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Transformer with Explainable AI: A Synergistic Approach to Smart Grid Stability Analysis

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Abstract—**Smart grid technology is revolutionizing the electrical industry by enabling an efficient, digitized energy ecosystem that allows smooth energy flow from production to end consumers. Traditional grid systems that are not smart enough to estimate the user's power requirements are unreliable. The concept of smart grids was therefore birthed from there, with smart technologies such as IoT, AI, and decentralized energy management platforms that aim at maximizing energy distribution and reducing transmission losses. This research introduced machine learning (ML) and deep learning (DL) models for smart grid stability prediction. Our proposed model, TabTransformer obtained the best results on the assessed methodologies at 99.40% test accuracy and an AUC-ROC score of 1.0. Additionally, our research combined with explainability approaches in the form of SHAP and LIME that will further provide insight into the feature contributions that give assurances of dependability and robustness. Our research results show the great potential artificial intelligence-based methodologies have on smart grids with sustainable and efficient energy systems. This research promotes the use of advancement to attain energy stability and resilience in the modern power environment.**

Keywords— Smart grid stability, Machine learning, Deep learning, Smart grid, Explainable AI, Decentralized smart grid

I. Introduction

The world's population is quickly growing, accompanied by an unparalleled increase in power usage. As more people have access to contemporary comforts and technology, the need for power increases. This increasing trajectory in population expansion, along with growing energy demand, presents considerable problems to existing power systems [1]. The load on conventional grid infrastructure causes inefficiencies, reliability difficulties, and the possibility of power outages. Furthermore, the environmental effect of traditional energy sources fuels worries about sustainability and climate change. Traditional power infrastructures are under enormous strain as a result of rising population and energy consumption. These networks are frequently underprepared to manage surges in demand, leading in frequent outages, grid instability, and increased vulnerability to disturbances. Fig.1 represents consumers electricity usage patterns and their implications for smart grid stability.

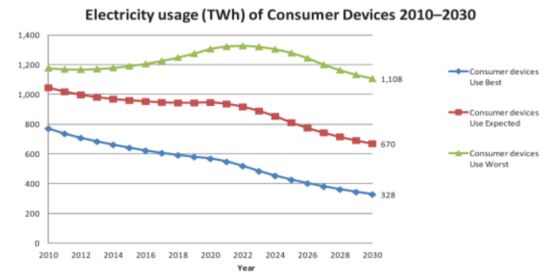

Fig. 1 Electricity usage of consumer 2010-2030 [1]

As the world's population grows, the use of renewable energy technology becomes increasingly important in meeting rising electrical demands while minimizing environmental damage [2]. Smart grids support sustainability initiatives by seamlessly showed in Fig.2 where integrating renewable energy supplies into system infrastructure [3]. In the backdrop of an increasing population, smart grids have several advantages. These include increased grid resilience, higher energy efficiency, and more adaptability to changing demand patterns. Smart grids allow users to actively engage in energy management by utilizing demand response systems and real-time usage monitoring [4].

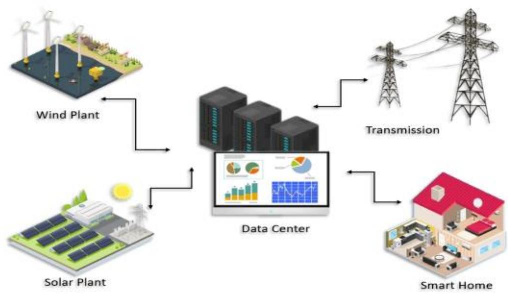

Fig.2 Interconnected Smart Grid Elements

Machine learning is critical to improving the smart grid [5]. Algorithms based on machine learning can optimize grid operations, forecast demand changes, and discover abnormalities in real-time by analyzing massive volumes of data through grid sensors, consumer behavior patterns, and energy from renewable sources. This enables proactive upkeep, balance of load, and efficient allocation of resources, resulting in increased grid stability and dependability. In contrast to conventional grids, smart grids with machine learning capacity can adapt to evolving circumstances and optimize grid operations in real-time. Algorithms using machine learning recognize multifaceted patterns and correlations inside grid data, enabling maintenance planning, detection of faults, and demand projections with unprecedented accuracy. Machine learning additionally encourages the pairing of diverse energy resources and permits autonomous decision-making. The widespread use of machine learning systems in smart grid networks promises revolutionary effects that go well beyond simple efficiency benefits.

The main goal of this research are providing below:

(a) Evaluate the efficacy of machine learning and deep learning algorithms in projecting smart grid stability using a dataset of 10,000 data points and 12 variables representing consumers as well as manufacturers in the grid infrastructure.

(b) Determine the best method for forecasting smart grid stability by systematically comparing predicted accuracy, precision, and scaling across many machine learning and deep learning systems.

(c) Investigate the use of machine learning techniques to improve smart grid activities such as load balancing, defect detection, and prediction of demand, to increase grid stability, dependability, and resilience.

(d) Integration of XAI techniques, such as SHAP and LIME, can provide more transparency and interpretability of model predictions to increase smart grid stability and empower stakeholders to understand the critical factors affecting grid performance and to make data-driven decisions.

Our key contribution for predicating smart grid stability summarized as follows:

(a) Developed and applied different algorithm in machine and deep learning (DL) including the proposed TabTransformer, to accurately predict smart grid stability,

(b) Integrated explainable AI techniques (SHAP and LIME) to provide interpretable insights into the predictive models in improving grid operations and decision-making.

(c) To evaluate the efficacy of these models in anticipating critical events and anomalies in the smart grid infrastructure, use the characteristic curve like (AUC-ROC) measure.

This paper segment into five sections. Section 2 will present the related works where others researchers findings, thoughts are uplifted. Section 3 presents proposed methodology described about models that has been used in work. Applied models analysis, comparison and different metrics are shown in section 4. After we conclude our study with future scopes in section 5.

II. Related Works

In this paper, grid stability depends on how efficiently the system uses machine learning to predict customer fluctuating power, which can be used to predict energy consumption and grid stability. Lakshmanarao Annemneedi uses machine learning (ML) and deep learning (DL) together. Five ML algorithms for smart grid stability testing, namely support vector machine (SVM), decision tree (DT), K-nearest neighbor (KNN), random Forest (RF), and logistic regression (LR), are applied. dL Artificial Neural Network (ANN) is used. with ML SVM and. DL Artificial Neural Network (ANN) both achieves accuracy of 98.92% [6]. Franović, Baressi Šegota attempts to develop models for adjusting power and price elasticity coefficients and predicting DSGC system stability. Two classifications of stable' and 'unstable' conditions are arranged. Four different approach models were used [7]. Saeed Mohsen, Mohit Bajaj said that Smart grid stability is predicted through an artificial neural network (ANN) model for decentralized smart grid control (DSGC) and Testing accuracy of 97.36% [8]. Gauli, M. K. Phoungthong, K.a complete DG system is provided by integrating a PV module with a smart grid using ANN algorithm. Only ANN model is used in this paper which provides 99.91% accuracy [9]. In this paper an attempt is made to generalize the problem with both classification and regression methods for smart grid stability prediction related to Gradient Boosting Machine (GBM). GBM is a powerful strategy in which complex non-linear functions continue to predict dependence and adapt to various practical needs [10]. Dewangan and Biswal propose an improved GA-based extreme learning machine (ELM) model for predicting smart grid stability, achieving 98% prediction accuracy compared to other ML techniques [11]. Mishra, M, Nayak, J, Smart grids are deployed to ensure affordable power supply to Cyber-Physical Systems. The new ELM model is used in Smart grids to avoid Cyber-Physical Systems (CPS) reverse feedback, the model achieves 99.75% accuracy [12]. Different ML algorithms are used to predict the stability of smart grids such as SVM, Naïve Bayes, KNN, Decision Tree and Neural Network. The XGBOOST algorithm is giving 100% accuracy. So XGBOOST is used in this paper as the best algorithm [13]. Ayushi Chahal, Preeti Gulia used among all predictive models, the ANN model gave 97.27% accuracy, which optimizes the grid system [14]. Different ML models are used including XGBoost provides higher accuracy when combined with random oversampling in the latter XGBoost prediction improves to 96.8% [15]. 60,000 data in this paper using machine learning mode. Like a random forest decision tree, ANN - MLP, SVM, K- NN, Logistics Regression However, the random forest technique gives the best performance with an accuracy of 0.935 [16]. Sallam, N. M. Improvements to the Deep Learning (DL) technique for solving smart grid forecasting problems. Achieves 97.3% test accuracy through most neural network (NN) accuracy checks for stable and unstable tests [17]. Mostafa, N, Ramadan, deals with three main tasks. First, a review is made on previous recent work on the use of BDA in energy applications. The second to formulate a framework for possible implementation of BDA by utilities for smart grid and renewable energy. Three different machine learning methods are used on the third smart grid dataset for stability prediction [18]. R. F. Arritt and R. C. Dugan, said that grid stability depends on how efficiently the system uses machine learning to predict customer fluctuating power, which can be used to predict energy consumption and grid stability. Machine learning uses many models. Of which, a model designed using a vector machine (SVM) classifier showed 89% accuracy, the highest accuracy in recall, F-score and accuracy scales [19]. F.R. Armitt and R.C. Dugan [20] W.

Ahmed et al. Presented review for improved control system in distribution system, where DG emphasis is placed on learning about security experiences. ML and Process Regression (GPR) are integrated to reduce the complexity of EMM and predict performance parameters to generate models that optimize Prosumer Energy Surplus (PES), Prosumer Energy Cost (PEC), and Grid Revenue (GR). In the second step Genetic Algorithm (GA) is similarly optimized and predicted [21].

III. Methodology Of Research

Smart grid stability analysis with various numeric data. With this, it's easier to predict either it's stable or not. Fig. 3 represents the system architecture of proposed model to analysis of smart grid stability.

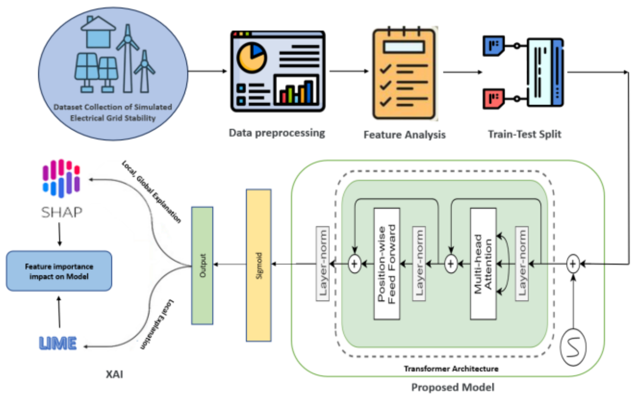

Fig. 3 Methodology Smart grid Stability analysis.

Fig.3 represents the methodology were starting with energy adaptive simulated set of info. collected from, University of California (UCI) ML Repository [22], where dataset includes 12 characteristics including 10,000 rows of info. The grid's stability value is determined using 12 characteristics, and it is characterized as stable or unstable. In this smart grid dataset, there are 12 features. First four are tau-1, tau-2, tau-3, tau-4 where tau-1 represents provider branch and rest of tau-(2-4) are consumer network. In dataset, p1-4 represent power produced and consumed by each participant. Next g1-4 feature represents price elasticity and finally, last two feature including stab and stabf represent either power grid stable or not. Table-1 shows feature analysis below.

Table-1 Feature Analysis of dataset

Features	Feature Name	Value Range	Comment
tau-1, tau-2, tau-3, tau-4	Participant of the branch	0.5-10	tau-1- provider tau-(2-4)- Consumer
p1, p2, p3, p4	Power produced and consumed	-2 to -0.5	p1-Supplier p (2-4)- Consumer '+' – Power Produced '-'- Power Consumed
g1, g2. g3. g4	Price Elasticity co-efficient	0.05-1	g1- Supplier g (2-4)- Consumer
Stab, stabf	Stability	-0.08-1	'+' – Unstable '-'- Stable

This dataset is already preprocessed justifying by applying preprocessing techniques likes null value find out, outlier and so on. The train-test split technique used in our study seeks to lay a solid basis for building a model, allowing us to analyze the ability of smart grid reliability forecasting. In our scenario, the dataset contains features, whereas the target variable, indicated as 'stabf', comprises stability labels. To assist the train-test division, we label the goal variable 'y' and the supplied variables 'X'. The split ratio is 80% training and 20% testing.

IV. Different Algorithm Result Analysis

In this section we see different algorithm's including proposed model details and performance analysis

A. Logistic Regression

Logistic regression is a popular statistical approach for binary classification assignments [23], making it a good fit for forecasting smart grid stability. It calculates the likelihood of a binary result (such as stable or unstable) by considering input features in Eq.1.

$$P(Y = 1) = \frac{1}{1+e^{-(\beta_0+\beta_1 X_1+\beta_2 X_2+\cdots+\beta_n X_n)}} \qquad (1)$$

Here, probability is P, β_(0,1,2,..n) represent model coefficient and X1,2,.., n are input features.

B. Support Vector Machine

Support Vector Machine (SVMs are powerful machine-learning techniques that are commonly utilized to forecast the stability of smart grids. SVM seeks to identify a hyperplane that optimizes the margin across classes, taking into account either linear and non-linear correlations between characteristics and outcomes [24].

$$f(\mathbf{x}) = \text{sign}\,(\mathbf{w}\cdot\mathbf{x} + b) \qquad (2)$$

C. k-nearest neighbor (KNN)

KNN is a small number of parameter, instance-based learning algorithm, mainly used for classify and regression [25]. The algorithm works by comparing one data point with the 'k' closest data points from the training set and predicts, based on the majority class in the case of classification or mean value in the case of regression, of its nearest neighbors.

D. Artificial Neural Network (ANN)

Utilizing Artificial Neural Networks (ANNs) in smart grid reliability prediction, these algorithms utilize incoming data to predict grid stability and improve operations. Fig.4 represents the architecture of ANN algorithm that employ backpropagation, regularization, and hyperparameter adjustments to minimize errors and avoid overfitting [26].

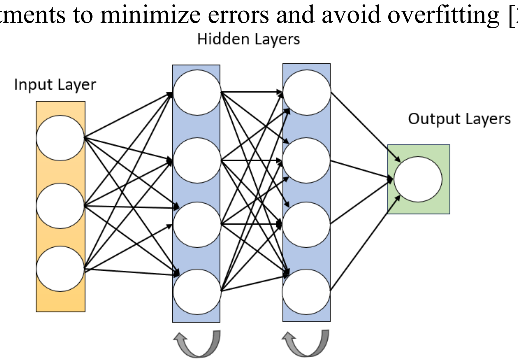

Fig. 4 ANN architecture.

E. TabTransformer

TabTransformer [27] is a deep learning model designed for handling structured data like numbers and categories. It uses a transformer-based design that employs self-attention mechanisms to reason over complex relationships among features showed in Fig.5. By treating a table as a sequence, TabTransformer finds patterns across the rows of the data, enhancing its performance.

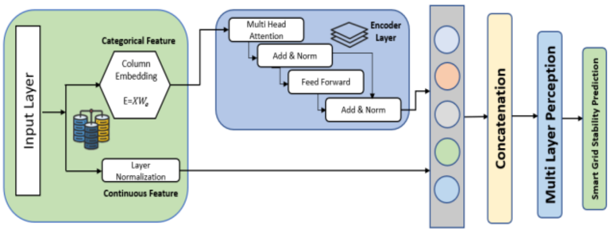

Fig. 5 TabTransformer architecture.

The performance of various machine learning and deep learning algorithms, including Logistic Regression, Support Vector Machine, XGBoost, LSTM, Recurrent Neural Network, and Artificial Neural Network, comparing their accuracy and loss graphs.

Machine learning evaluation indicators assess model performance, including accuracy, precision, recall, F1 score, and AUC. These metrics evaluate model accuracy, recall, F1 score, and ability to differentiate positive and negative examples.

$$Accuracy, A = (tp + tn)/(tp + tn + fp + fn) \tag{3}$$

$$Precision, P = tp/(tp + fp) \tag{4}$$

$$Recall, R = tp/(tp + fn) \tag{5}$$

$$F1 - score = 2 * R * P/R + P \tag{6}$$

Table.2 Machine Learning and Deep Learning Model Result with Performance Metrics

Model	**Accuracy %**	**Precision**	**Recall**	**F1-Score**	**AUC(ROC)**
Logistic Regression	90.9	0.62	1.00	0.77	0.99
Support Vector Machine	95.6	0.70	1.00	0.82	0.993
k-nearest neighbor (KNN)	80.1	0.36	1.00	0.53	0.51
Artificial Neural Network (ANN)	99.00	0.99	0.97	0.98	0.99
TabTransformer	99.40	0.99	0.99	0.99	1.00

In Table.2, We see various model performance metrics. Among them TabTransformer model get the highest accuracy. Also, using various algorithms we see, Artificial Neural Network accuracy of 99%. Fig. 6 shows the accuracy of proposed model models.

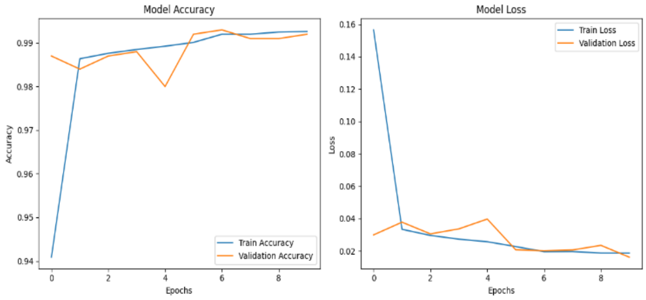

Fig.6 Accuracy of proposed architecture.

In smart grid stability forecasting, high AUC-ROC values imply models that can distinguish either stable or unstable network states. Fig.7 shows the AUC(ROC) curve of all models.

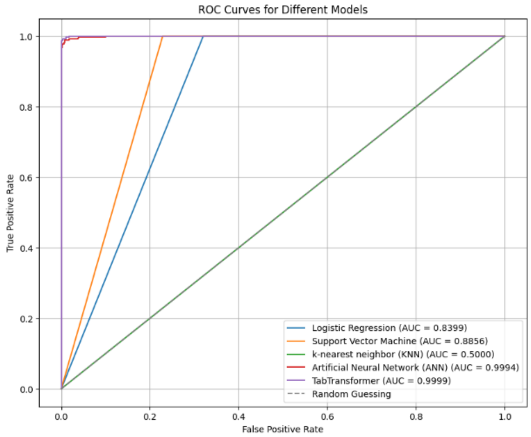

Fig.7 Models AUC ROC CURVE

Various ML and DL models are giving good results. Fig.8 shows the confusion matrix of all models.

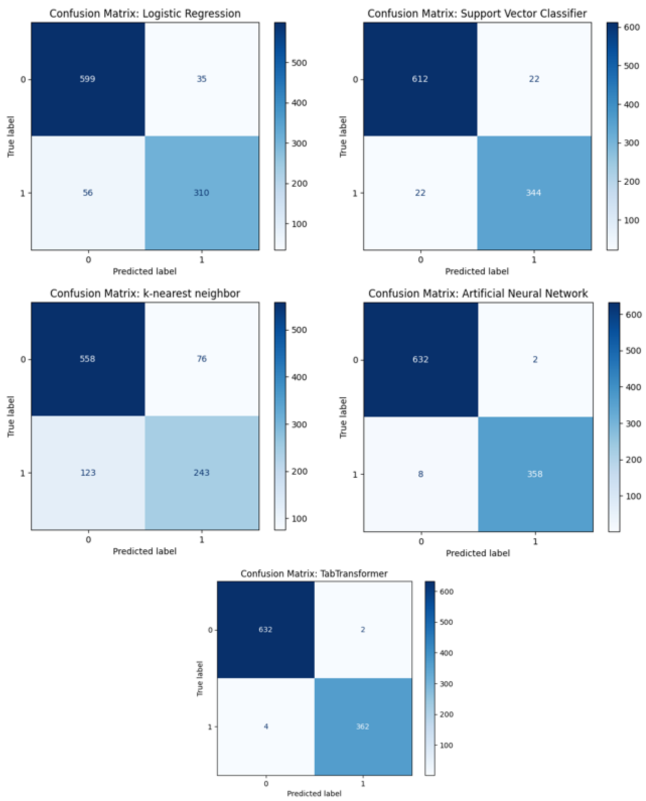

Fig.8 Confusion matrix of applied algorithms

The architecture of the TabTransformer model is integrated with XAI [28] techniques like SHAP and LIME to give more insight into its decision-making process. In Fig. 9, the feature "stab," representing grid stability, influences the model's output to the largest extent. Other important features influencing the predictions include tau1, tau2, p1, and tau4. The color gradient in the plot corresponds to feature values, with red meaning higher values while blue represents lower values. Certain ranges of these features therefore have a strong correlation—either to stability or instability.

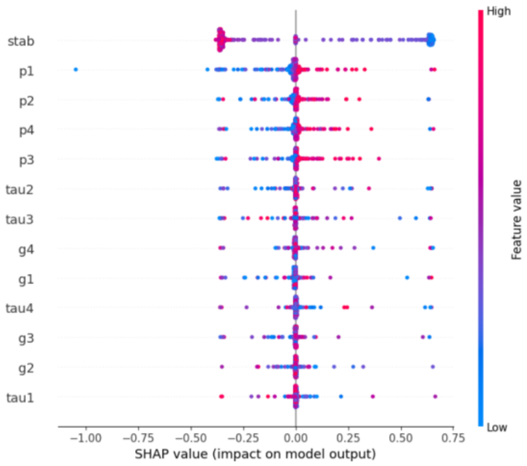

Fig.9 SHAP Summary Plot Highlighting Feature Impact

The plot of dependency in Fig. 10 shows the effect of the "stab" feature on model outputs for different ranges of values. Here clearly showing the shift between stable and unstable states. This information is very important for real-time monitoring because it gives a numerical threshold for grid instability. This analysis will help grid operators implement preemptive actions to reduce possible failures or instabilities.

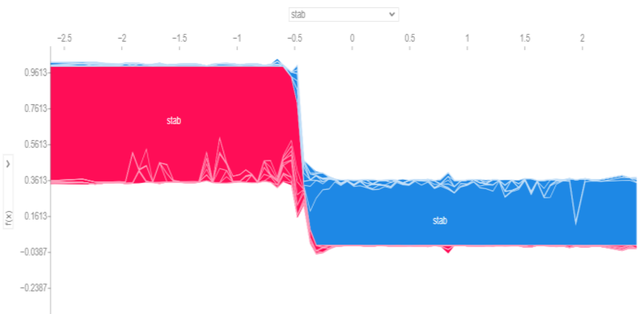

Fig.10 Stability vs Feature Values

The LIME visualizations shown in Fig.11 explain how the TabTransformer model predicts smart grid stability. They point out important features that affect model predictions

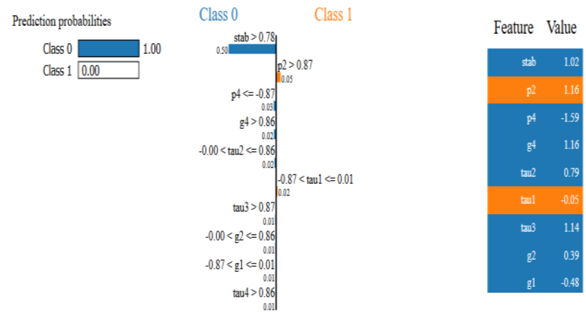

Fig.11 Proposed model LIME visualization

In Fig.12 "stab," "p2," "p4," and "tau2," which impact the smart grid's stability. Features like "stab > 0.78" are crucial for deciding grid stability, while others, such as "p2 > 0.87," have a lesser influence. In Fig. 12 green bars show features that help stability, while red bars indicate those that harm it.

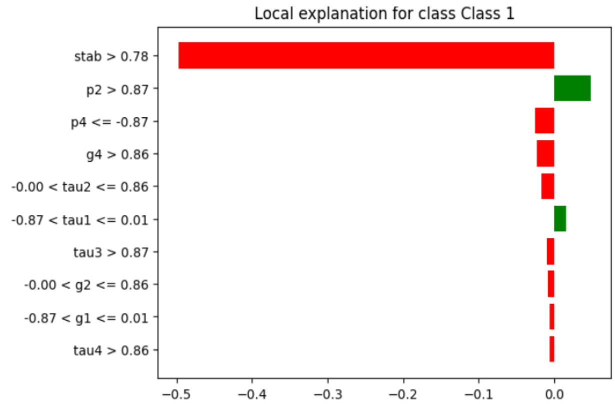

Fig.12 Feature Contributions to the Prediction using LIME

In our research, SHAP and LIME analyses enhance the TabTransformer model by providing interpretable insights into feature importance and their impact on grid stability predictions.

In recent research on smart grid stability modeling, several machine learning and neural network algorithms have been investigated. Multiple models were utilized in [11], including MLP, XGB, SVMs, and GP, with XGB outperforming the others at 98.20% and 98.15% reliability. However, the study lacks deep learning models. Similarly, [12] used an ANN model and achieved a test precision of 99.91%, yet only with one model. In [13], a suggested neural network obtained 97.36% test accuracy while being constrained to a single model. Another research in [21] looked at many machine learning models, and SVM achieved 98% accuracy. However, all of these models employed machine learning approaches, and some only operated with simulated data. The TabTransformer model, in spite of its limitations, performed well under different grid conditions, demonstrating its robustness for real-world use due to its capability to manage varying load demands. Our suggested strategy outperforms them with 99.40% accuracy with AUC 1.00 by employing attention based TabTransformer algorithm with XAI providing actionable insights that traditional models often lack.

V. CONCLUSION

Smart grid stability is critical in ensuring the reliability, efficiency, and sustainability of modern power systems. This work was an evaluation of several algorithmic approaches, including Logistic Regression, Support Vector Classifier (SVC), K-Nearest Neighbors (KNN), Artificial Neural Network (ANN), and our novel TabTransformer model on a dataset of 10,000 data points. Among these, the TabTransformer achieved the highest performance with test accuracy of 99.40%, AUC-ROC score of 1.0000, correctness of 0.9945, recall score 0.9891, and F2 score of 0.9902. The effectiveness of the attention mechanism in the TabTransformer to capture intricate patterns and relationships in tabular data. Explainability of the predictions was further enhanced by the use of XAI in the form of SHAP and LIME; this increased transparency allowed to identify critical factors related to stability. Advanced AI models, as demonstrated in this research, can be used to predict grid stability, detect anomalies, and prevent cascading failures. Future research endeavors will investigate more extensive and varied datasets, while additionally refining preprocessing methods to guarantee enhanced scalability and adaptability within the fluctuating contexts of smart grid environments.

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