Microgrid Grid," *IEEE Access*, vol. 11, pp. 58994–59001, 2023, doi: 10.1109/ACCESS.2023.3284545.
10. P. Lahon, A. B. Kandali, U. Barman, R. J. Konwar, D. Saha, and M. J. Saikia, "Deep Neural Network-Based Smart Grid Stability Analysis: Enhancing Grid Resilience and Performance," *Energies*, vol. 17, no. 11, p. 2642, May 2024, doi: 10.3390/en17112642.
11. L. J. Lepolesa, S. Achari, and L. Cheng, "Electricity Theft Detection in Smart Grids Based on Deep Neural Network," *IEEE Access*, vol. 10, pp. 39638–39655, 2022, doi: 10.1109/ACCESS.2022.3166146.
12. A. Alsirhani, M. Mujib 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," *Alex. Eng. J.*, vol. 74, pp. 495–508, Jul. 2023, doi: 10.1016/j.aej.2023.05.063.
13. S. O. Tehrani, M. H. Y. Moghaddam, and M. Asadi, "Decision Tree based Electricity Theft Detection in Smart Grid," in *2020 4th International Conference on Smart City, Internet of Things and Applications (SCIOT)*, Mashhad, Iran: IEEE, Sep. 2020, pp. 46–51. doi: 10.1109/SCIOT50840.2020.9250194.
14. E. De Santis and A. Rizzi, "Modeling failures in smart grids by a bilinear logistic regression approach," *Neural Netw.*, vol. 174, p. 106245, Jun. 2024, doi: 10.1016/j.neunet.2024.106245.
15. S. Mohsen, M. Bajaj, H. Kotb, M. Pushkarna, S. Alphonse, and S. S. M. Ghoneim, "Efficient Artificial Neural Network for Smart Grid Stability Prediction," *Int. Trans. Electr. Energy Syst.*, vol. 2023, pp. 1–13, May 2023, doi: 10.1155/2023/9974409.
16. K. Tornai, A. Oláh, R. Drenyovszki, L. Kovács, I. Pinté, and J. Levendovszky, "Recurrent neural network based user classification for smart grids," in *2017 IEEE Power & Energy Society Innovative Smart Grid Technologies Conference (ISGT)*, Washington, DC, USA: IEEE, Apr. 2017, pp. 1–5. doi: 10.1109/ISGT.2017.8086043.
17. I. Fatema, X. Kong, and G. Fang, "Electricity demand and price forecasting model for sustainable smart grid using comprehensive long short term memory," *Int. J. Sustain. Eng.*, vol. 14, no. 6, pp. 1714–1732, Nov. 2021, doi: 10.1080/19397038.2021.1951882.