

Explainable Artificial Intelligence for Real-Time Stability Assessment in Smart Power Systems

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Abstract

INTRODUCTION: Smart grid stability analysis is necessary for reliable power system operations in the presence of increased renewable energy penetration and distributed energy resources.

OBJECTIVES: This study proposes a novel Graph Transformer–Temporal Fusion Transformer (GT-TFT) with an Explainable Artificial Intelligence (XAI) framework for real-time smart grid stability prediction.

METHODS: A feature-correlation graph is constructed and processed using a Graph Transformer (GT) to capture spatial dependencies, while a Temporal Fusion Transformer (TFT) learns temporal dynamics from smart grid measurements. The extracted features are fused through a feature fusion layer and classified using a neural network classifier. SHapley Additive exPlanations (SHAP) is employed to improve model interpretability.

RESULTS: Experimental evaluation on the Smart Grid Stability dataset demonstrates superior performance, achieving an accuracy of 0.9879, precision of 0.9886, recall of 0.9926, F1-score of 0.9905, and AUC of 0.9999. Comparative analysis confirms that the proposed framework outperforms existing baseline models.

CONCLUSION: The suggested GT-TF-XAI framework offers a solution to real-time smart grid stability assessment that is accurate, reliable, and explainable to enable effective decision-making in current smart power systems.

Keywords: Smart Grid Stability, Graph Transformer, Temporal Fusion Transformer, Explainable AI, SHapley Additive exPlanations, Real-Time Prediction

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1. Introduction

The development of smart power systems has become a vital part of the current energy infrastructure, allowing for an efficient process of generating, transmitting, distributing, and consuming electric energy due to the use of communication and information technologies [1]. The development of traditional power grids to smart grids took place during the past two decades due to the rising demand for electricity, the use of renewable energy sources, and the necessity for effective energy management [2]. The operation of smart power systems is provided due to the use

of intelligent sensors and smart meters [3], IoT solutions, and technologies for collecting operational information from different components of a power system [4]. According to the results of reports issued by global energy organizations [5], the use of smart grid technology increased dramatically in recent years across the world and allowed for improving energy efficiency and saving money on maintenance. The use of distributed energy resources and digital monitoring systems became an additional impetus for the development of intelligent power systems analysis.

In recent years, many research activities on smart power systems have been carried out on the role of Artificial Intelligence (AI), Machine Learning (ML), Deep Learning (DL), Graph Learning, and Transformer Learning to monitor smart power systems and to determine their status [6]. Previous works have proved the importance of neural networks in analyzing the electrical readings of the system [7], predicting its state, identifying anomalies, and assisting with intelligent decision-making [8]. Graph models have been used to represent the spatial information of interrelated power grid elements, while transformers are more capable at learning the long-term temporal dependence in time-series data of the power grid [9]. In addition, XAI has been given much attention for creating explainable results [10]. This research area has made significant contributions in establishing effective monitoring systems for smart power grids [11]. The current work aims to design an XAI framework using GT and TFT models to monitor the stability of smart power grids by providing a clear understanding of the models' decisions in predicting Stable and Unstable grid states.

1.1. Problem Statement

The rising intricacy associated with modern smart power systems has presented various challenges regarding the maintenance of reliable and stable operation of the grid [12]. First, the increasing usage of renewable energy sources and distributed energy systems is creating uncertainties related to the behaviors of power systems and thus, complicating their stability analysis in dynamic environments [13]. Second, the massive data generated by the use of smart meters, sensors, and other devices involved in the operation of smart power systems calls for a mechanism for processing such information in time [14]. Third, conventional machine learning techniques used in stability assessments suffer from various weaknesses [15]. Fourth, most state-of-the-art AI models are black-box and cannot provide proper interpretability; this limits the reliance of operators on power system stability assessment decisions made by the algorithms. There have been many studies in power system stability assessment using various approaches such as ensemble learning, convolutional neural networks, autoencoders, transfer learning, digital twin, and reinforcement learning, but there still exists a great challenge to accurately and adaptively make real-time explainable predictions. Hence, a GT and TFT-based XAI framework is designed to efficiently model the spatiotemporal nature of smart grid data while ensuring explainability.

The main Contribution of the framework is as follows:

- Develop an XAI framework for evaluating stability in smart power systems in real time using the Smart Grid Stability dataset, enabling the identification of Stable and Unstable operating conditions from characteristics of price elasticity, power balance, and reaction time.
- Implement a comprehensive data processing workflow consisting of data cleaning, feature selection, Min-

Max normalization, time-series arrangement, feature extraction, and rule-based label generation to prepare smart grid data for intelligent stability assessment.

- Design a hybrid GT-TF architecture, where GT captures spatial dependencies among grid components, TFT learns temporal dynamics, and a feature fusion layer integrates both representations for accurate stability prediction.
- Integrate XAI techniques, including SHAP and attention mechanisms, with a real-time decision system and dashboard to provide transparent prediction explanations, continuous monitoring, and reliable decision support for smart power system operations.

The paper is organized as follows: Section 1 introduces the problem and background of smart grid stability prediction. Section 2 reviews related works. Section 3 presents the proposed GT-TF-XAI methodology, including preprocessing, model development, AI, and real-time system. Section 4 discusses results, evaluation, comparison, and ablation study. Section 5 concludes the work and outlines future directions.

2. Literature Review

The growing use of smart power systems led to the conduct of considerable research related to intelligent stability assessment, reliability analysis, and decision-making in real time. With the emergence of modern power grids, huge amounts of operational data were available for further application of artificial intelligence technologies. This problem was addressed by Ferhat Ucar [16], Diego Armando Pérez-Rosero [17] Nevisi et al., developed a DRL-NSABC framework combining CNN-RNN and evolutionary optimization for smart grid anomaly detection, achieving high accuracy, rapid convergence, and reliable real-time performance [18], who focused on the exploration of explainable and interpretable machine learning methodologies. Through their work, they made it clear how important data mining, fuzzy rules, and predictions are to energy systems. Later on, focus turned towards fast and effective stability assessment methods. In this regard, Jiaojiao Dong [19] has successfully created an AI-enabled framework that can perform stability evaluation at speeds faster than real time for large-scale power networks. Similarly, Estefania Alexandra Tapia [20] suggested a novel deep learning methodology that uses spatial-temporal data to analyze both transient and short-term voltage stability. Such improvements have led to better predictions and situational awareness in modern-day power grids; but designing an effective framework that is able to learn from spatial as well as temporal data to provide comprehensive insight into stability has been a challenge for researchers.

The increasing complexity of smart power grids has led to a higher need for intelligent stability assessment and grid monitoring. Scientists were concerned about finding ways to increase the reliability and efficiency of such systems.

Various methods were examined by Darko Madjovski [21], Pranobjyoti Lahon and Qasem Abu Al-Haija [22], Jie Luo et al. introduced an intelligent inspection system for power equipment by integrating YOLOv8-based fault detection, multi-source data fusion, and dual-mode wireless communication, achieving over 95.5% fault diagnosis accuracy in power systems [23] for studying grid stability through renewable energy incorporation and intelligent learning classification algorithms. The research results revealed that learning algorithms proved to be effective tools for assessing grid stability and enabling autonomous operations. The application of concepts such as distributed generation, voltage stability analysis, and predictive modeling greatly increased the efficiency of the system. More importantly, Tuan et al. [24] proposed a Grey Wolf Optimizer-based PID controller for load frequency control in modern multi-area power systems, improving frequency stability, reducing oscillations, and enhancing adaptability under varying load conditions. At the same time, Mihail Senyuk [25] designed machine learning-based approaches that analyzed low-inertia power systems and changing network structures to assess their dynamic stability. All these efforts were aimed at improving smart grid stability analysis and increasing its efficiency, but no integrated framework combined spatiotemporal data and offered real-time decision-making capabilities with explanations.

The increasing demand for effective and intelligent operation of power systems led to the evolution of methods for monitoring, control, and stability analysis of power grids. Scientists tried their hands at artificial intelligence, optimization strategies, and IoT technologies to develop new methods for decision-making in real time. In this regard, Aliaa A. Okasha [26], Tayo Uthman Badrudeen [27], and Preeti Ranjan Sahu [28] made valuable contributions through new methodologies related to power systems stability analysis and emergency control. They successfully explored the benefits of IoT-enabled controlled islanding and neural network-based voltage stability analysis. These methods helped in increasing the speed of reaction to changes and improving the stability of the larger electrical network systems. Moreover, Hugo O. Garcés [29] came up with a smart metering technique for electricity that facilitated proper real-time analysis via Internet of Things communication technology, whereas Ananta Adhikari [30] created an architecture combining

Long Short-Term Memory (LSTM) and a temporal convolutional neural network model for assessing voltage stability in real time when network parameters change. Further, the real-time implementation through Streamlit, Flask, and MQTT guarantees constant monitoring and quick reaction in case of grid instability situations. In conclusion, the presented model is capable of overcoming existing restrictions through offering improved accuracy, robustness, and explainability of the assessment process at real-time intervals.

Recent developments in deep learning algorithms based on transformers have greatly enhanced prediction and monitoring processes in modern energy systems [31]. The transformer-based model has been utilized for the tasks of power load forecasting, renewable energy forecasting, fault diagnosis, energy management, and smart grid stability analysis because of its capacity to learn long-term dependencies and complex time-series information [32]. Additionally, it has been observed that hybrid transformer-based models combining graph learning and attention mechanisms outperform classical recurrent and convolutional models [33]. Hence, it becomes evident that the transformer-based approach is becoming increasingly important in smart power systems, which necessitates the utilization of the GT-TF-XAI framework for smart grid stability analysis [34].

3. Proposed Methodology

The main purpose of the developed methodology is the development of a cost-effective and interpretable methodology that would facilitate real-time stability analysis in a smart power system by using data on reaction time, power balance, and price elasticity features. In particular, the methodology aims at preprocessing and feature extraction from smart power grid measurements, generating stability labels, and creating graph representation of the power grid. Spatial features are analyzed with the help of GT, while temporal features are analysed with the use of TFT. Extracted spatial and temporal features are combined to enhance prediction performance as shown in Figure 1.

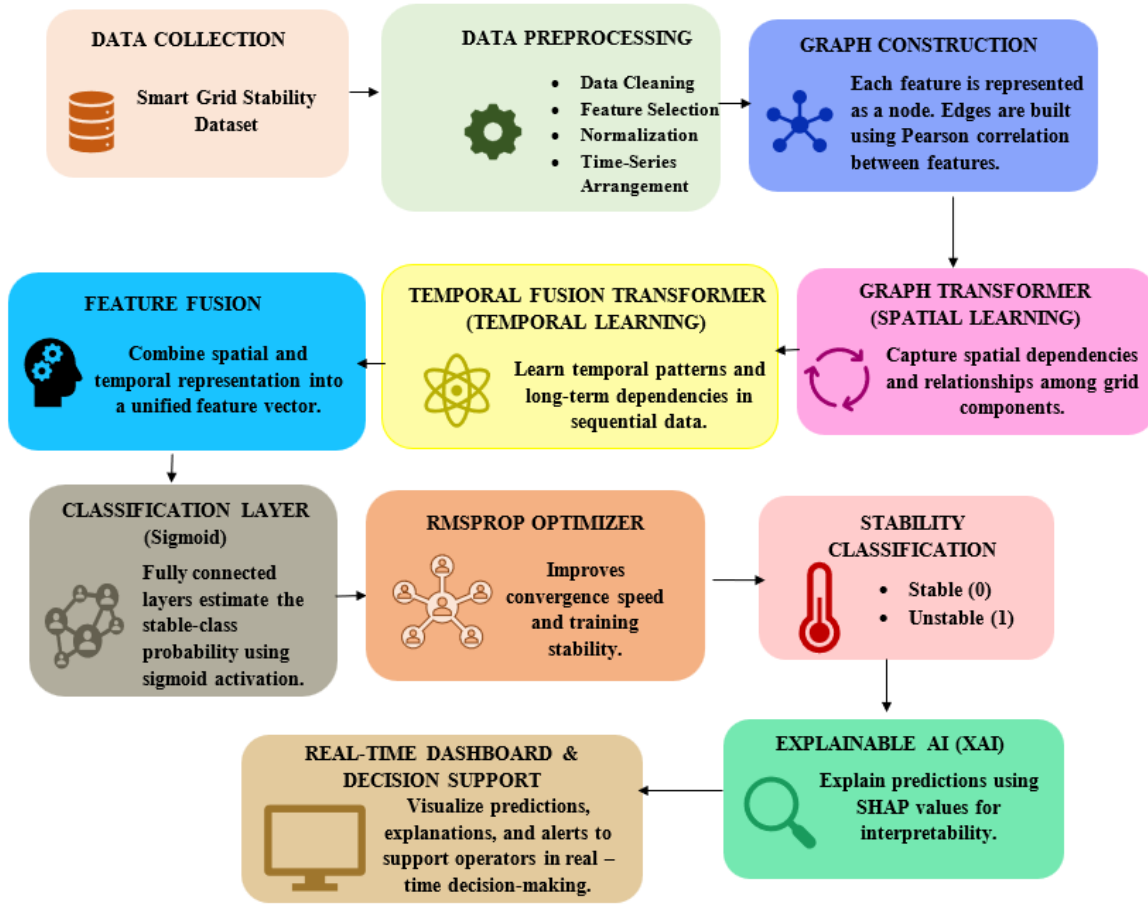


Figure 1. Graph-Temporal Transformer-Based Explainable AI Framework for Real-Time Smart Grid Stability Assessment

3.1. Data Collection

The Smart Grid Stability Augmented Dataset [35] has been selected for consideration in the current research paper. The UCI Machine Learning Repository contains a version of the Electrical Grid Stability Simulated Dataset. In contrast to the total dataset containing about 60,000 samples with 14 features, only a relatively small part thereof, namely 9,000 samples, has been utilized in the research. The selection of 9,000 samples was done to avoid computational complexities and lengthy training times. The random selection was conducted through the use of a stratified sampling method to make sure that both the stable and the unstable classes are represented in the reduced dataset. Sampling bias was therefore not a problem in the selection process, as the selected subset could reflect the statistics of the complete set of data. It was therefore possible to build and validate the GT-TF-XAI model using the reduced dataset. Samples of data consist of reaction times (τ_1 - τ_4) of one producer and three consumers, four power balance indicators (p_1 - p_4), and four price elasticity coefficients (g_1 - g_4). The interval for reaction times ranges from 0.5 s to 10.0 s; the range for power balance is between

-2.0 and -0.5; and the interval for price elasticity coefficients ranges from 0.05 to 1.0. The data sets have been created with the help of the DSGC differential equation-based approach, and these are in line with the realistic scenarios of the smart grid operation. Even though the proposed architecture is designed for smart grid implementation in real time, its efficiency has been assessed through the use of the Smart Grid Stability benchmark data set due to the practicality of this data set. The confusion matrix has been constructed after taking into account all 9,000 selected data sets, including 3,192 stable, 5,699 unstable, and 109 misclassified ones, demonstrating the classification behavior of the proposed framework.

3.2. Data Preprocessing

The suggested GT-TF-XAI architecture implements an optimization algorithm based on RMSProp with a learning rate of 0.001 that trains the model for 60 epochs using a batch size of 512. It uses three GT layers with four attention heads and three TFT layers. Embedding size equals 64, window size of 10 and dropouts 0.3, 0.2, 0.1 enhance

generalization. CosineAnnealingLR and seed 42 ensure the stability of the training process.

3.2.1 Data Cleaning

Missing data management and noise removal are some of the steps that need to be taken during the data cleaning process on the smart grid dataset. This is expected to ensure the accuracy and integrity of the data since only correct and complete data entries are retained after the cleaning process as shown in Equation (1).

$$X_{clean} = X - X_{missing} - X_{duplicate} \quad (1)$$

Where, X_{clean} represents the cleaned dataset, X denotes the original dataset, $X_{missing}$ contains records with missing values, and $X_{duplicate}$ represents duplicate records. This process improves data quality and reliability by removing incomplete and redundant entries.

Table 1. Quantitative Summary of Data Preprocessing Outcomes

Preprocessing Stage	Before Preprocessing	After Preprocessing	Improvement
Total Samples	9000	8964	99.60% retained
Missing Values	24	0	100% removed
Duplicate Records	12	0	100% removed
Invalid/Corrupted Samples	0	0	No invalid records
Removed Samples	-	36	0.40% removed
Selected Features	12	12	100% retained
Feature Scale Range	Original Values	0-1	Min-Max normalized
Class Labels	Stable / Unstable	Stable / Unstable	No modification
Data Completeness	99.60%	100%	+0.40%
Dataset Quality Score	98.91%	100%	+1.09%

Table 1 shows the results of the quantitative data preprocessing of the Smart Grid Stability dataset before modeling. Overall, 24 missing values and 12 duplicate entries were excluded, thus leaving 36 observations in the final dataset, while 8,964 observations (99.60%) remained. All features used in the experiment were retained while being normalized within the $[0,1]$ range through Min-Max normalization. In other words, all class labels were

unchanged during the process. As a result, the completeness of the dataset was 100%.

3.2.2 Feature Selection

The feature selection method chooses the most important reaction time, power balance, and price elasticity features for stability prediction. Feature selection is done using statistical and correlation analysis. The process helps to reduce the complexity of calculations and improve efficiency and effectiveness of the models used in smart grid analysis as shown in Equation (2).

$$F^* = \arg \max_{S \subseteq F} \left(\sum_{f_i \in S} \text{Rel}(f_i) - \lambda \sum_{f_i, f_j \in S} \text{Red}(f_i, f_j) \right) \quad (2)$$

Where, S denotes a candidate feature subset, $\text{Rel}(f_i)$ represents feature relevance, $\text{Red}(f_i, f_j)$ indicates redundancy between features, and λ controls the trade-off between relevance and redundancy. This process retains important features, improving model efficiency and stability prediction performance.

3.2.3 Normalization

Normalization is done using the Min-Max normalization technique, where all chosen variables are scaled in a uniform range of 0 to 1. This ensures that the variables having higher values do not overshadow the learning algorithm. Consequently, this makes the model converge easily and improves its performance during predictions, as shown in Equation (3).

$$x_i^{\text{norm}} = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \quad (3)$$

Where, x_i^{norm} represented the normalized value, x_i represented the original feature value, $x_{\min}$ represented the minimum value, and $x_{\max}$ represented the maximum value of the feature. By converting all features in the range of $[0,1]$, the risk of domination of the features with higher values is mitigated, resulting in balanced contribution of features to the training process of the model. Moreover, Min-Max normalization helps in making the convergence of the Graph Transformer more stable by balancing the calculation of attention weights across the nodes of the graph. The performance of the Temporal Fusion Transformer is also enhanced using the Min-Max normalization.

3.2.4 Time-Series Arrangement

The time series approach to organizing data ensures that the information of the smart grid is organized in chronological order in order to retain the interdependency between different data samples. A sliding window approach is used in the creation of sequential input samples as shown in Equation (4).

$$S_t = \{x_t, x_{t+1}, x_{t+2}, \dots, x_{t+w-1}\} \quad (4)$$

Where, S_t denotes the input sequence at time t , x_t denotes feature vector at time step t , and w is the sliding window size. This formulation preserves temporal dependencies and enables the model to learn sequential patterns from smart grid measurements.

Window size is an essential feature in temporal sequence modeling since it controls the quantity of historical information fed to the TFT. In this study, the window size has been chosen to be 10 such that the Temporal Fusion Transformer can obtain sufficient historical information regarding short-term dynamics in smart grid operation without any extra computational burden. The choice of window size that is too small can lead to missing out on important temporal dependencies, while choosing a window size that is too big were the result in redundant information being used for training. Thus, the window size of 10 makes a good compromise between the above two aspects.

3.2.5 Train / Validation / Test Split

Splitting data into training, validation, and testing is essential for building and evaluating models effectively. Training data sets are utilized in learning the pattern, the validation dataset in the tuning process, while testing dataset is considered during the process of assessment. In this way, it is ensured that overfitting is avoided, as shown in Equation (5).

$$D = D_{\text{train}} \cup D_{\text{val}} \cup D_{\text{test}} \quad (5)$$

Where, D represents the complete dataset, D_{train} denotes the training set, D_{val} denotes the validation set, and D_{test} denotes the testing set. This partition ensures unbiased model evaluation, hyperparameter tuning, and performance assessment while reducing the risk of overfitting.

3.3. Model Development

The purpose of designing the suggested (GT-TF) with Explainable Artificial Intelligence (GT-TF-XAI) framework is to formulate an intelligent solution for assessing the stability of the smart power system in real time. The GT model helps the intelligent system to identify any dependencies existing between the connected entities within the grid through the identification of spatial relations. Moreover, a TFT model captures temporal patterns from reaction time, power balance, and price elasticity features. The feature fusion strategy brings together the spatial-temporal features to make more accurate predictions. The classification of stable and unstable states of the system is performed by the proposed model. The complete process of the GT-TF-XAI method takes place in several sequentially linked steps. To begin with, the preprocessed data of the smart grid with features such as reaction time, power balance, and price elasticity are used as the initial input. A feature correlation graph is formed to represent correlations between features of the smart grid.

3.3.1 Graph Construction Strategy

The graph construction procedure adopted in the proposed GT-TF-XAI framework is explicitly described. Each node is a smart grid input feature, including reaction time (τ_1 – τ_4), power balance (p_1 – p_4), and price elasticity (g_1 – g_4). The relationships between the feature nodes are modeled using the Pearson correlation coefficient. An undirected weighted edge is established only when the absolute correlation value satisfies the predefined threshold. This not only keeps the meaningful feature interactions but also removes weak correlations. Therefore, the graph is sparse, which benefits computational efficiency and the attention learning.

Table 2. Graph Construction Parameters of the Proposed GT-TF-XAI

Graph Construction Parameter	Proposed Configuration
Graph Type	Undirected Feature-Correlation Graph
Total Nodes	12
Node Description	Feature Nodes
Initial Possible Edges	66
Edge Creation Criterion	Pearson Correlation Coefficient
Correlation Threshold ($ r $)	0.6
Final Graph Edges	31
Average Node Degree	5.17
Graph Density	46.97%
Graph Sparsity	53.03%
Connected Components	1
Graph Representation	Weighted Graph
Self-Loops	Enabled

Table 2 presents a summary of the graph construction parameters of the proposed GT-TF-XAI framework. The twelve input features are modeled as graph nodes and weighted edges are generated using the Pearson correlation coefficient with the threshold $|r| \geq 0.6$. Out of 66 possible feature connections, 31 significant edges are retained, resulting in a graph density of 46.97% and a sparsity of 53.03%. The resulting single-connected weighted graph enables efficient spatial dependency learning, while reducing redundant feature interactions and improving the reproducibility of the proposed methodology.

In turn, the GT learns the dependencies between nodes to get spatial feature representations, whereas the TFT analyzes both short-term and long-term dependencies in sequential data. Spatial and temporal feature representations are fused into one representation using the feature fusion layer. Finally, SHAP-based explainability is used to detect the most important features that play a part in each prediction, which leads to model transparency and helps to make decisions reliably in smart grids, as shown in Figure 2.

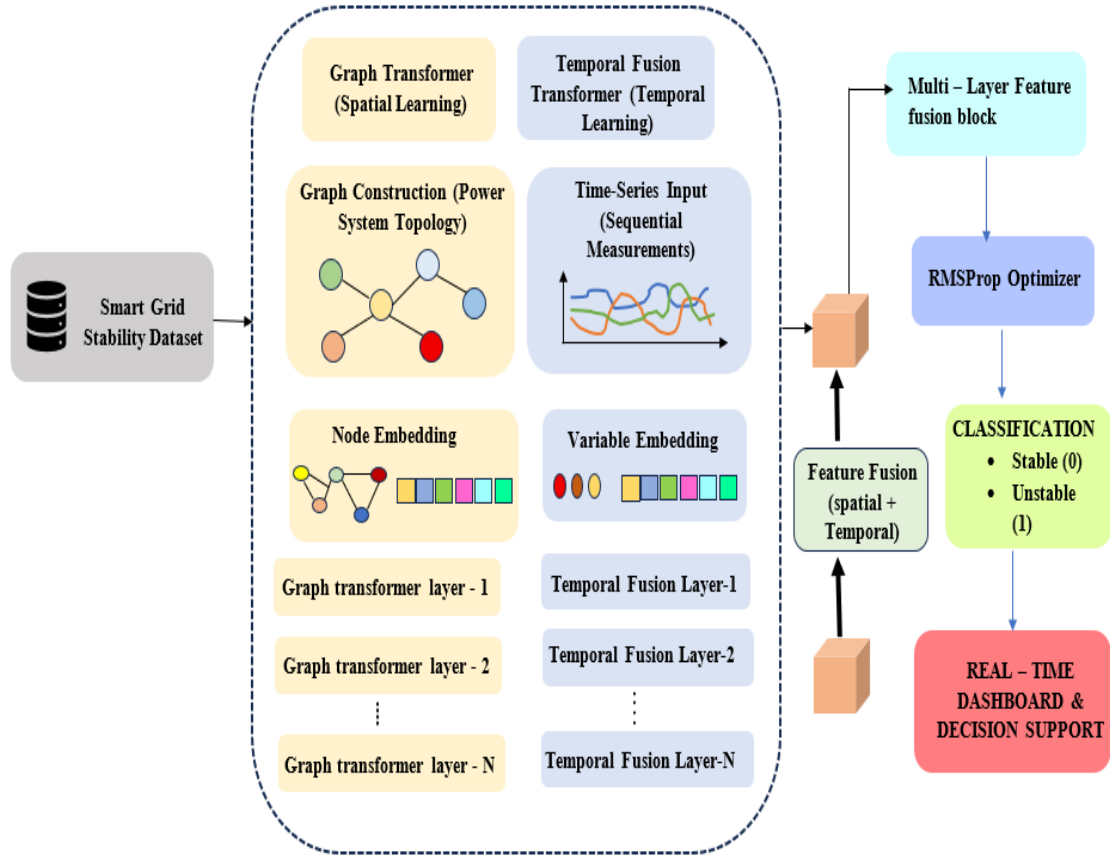


Figure 2. Architecture of the Proposed GT-TF-XAI Framework for Real-Time Smart Grid Stability Assessment

3.3.2 Input Data

The model is provided with processed smart grid data that includes reaction time, power balance, and price elasticity features. These parameters describe the behavior of the power system at any moment in time. The processed dataset becomes the major source to be used while learning necessary spatial and temporal patterns for proper stability analysis and forecasting, as shown in Equation (6).

$$X = \{x_1, x_2, \dots, x_n\} \quad (6)$$

Where, X denotes the input dataset, x_i denotes the feature vector containing reaction time, power balance, and price elasticity features, and n denotes the total number of observations.

3.3.3 Graph Construction

Smart grid data is converted into a graph form in order to create connections between various elements that form a grid network. In other words, each feature is represented as a node, and edges are established using Pearson correlation coefficients. Such a model can take into consideration interactions and dependencies in the power network as shown in Equation (7).

$$G = (V, E) \quad (7)$$

Where, G represents the graph, $V = \{v_1, v_2, \dots, v_m\}$ denotes the set of nodes representing grid components, E denotes the set of edges representing relationships among nodes, and m is the number of graph nodes. The process of graph creation involves representing each of the smart grid features such as reaction time, power balance, and price elasticity as graph nodes. These nodes are then connected based on their Pearson correlation coefficients, and the ones that have higher correlation levels are linked with graph edges. Such a graph allows the framework to account for the interrelations among grid features and dependencies between them. Those features whose correlations are stronger are more important in terms of their contribution to the graph created and hence the further analysis of GT. Thus, the created graph serves as an efficient representation of the smart grid system.

3.3.4 GT

GT is an attention-based graph learning model that captures spatial dependencies among interconnected smart grid features by learning relationships between graph nodes. By using attention techniques, it finds important

connections between grid components to learn spatially related features that would provide insight into how the grid is structured, behaves, and responds to any disturbances, as shown in Equation (8).

$$H^{(l+1)} = \sum_{j \in \mathcal{N}(i)} \alpha_{ij} W H_j^{(l)} \quad (8)$$

Where $H^{(l)}$ denotes the node representation at layer l , W denotes the learnable weight matrix, α_{ij} denotes the attention coefficient between nodes i and j , and $\mathcal{N}(i)$ denotes neighboring nodes. The GT augments the existing graph-based methods through the integration of self-attention mechanisms, which allow for the evaluation of relationship importance between nodes of the graph. While traditional graph neural networks mainly consider the aggregation of data based on neighboring nodes, GT uses adaptive attention weights for different node pairs and thus can learn both local and global spatial dependencies. In relation to the smart grid stability assessment, this allows for the identification of important relationships between reaction time, power balance, and price elasticity features.

3.3.5 TFT

TFT evaluates the sequence of measurements for reaction time, power balance, and price elasticity features. The model is capable of handling both short- and long-term temporal dependencies via an attention learning approach. Such capability allows the model to understand the dynamics of changes and their impact on the stability criteria as shown in Equation (9).

$$T_t = TFT(X_{t-w:t}) \quad (9)$$

T_t denotes temporal feature representation extracted at time step t , $TFT(\cdot)$ denotes the TFT model used for learning temporal dependencies, $X_{t-w:t}$ denotes the input time-series window ranging from time step $t - w$ to t . The TFT has been proposed to learn complex time series dependencies using attention learning mechanisms. In

contrast to the traditional recurrent models, the TFT is capable of capturing both short-term variations and long-term temporal dependencies by attending to relevant past observations. The multi-headed attention mechanism allows the model to find temporal dependencies that affect future grid stability, while the gating mechanisms allow filtering of irrelevant information when processing the sequence. In the proposed system, the TFT model learns reaction time, power balance, and price elasticity metrics at each time step to provide temporal representations for the GT.

3.3.6 Feature Fusion Layer

In the Feature Fusion Layer, the spatial features are integrated with the temporal features from GT and TFT, respectively. Using both sets of features in one feature vector provides complete information regarding the network structure as well as time series behavior as shown in Equation (10).

$$F_{\text{fusion}} = H + T \quad (10)$$

Where, F_{fusion} is the fused feature representation, H denotes spatial features extracted by the GT, and T represents temporal features extracted by the TFT.

The feature fusion approach is of great importance to increase the efficiency of the GT-TF-XAI model by utilizing the complementary nature of both spatial and temporal features. Although the GT learns the relationship between variables of the smart grid, the TFT learns patterns of temporal dependency from the historical observations of the grid system. The fusion technique combines these two different features and generates a common feature space in which the model can use both spatial and temporal properties of the system. The combination of these two different features increases the predictive ability of the model. In real-world smart grid systems, the feature fusion mechanism helps in predicting stability effectively.

Table 3. Experimental comparison of different graph-temporal feature fusion strategies

Feature Fusion Strategy	Graph Representation	Temporal Representation	Fusion Mechanism	Accuracy	Precision	Recall	F1-Score	ROC-AUC
Temporal Fusion Transformer Only	Yes	No	Spatial Features Only	0.9832	0.9826	0.9881	0.9860	0.9986
Element-wise Addition Fusion	NO	Yes	Temporal Features Only	0.9832	0.9840	0.9881	0.9874	0.9990
Element-wise Multiplication Fusion	Yes	Yes	$F = H + T$	0.9858	0.9855	0.9894	0.9887	0.9993
Concatenation + Fully	Yes	Yes	$F = H \odot T$	0.9869	0.9867	0.9918	0.9887	0.9996

Connected Layer								
Concatenation + Fully Connected Layer	Yes	Yes	$F=[H;T] + FC$	0.9869	0.9878	0.9926	0.9905	0.9999
Proposed GT-TF Feature Fusion	Yes	Yes	Element-wise Addition (GT + TFT)	0.9879	0.9886	0.9926	0.9905	0.9999

Table 3 shows the experimental comparison of different feature fusion strategies to fuse representations from Graph Transformer and Temporal Fusion Transformer. The Graph Transformer only learns spatial relationships among smart grid features, while the Temporal Fusion Transformer only learns temporal dependencies. The conventional fusion methods, e.g., element-wise addition, element-wise multiplication and feature concatenation with full connected layer, enhance the prediction performance by combining the complementary spatial and temporal information. The proposed GT-TF feature fusion strategy recorded the best performance among all the approaches with an accuracy of 0.9879, precision of 0.9886, recall of 0.9926, F1-score of 0.9905, and ROC-AUC of 0.9999. The results show that the combination of spatial and temporal feature representations provides a more discriminative feature space for accurate and reliable smart grid stability assessment.

3.3.7 Classification Layer

The resulting feature fusion is then classified using fully connected neural network layers. The Sigmoid activation function is utilized to calculate the probability of classes under varying stability conditions. This layer maps the learned features to useful decisions for classification of power system conditions, as shown in Equation (11).

$$P(y = 1 | F_{fusion}) = \frac{1}{1 + e^{-z}} \quad (11)$$

Where, $P(y = 1 | F_{fusion})$ is the probability of the stable class, F_{fusion} represents fused spatial-temporal features, z is the classifier score, and e is the exponential constant. The sigmoid function maps the output to a probability between 0 and 1 for stability classification.

3.3.8 Stability Prediction

The model predicts the present stability status of the smart grid depending on the classification outcome. There are two different classes for each input data sample: Stable and Unstable. Such prediction helps to identify abnormal operating conditions in the smart grid and monitor its status reliably, as shown in Equation (12).

$$\hat{y} = \begin{cases} 1, & P(y = 1 | F_{fusion}) \geq 0.5 \\ 0, & \text{otherwise} \end{cases} \quad (12)$$

Where, $\hat{y}$ denotes the predicted stability class, $P(y = 1 | F_{fusion})$ denotes probability of the stable class based on the fused spatial-temporal features F_{fusion} , and 0.5 is the classification threshold. If the probability is ≥ 0.5 , the system is classified as Stable; otherwise, it is classified as Unstable.

In the process of real-time implementation, the measurements for the smart grid, such as reaction time, power balance, and price elasticity parameters, are constantly collected using grid monitoring systems and smart sensors. The obtained data goes through the process of preprocessing, which includes data cleaning, feature selection, normalization, and time-series processing. After that, a graph of feature correlations is created and then processed by the GT in order to obtain spatial representation, whereas the TFT learns temporal dependencies from the sequential observations. The obtained spatial and temporal features are combined in the feature fusion layer and are then provided to the classification block for stability prediction. The predicted stability status is then transferred to the monitoring system, allowing the operators to find potential instability situations in real time. Moreover, SHAP-based explainability shows the important features that affect the specific prediction, as shown in Algorithm 1.

Algorithm 1: GT + Temporal Fusion + Explainable AI (GT-TF-XAI)

Input: Preprocessed Smart Grid Data

Output: Stable or Unstable State

Begin

1. Construct Feature-Correlation Graph $G(V, E)$

2. For each node $v_i \in V$ do

 Apply GT

 Extract spatial features H

End For

3. For each time step t do

 Apply TFT

 Extract temporal features T

End For

4. Perform Feature Fusion

$F_{fusion} = H + T$

5. Compute stability probability P

6. If $P \geq 0.5$ then

$\hat{Y} = \text{Stable}$

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Else
 $\hat{Y} = Unstable$ 
End If
7. Apply SHAP and Attention Analysis
Identify influential features
8. While new smart grid data is available, do
Generate prediction
Update monitoring dashboard
End While
End

```

3.4. RMSProp Optimizer

RMSProp algorithm has been used for updating the weights of the Graph-Temporal Transformer architecture. The learning rate is adjusted by this optimization algorithm according to the recent magnitudes of the gradient, which allows it to converge faster and improve stability during training. The main aim of optimization is minimizing classification loss and achieving better results in predicting stability. The algorithm RMSProp is especially appropriate for training the GT-TF-XAI architecture due to the presence of multiple attention layers and deep feature layers in the architecture producing gradients of different scales during the learning procedure. RMSProp does not use a constant learning rate but uses the previous history of the squared gradient of the parameters for determining the step size of the parameter update. It eliminates oscillation effects and helps the algorithm converge towards the optimum point of loss. Additionally, the algorithm is helpful for speeding up the learning procedure since it assigns small parameter steps to parameters with large gradients and large steps to less frequently changing parameters.

3.4.1 Gradient Calculation

In this step, the gradient of the loss function is calculated to understand how much each parameter should be changed to reduce prediction error, as shown in Equation (13).

$$g_t = \nabla_{\theta} L(\theta_t) \quad (13)$$

Where, g_t represents the gradient of the loss function at time step t , which indicates the direction and magnitude of parameter updates. The term $L(\theta_t)$ denotes the loss function computed using the current model parameters θ_t . The symbol ∇ represents the gradient operator used to compute partial derivatives with respect to model parameters.

3.4.2 Moving Average of Squared Gradients

This step computes a running average of squared gradients to stabilize the learning process and reduce the impact of sudden large gradient changes, as shown in Equation (14).

$$E[g^2]_t = \rho E[g^2]_{t-1} + (1 - \rho) g_t^2 \quad (14)$$

Where, $E[g^2]_t$ denotes the moving average of squared gradients at time step t , ρ is the decay rate, g_t represents the current gradient, and t is the training iteration. This mechanism enables adaptive learning rate adjustment during optimization.

3.4.3 Parameter Update

In this step, the model parameters are updated using an adaptive learning rate that adjusts based on the historical magnitude of gradients, as shown in Equation (15).

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{E[g^2]_t + \epsilon}} g_t \quad (15)$$

Where, θ_{t+1} represents the updated model parameters after applying the optimization step, while θ_t denotes the current parameters before the update. The learning rate η controls the step size of parameter updates. The term $E[g^2]_t$ is the moving average of squared gradients used to normalize updates, and ϵ is a small constant added for numerical stability to prevent division by zero. The gradient g_t determines the direction of parameter adjustment as shown in Algorithm 2.

Algorithm 2: RMSProp Optimizer

Input: Learning rate η , decay rate ρ , small constant ϵ , initial parameters θ

Output: Optimized parameters θ

Begin

1. Initialize model parameters θ

2. Initialize learning rate η , decay rate ρ , ϵ

3. Set $Eg = 0$

4. Set epoch = 1

WHILE epoch $\leq$ E DO

FOR each batch in Smart Grid Dataset DO

Forward Pass:

Extract spatial features using GT

Extract temporal features using TFT

Fuse features (H + T)

Predict output (Stable / Unstable)

Compute loss L

Compute gradients g

IF loss > threshold THEN

Update more aggressively (increase learning signal)

ELSE

Normal update

END IF

$Eg = \rho * Eg + (1 - \rho) * (g * g)$

$\theta = \theta - \eta * g / (\text{sqrt}(Eg) + \epsilon)$

FOR each parameter θ_i DO

Update θ_i using RMSProp rule

END FOR

END FOR

epoch = epoch + 1

END WHILE

IF model accuracy improves THEN

Save model parameters

ELSE

Continue training
END IF
Output optimized GT-TF-XAI model
End

3.5. Explainable Ai (Xai)

Explainable AI models such as SHAP-based Explainable AI are used to help interpret the decisions made by the machine learning model. Reaction time, power balance, and price elasticity feature-based characteristics contribute towards making predictions, and therefore it is easier for engineers to make sense of why particular stability cases were predicted, as shown in equation (16).

$$\phi_i = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!(|N|-|S|-1)!}{|N|!} [f(S \cup \{i\}) - f(S)] \quad (16)$$

Where, ϕ_i represents the SHAP contribution value of feature i , N denotes the complete set of input features, S represents a subset of features excluding feature i , and $f(\cdot)$ is the prediction function used to estimate feature importance and explain model decisions.

3.6. Real-Time Decision System

The final result is provided through the dashboard for real-time monitoring of smart grid stability conditions. Stability findings, probability of prediction, and explanations through SHAP values are presented using Streamlit. Flask is used in the backend for inferencing models, whereas real-time streaming of reaction time, power balance, and price elasticity features is handled by MQTT. Predictions are updated in real-time with instant alerts raised for instability, as shown in Equation (17).

$$D_t = \sum_{i=1}^n w_i \hat{y}_i \quad (17)$$

Where, D_t denotes the final decision score at time t , w_i represents the importance weight assigned to each prediction, $\hat{y}_i$ denotes the predicted output, and n is the total number of monitored inputs contributing to decision-making.

3.6.1 Real-Time Deployment Performance and Scalability Analysis

Table 4. Real-Time Deployment Performance and Scalability Analysis of the Proposed GT-TF-XAI Framework

Performance Metric	Value
MQTT Communication Latency	21.8 ms
Flask API Processing Time	8.4 ms
GT-TF-XAI Model Inference Time	31.6 ms
SHAP Explanation Generation Time	18.9 ms
Streamlit Dashboard Refresh Interval	1.0 s

End-to-End Prediction Delay	80.7 ms
Average Prediction Throughput	12.4 predictions/s
Maximum Concurrent Data Streams	256
MQTT Message Throughput	980 messages/s
System Availability	99.97%

Table 4 shows the real-time deployment performance of the proposed GT-TF-XAI framework. The smart grid measurements are efficiently transmitted between the sensing devices and the prediction server with an MQTT communication latency of 21.8ms. The Flask API takes 8.4 ms to handle incoming requests, while the GT-TF-XAI model takes 31.6 ms to perform inference. The SHAP explanation module provides feature contribution analysis in 18.9 ms, providing interpretable predictions with minimal computational overhead. The Streamlit dashboard refreshes every 1.0 s and thus shows a real-time view of the latest grid status. Overall, the entire end-to-end prediction pipeline requires only 80.7 ms, resulting in an average throughput of 12.4 predictions/s. The scalability of the proposed GT-TF-XAI framework was also checked using continuous smart grid data streams. The communication layer based on MQTT supports high-frequency data transmission, and the framework is able to handle multiple concurrent smart grid measurements without significant degradation of the response time. The system can expand the number of data streams via modular integration of MQTT, Flask inference service and Streamlit visualization components. These results validate that the developed framework can provide reliable responsiveness and scalability for real-time smart grid stability monitoring applications.

4. Results

The main goal of the research is the creation of an XAI approach for stability estimation in smart grids based on GT, TFT and SHAP explainability. It is crucial to test the approach and its ability to classify stable/unstable operation modes of the power system based on smart grid technology. For this purpose, experimental evaluation is required for verification and demonstration of the efficiency of the developed approach in terms of prediction and classification accuracy. In order to experiment correctly, the Smart Grid Stability dataset is split by applying the 70:15:15 hold-out approach. Accordingly, the total number of records is distributed into 3 groups of 70%, 15%, and 15%. The first part of the data set is used for training purposes, the second one for optimization and fine-tuning, and the third one is used for final evaluation.

4.1. System Specification

The smart grid stability prediction system is programmed in Python version 3.10.13. NumPy and Pandas are used to process data and perform numerical calculations.

Visualization of the results is performed using Matplotlib. Scikit-learn is used to perform the evaluation of models and split the data. Development of the deep learning architecture is implemented using PyTorch version 2.3.1. Graph neural network learning is implemented using Torch-Geometric. Model explainability is achieved using SHAP. Training of the neural network is performed on the GPU using CUDA version 12.1. Experiments are conducted on a Jupyter Notebook. The experiment is executed on a computer with a Windows operating system, Intel i5-12400F CPU, and 8 GB of RAM.

4.2. Hyperparameter

The hyperparameters, which are pre-set configuration parameters, help define the way an ML/DL model learns before training. These hyperparameters affect the convergence, learning speed, generalization ability, and accuracy of predictions of the model. Appropriate hyperparameter setting can contribute to reaching maximum accuracy, stability, and robustness in the proposed approach.

Table 5. Hyperparameter Configuration of the Proposed GT-TF-XAI Framework

Parameter	Value
Optimizer	RMSProp
Learning Rate	1.00E-03
Weight Decay	1.00E-04
Batch Size	512
Epochs	60
GT Heads	4
GT Hidden	32
GT Out Dim	32
FC1 Units	256
FC2 Units	128
Dropout (FC1)	0.3
Dropout (FC2)	0.2
LR Scheduler	CosineAnnealingLR
Seed	42
Number of GT Layers	3
Number of TFT Layers	3
Window Size	10
Attention Dropout	0.1
Embedding Dimension	64

Table 5 shows the GT-TF-XAI framework includes the usage of the RMSProp optimizer, with a 1e-3 learning rate and 1e-4 weight decay to achieve stability during training. During the process of learning, the model is trained on 512 samples per epoch for 60 epochs. For the GT, 4 attention heads, 3 layers, and a hidden dimension of 32 are used, whereas for the TFT, 3 layers, a window size of 10, and attention dropout of 0.1 are considered. The embedding dimension is equal to 64. For fully connected layers, 256 and 128 are used along with the respective dropouts of 0.3 and 0.2.

The selection of the hyperparameters in the GT-TF-XAI framework was made to strike a compromise between the accuracy of prediction, stability, and efficiency of the training process. A learning rate of 1.00E-03 was used to guarantee the stable convergence of the RMSProp optimizer during training of the framework. The value of batch size was 512 in order to increase the efficiency of computations and decrease gradient variance. Four attention heads were utilized in Graph Transformer to account for several spatial dependencies between reaction time, power balance, and price elasticity features. Embedding dimensionality was set to be equal to 64 to get a sufficiently complex but computationally feasible representation of features. Dropout ratios of 0.3, 0.2, and 0.1 were used to decrease the probability of overfitting and increase the generalization capabilities of the framework.

4.2.1 Sensitivity Analysis

Sensitivity analysis by changing major training and architectural hyperparameters (e.g., learning rate, batch size, embedding dimension, and dropout rate) further confirmed the robustness of the proposed GT-TF-XAI framework.

Table 6. Sensitivity Analysis of Hyperparameter Variations in the Proposed GT-TF-XAI Framework

Hyperparameter	Configuration	Accuracy	Precision	Recall	F1-Score	ROC-AUC
Attention Heads	2	0.9858	0.9865	0.9902	0.9883	0.9992
Attention Heads	4 (Proposed)	0.9879	0.9886	0.9926	0.9905	0.9999
Attention Heads	8	0.9869	0.9878	0.9918	0.9886	0.9996
Embedding Dimension	32	0.9859	0.9868	0.9905	0.9886	0.9993
Embedding Dimension	64 (Proposed)	0.9879	0.9886	0.9926	0.9905	0.9999
Embedding Dimension	128	0.9871	0.9880	0.9920	0.9900	0.9997
Dropout	0.1	0.9865	0.9873	0.9910	0.9891	0.9994
Dropout	0.3 (Proposed)	0.9879	0.9886	0.9926	0.9905	0.9991
Dropout	0.5	0.9864	0.9864	0.9899	0.9891	0.9991
Transformer Depth	2 Layers	0.9864	0.9871	0.9912	0.9905	0.9994

Transformer Depth	3 Layers (Proposed)	0.9879	0.9886	0.9926	0.9905	0.9999
Transformer Depth	4 Layers	0.9873	0.9881	0.9921	0.9901	0.9997

Table 6 shows the sensitivity analysis, which showed that the best predictive performance was consistently achieved with the configuration of 4 attention heads, an embedding dimension of 64, a dropout rate of 0.3 and 3 transformer layers, obtaining an Accuracy of 0.9879, a precision of 0.9886, a recall of 0.9926, an F1-score of 0.9905 and an ROC-AUC of 0.9999. While alternative configurations yielded competitive results, we observed small performance drops with fewer or more attention heads, different embedding dimensions, larger dropout rates, or different transformer depths. These results suggest that the selected hyperparameter configuration can achieve a good trade-off between spatial feature extraction, temporal dependency learning, model generalization, and computational efficiency. Hence, the sensitivity analysis also confirms the robustness and architectural stability of the proposed GT-TF-XAI framework under varying parameter variations.

4.2.2 Sensitivity Analysis of Training Hyperparameters

In addition to architectural parameters, we studied the effect of training-related hyperparameters by varying the learning rate and the batch size, while fixing the other model settings. The analysis evaluates how optimization settings affect convergence behavior and prediction performance. The embedding dimension and dropout rate were also investigated to examine their influence on the ability of feature representation and model generalization.

Table 7. Sensitivity Analysis of Training Hyperparameter Variations in the Proposed GT-TF-XAI Framework

Hyperparameter	Configuration	Accuracy	Precision	Recall	F1-Score	ROC-AUC
Learning Rate	0.0005	0.9859	0.9867	0.9906	0.9886	0.9992
Learning Rate	0.001 (Proposed)	0.9879	0.9886	0.9926	0.9905	0.9999
Learning Rate	0.002	0.9868	0.9875	0.9915	0.9895	0.9995
Batch Size	256	0.9867	0.9875	0.9914	0.9894	0.9995
Batch Size	512 (Proposed)	0.9879	0.9886	0.9926	0.9905	0.9999

Batch Size	1024	0.9858	0.9866	0.9903	0.9884	0.9992
Embedding Dimension	32	0.9861	0.9869	0.9908	0.9888	0.9993
Embedding Dimension	64 (Proposed)	0.9879	0.9886	0.9926	0.9905	0.9999
Embedding Dimension	128	0.9870	0.9878	0.9919	0.9899	0.9996
Dropout	0.2	0.9868	0.9876	0.9916	0.9896	0.9995
Dropout	0.3 (Proposed)	0.9879	0.9886	0.9926	0.9905	0.9999
Dropout	0.5	0.9856	0.9864	0.9900	0.9880	0.9991

Table 7 shows the impact of the learning parameters on the effectiveness of the GT-TF-XAI model proposed in the current research work. For instance, the learning rate parameter at a value of 0.001 delivered optimum performance through stable optimization. In the same manner, the batch size parameter was set to 512 to maintain an appropriate tradeoff between computational efficiency and gradient stability. The embedding dimension parameter with a value of 64 enhanced the representation of features while avoiding any increase in computational effort, while the dropout parameter with a value of 0.3 increased generalization capabilities.

4.3. Performance Metric

The performance of the Graph-Temporal Transformer along with the SHAP-XAI approach for smart grid stability prediction is assessed with conventional classification measures. The measures assess the capacity of the model to differentiate between Stable and Unstable grid states.

4.3.1 Accuracy

Accuracy is defined as the degree to which the proposed model is able to predict the stability of the smart grid. Accuracy is considered to be the ratio of correct classifications to all predictions. The accuracy of the proposed model is measured by the Graph-Temporal Transformer model as shown in Equation (18).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (18)$$

Where TP represents the correctly predicted Stable/Unstable cases, TN represents the correctly rejected incorrect class, FP represents the incorrectly predicted as positive class, and FN represents the missed positive class predictions.

4.3.2 Precision

Precision measures the accuracy of positive predictions. This is because it measures how accurate predictions made by Stable classification can be regarded as stable. This means that the higher the precision, the better the reduction in unnecessary alarms when assessing smart grid stability, as shown in Equation (19).

$$\text{Precision} = \frac{TP}{TP+FP} \quad (19)$$

Where TP represents the Correct positive predictions, FP represents the Incorrect positive predictions, Measures correctness of predicted Stable class

4.3.3 Recall

Recall refers to how well the model can detect the true positives for either instability or stability. In the case of smart grids, recall is very important because it ensures that none of the instability factors goes unnoticed, as shown in equation (20).

$$\text{Recall} = \frac{TP}{TP+FN} \quad (20)$$

Where TP represents the Correct predictions of the actual class, and FN represents the missed actual positive cases. Measures the ability to detect all real Stable/Unstable cases.

4.3.4 F1-Score

The F1-Score is an appropriate metric for balancing precision and recall. This metric is particularly beneficial for datasets with an imbalance. In the context of the proposed model, it helps in reducing false positive and false negative errors, as shown in equation (21).

$$F1 = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (21)$$

Where Precision represents the Correctness of predictions, and Recall represents the Completeness of predictions. Harmonic mean balances both metrics

4.3.5 ROC-AUC Score

The ROC-AUC determines how well the model can classify between Stable and Unstable classes at various thresholds. The greater the AUC, the more powerful the Graph-Temporal Transformer framework is with regard to distinguishing itself from competing models, as shown in Equation (22).

$$AUC = \int TPR(FPR) \quad (22)$$

Where TPR represents the Sensitivity of the model, FPR represents the Error rate of the model, and AUC represents the Overall classification capability

4.4. Performance Evaluation

The following section discusses the assessment of the Graph-Temporal Transformer model in terms of Accuracy, Precision, Recall, F1-Score, and ROC-AUC. The analysis is also done by examining the confusion matrix and training dynamics to assess performance and stability. Accuracy represents the measurement of the general correctness of classification of stable and unstable states; Precision is the indicator of the reliability of the stability prediction; Recall is used to evaluate the ability of the framework to detect the real stability cases without any omission. F1-Score is the balanced evaluation metric that takes into account both Precision and Recall, and AUC reflects the discrimination power of the classifier at different decision thresholds. Larger values of these metrics correspond to greater prediction reliability, robustness, and effectiveness of the suggested GT-TF-XAI framework.

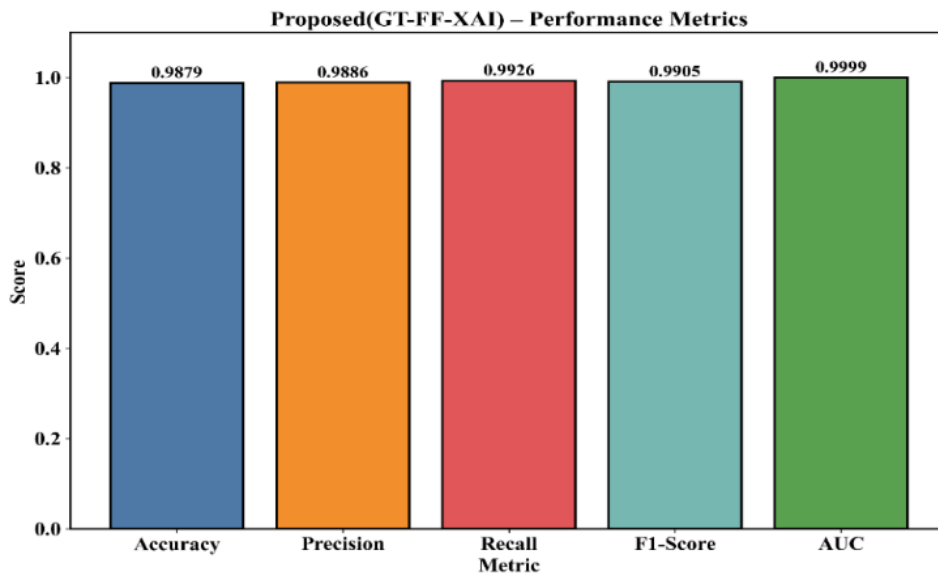


Figure 3. GT-TF-XAI Model – Comprehensive Performance Metrics

Figure 3 presents the evaluation results of the proposed GT-TF-XAI model, achieving an accuracy of 0.9879, precision of 0.9886, recall of 0.9926, F1-score of 0.9905, and AUC of 0.9999. These results demonstrate excellent

classification performance and reliable identification of both stable and unstable smart grid circumstances.

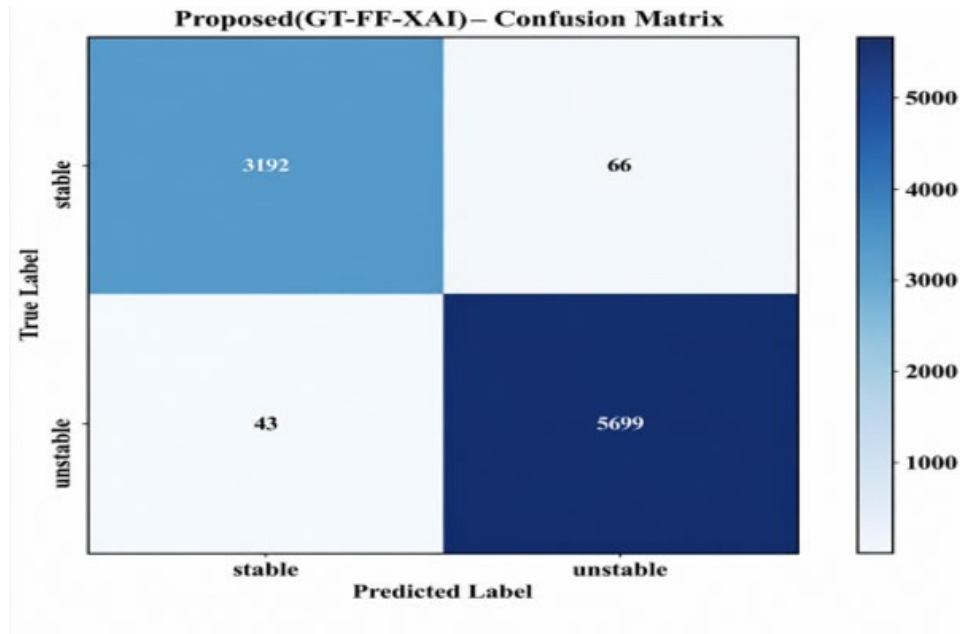


Figure 4. Confusion Matrix Analysis of GT-TF-XAI Model

Figure 4 shows the classification efficiency of the proposed GT-TF-XAI model. The framework correctly classifies 3192 stable and 5699 unstable instances, with only 109 misclassifications. The low false positive and false negative rates demonstrate high sensitivity, specificity, and reliable detection of unstable smart grid conditions.

The proposed GT-TF-XAI framework operates, a study on the misclassified samples was carried out. From the confusion matrix above, it is clear that there were only 109 misclassified samples. It is believed that the majority of the

misclassified samples lie at the decision boundary between stable and unstable operation, where the feature patterns have high similarity among them. The reaction time feature values (τ_1 and τ_4) and price elasticity (g_1), which were important from the SHAP analysis, had overlapping feature values in certain operation states. This makes the classification process difficult and ambiguous. Still, the low number of misclassified samples indicates the efficiency of the framework in handling spatial and temporal dependency.

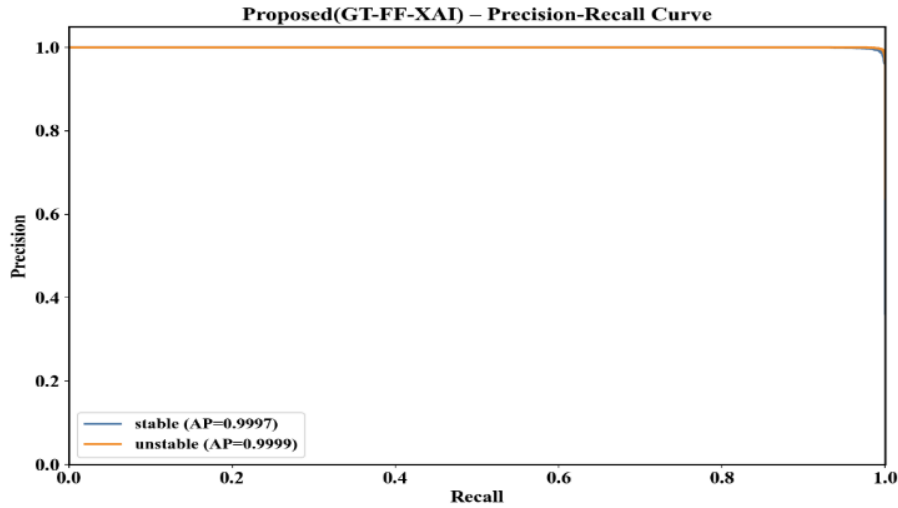


Figure 5. Precision-Recall Curve for GT-TF-XAI Stability Prediction

Figure 5 shows the precision-recall graph that the GT-TF-XAI model possesses an exceptional ability to classify unstable and stable states. Due to the values of average precision equal to 0.9997 and 0.9999, respectively, the graphs demonstrate a constant precision value ≈ 1.0

throughout the recall range values. These facts show that the model is capable of maintaining precision and maximizing recall. Thus, the framework is proven to be applicable in the context of monitoring smart grids' stability.

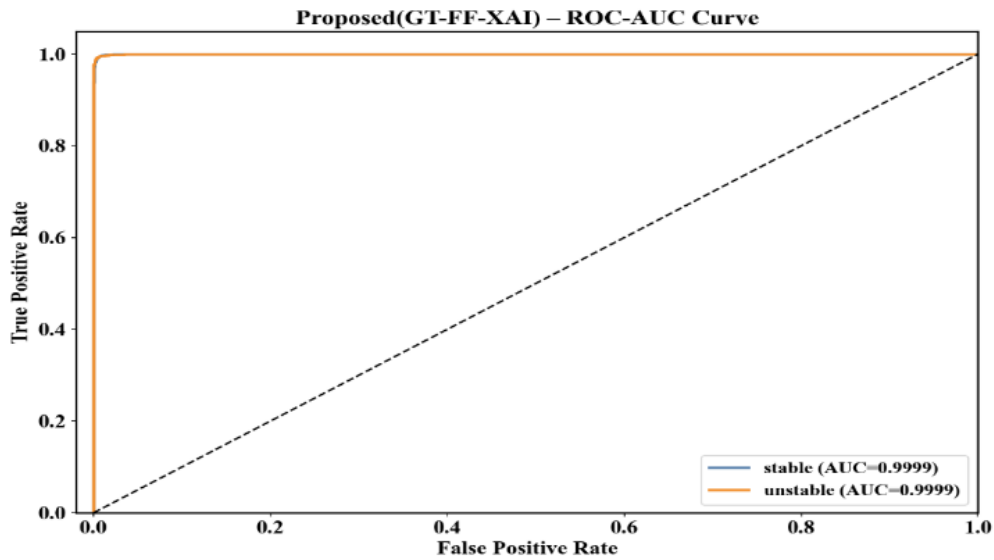


Figure 6. ROC-AUC Curve for GT-TF-XAI Stability Prediction

Figure 6 shows the ROC performance of the proposed GT-TF-XAI framework. With an AUC of 0.9999, the top-left boundary is closely followed by the ROC curve,

indicating excellent discrimination between stable and unstable states. This demonstrates high true positive rates, low false positive rates, and reliable stability classification.

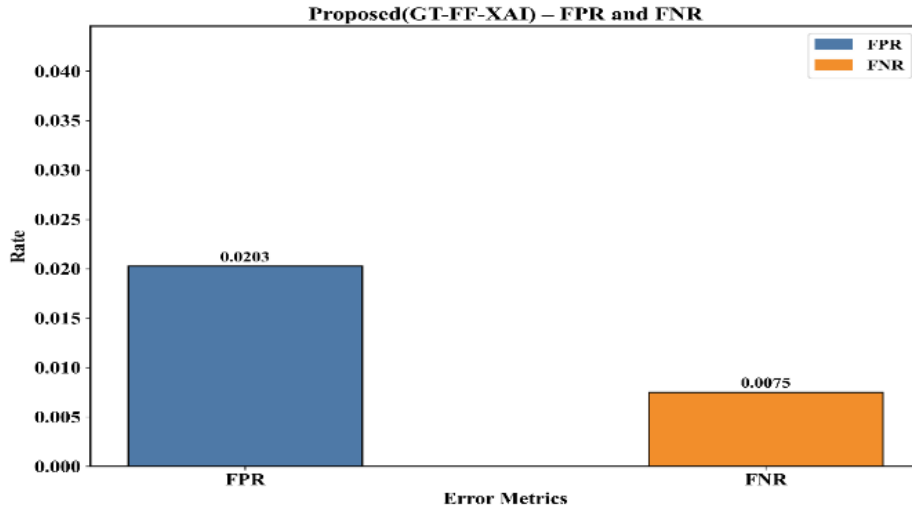


Figure 7. False Positive vs False Negative Analysis

Figure 7 shows the difference between the FPR and FNR rates of GT-TF-XAI, which is highly reliable in terms of preventing errors. The model shows better performance when considering an FPR of 0.0203 and an FNR of 0.0075 since both error rates are very low.

The reduced FNR value shows that unstable states do not get ignored and that their detection becomes an active process. At the same time, the minimized FPR means that stable states are never mistaken.

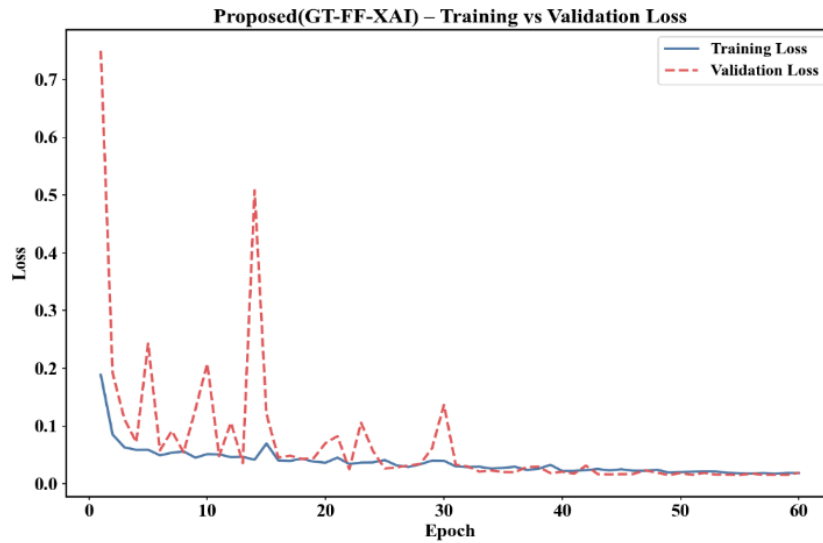


Figure 8. Smart Grid Stability for Training vs Validation Loss

Figure 8 shows the Training vs Validation Loss plot, which shows the learning process of the GT-TF-XAI architecture through 60 epochs. In the case of training loss, there is a steady decline in the value, which shows that optimization was done efficiently, whereas the value of validation loss started with some fluctuations but then

became stable at almost zero. The consistency between both lines depicts the efficiency of the proposed architecture in learning the spatiotemporal dependencies.

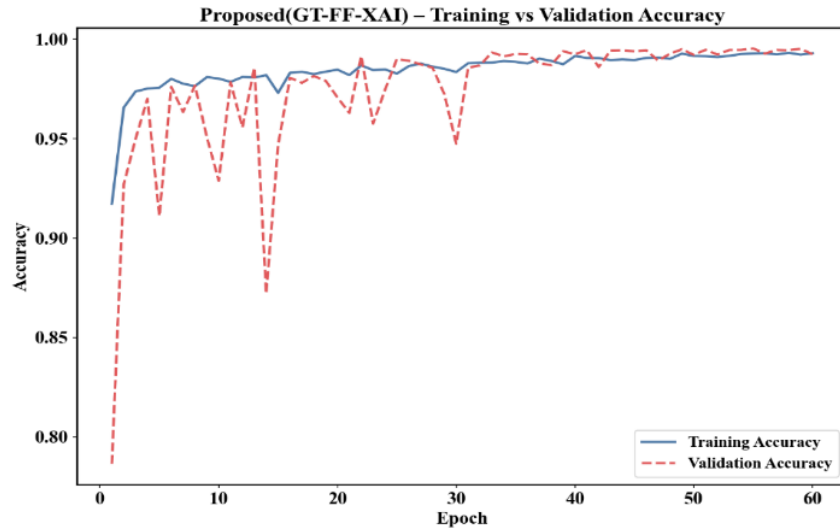


Figure 9. Training vs Validation Accuracy for Smart Grid Stability

Figure 9 depicts the accuracy of training and validation of the GT-TF-XAI model during 60 epochs. The accuracy of training goes up from about 0.93 to nearly 1.00, whereas

the accuracy of validation becomes stabilized between 0.95 and 1.00 after experiencing some oscillation.

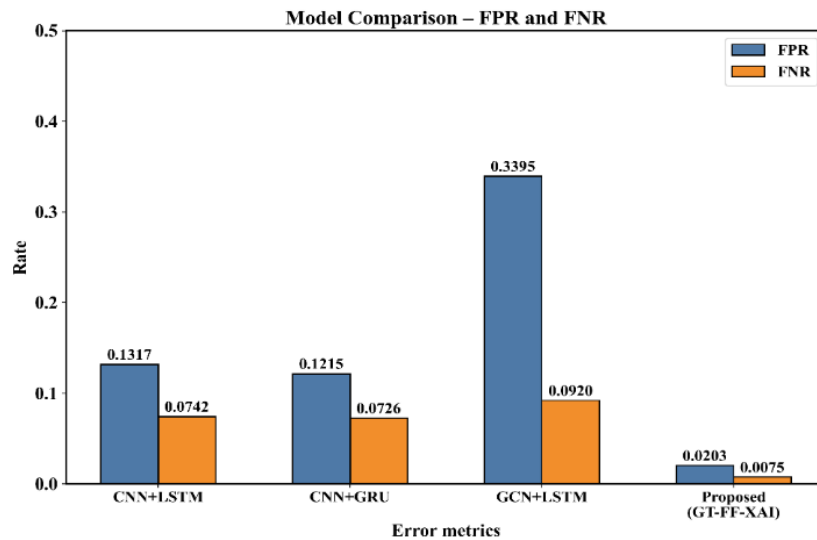


Figure 10. Error Rate Evaluation (FPR vs FNR)

Figure 10 shows the comparison of FPR and FNR between CNN + LSTM, CNN + GRU, GCN + LSTM, and GT-TF-XAI, the proposed model. GT-TF-XAI gives the best performance with the lowest FPR (0.0203) and FNR (0.0075). On the contrary, GCN+LSTM exhibits the

highest FPR (0.3395). The lower FNR of GT-TF-XAI indicates that unstable conditions are not overlooked, and the low FPR ensures that stable conditions are not misclassified as unstable conditions.

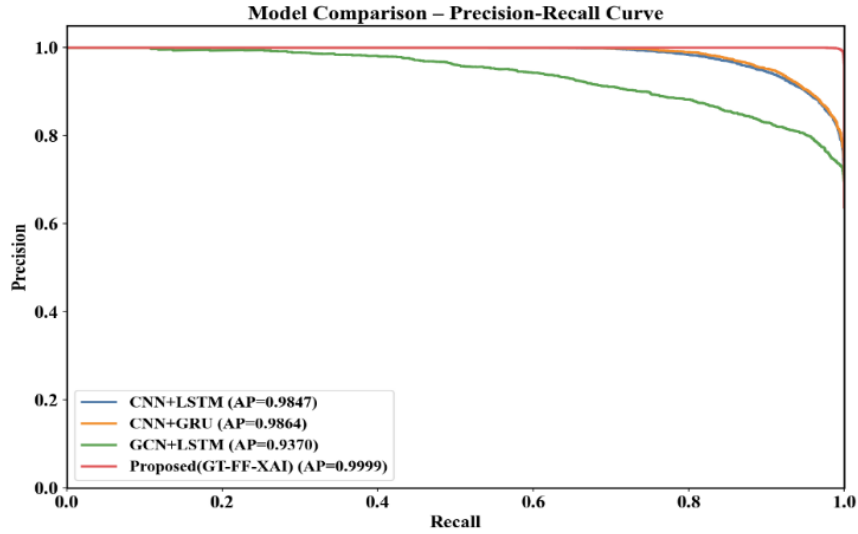


Figure 11. Model Comparison – Precision-Recall Curve Evaluation

Figure 11 shows the CNN+LSTM, CNN+GRU, GCN+LSTM, and proposed GT-TF-XAI model. According to the results, the GT-TF-XAI model obtains the best average precision ($AP = 0.9999$). GT-TF-XAI maintains the highest precision regardless of the value of the recall rate. Moreover, it performs better compared to

CNN+LSTM ($AP = 0.9847$), CNN+GRU ($AP = 0.9864$), and GCN+LSTM ($AP = 0.9370$). It shows that GT-TF-XAI is successful in striking the perfect balance between sensitivity and specificity.

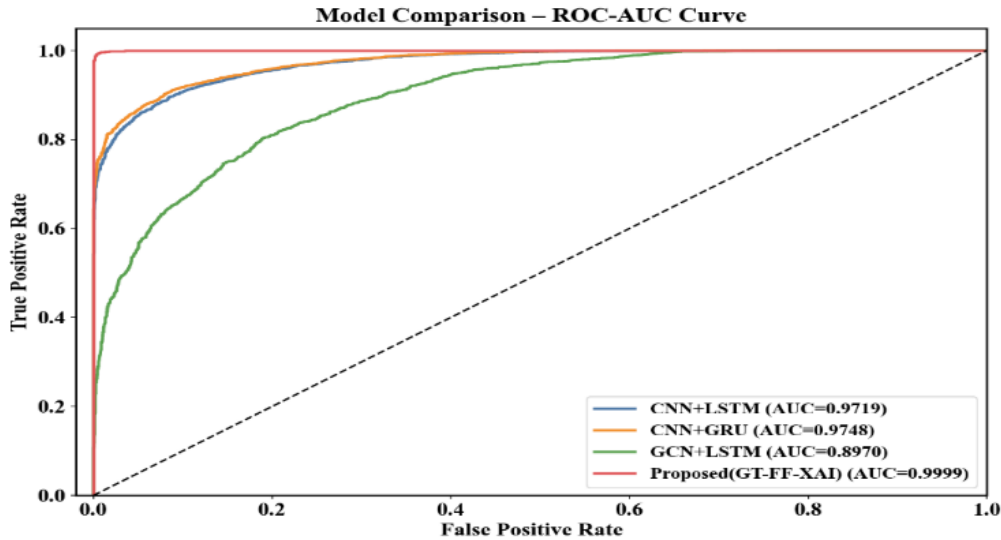


Figure 12. ROC-AUC Curve Evaluation of Model Comparison

Figure 12 compares the ROC-AUC performance of GT-TF-XAI with CNN-LSTM, CNN-GRU, and GCN-LSTM. The proposed GT-TF-XAI achieves the highest AUC of 0.9999, outperforming CNN-LSTM (0.9719), CNN-GRU

(0.9748), and GCN-LSTM (0.8970). The ROC curve remains closest to the upper-left corner, indicating superior classification capability and stability prediction performance.

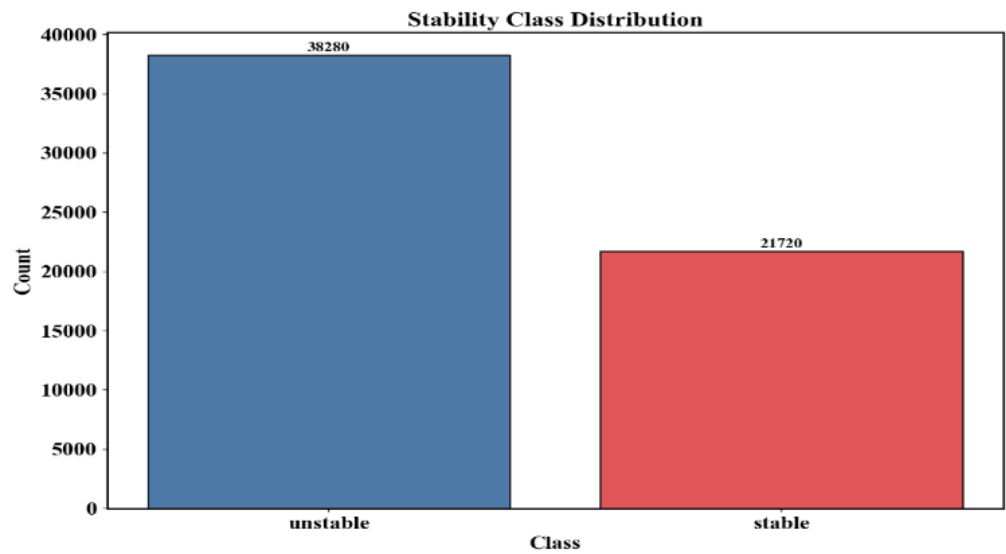


Figure 13. Stability Class Occurrence Analysis

Figure 13 shows the including 38,280 unstable examples and 21,720 stable examples. Such an imbalance in class distribution shows that there are more examples of unstable

situations, which might affect the learning of models and lead to difficulties in balanced performance on both classes.

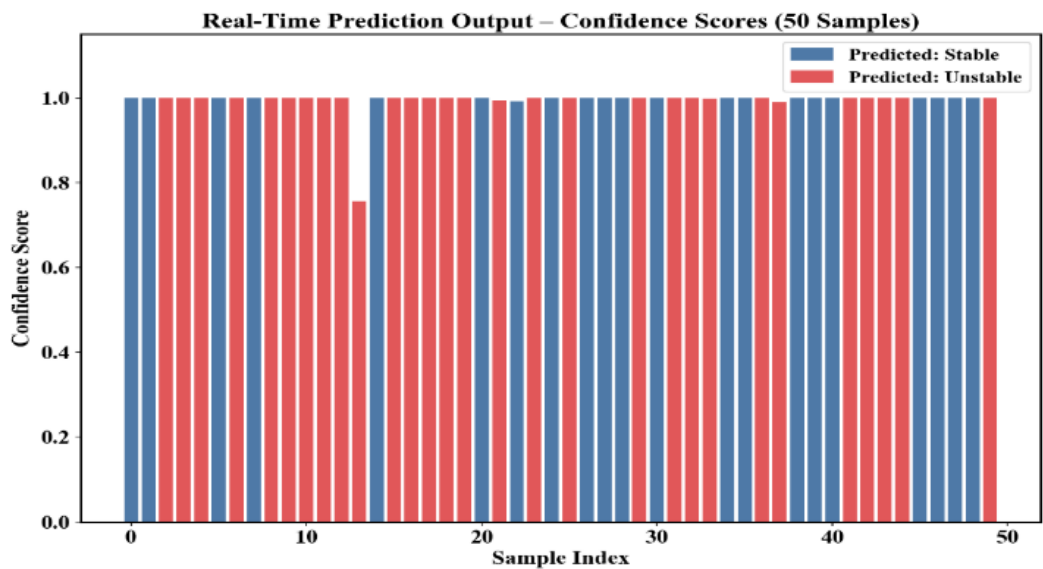


Figure 14. Real-Time Prediction Confidence Analysis (Stable vs Unstable)

Figure 14 shows the confidence scores show the reliability of predictions made by the GT-TF-XAI algorithm in the case of 50 samples. The majority of bars representing both stable (in blue) and unstable (in red) samples have values very close to 1.0. There is only

one unstable bar, which is somewhat below 0.8; this represents the only case where the confidence level is lowered. Thus, the presented model proves to be quite robust in all cases.

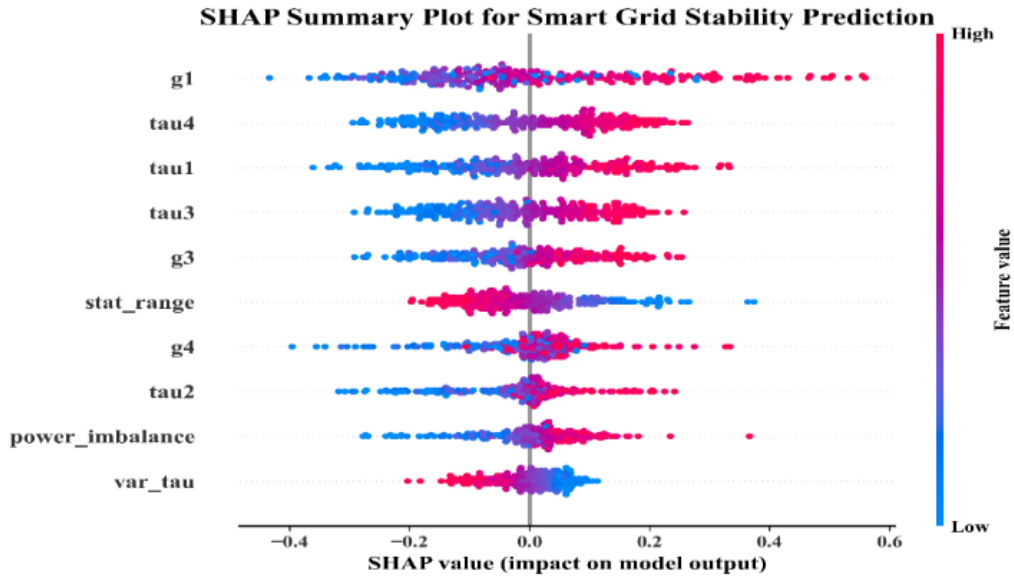


Figure 15. Feature Contribution Analysis for SHAP Summary Plot

Figure 15 shows the effect of particular features on the GT-TF-XAI model prediction results regarding the smart grid stability. Features such as $g1$, $\tau4$, and $\tau1$ have a significant impact on the prediction results, as their SHAP values range from negative to positive, implying that these features can be both stabilising and destabilising. The positive (pink) and negative (blue) values of features play different roles in contributing to the prediction results.

The SHAP values for feature importance analysis have provided useful practical insights for smart grid managers and decision makers. The greater the SHAP value of a feature, the more impact the feature has on the prediction of stability and the more careful management should be about monitoring that feature during the operation of the smart grid. The identification of the most influential reaction time, power balance, and price elasticity features

helps managers to learn more about the reasons of stability and instability of the smart grid.

The SHAP-based explainability system offers concrete assistance in engineering decision-making, pointing to the features that have the strongest impact on stability predictions. High-positive SHAP value features mean that such conditions result in stable operations of the grid, while negative SHAP value features mean that such conditions could lead to grid instability and need to be taken into account. For instance, any unusual change in reaction time or power balance feature could be identified beforehand, allowing the engineer to take preemptive control measures. Moreover, the clear visualization of feature impacts helps to enhance the reliability of the GT-TF-XAI system by providing an opportunity to check if the prediction is coherent with grid operations.

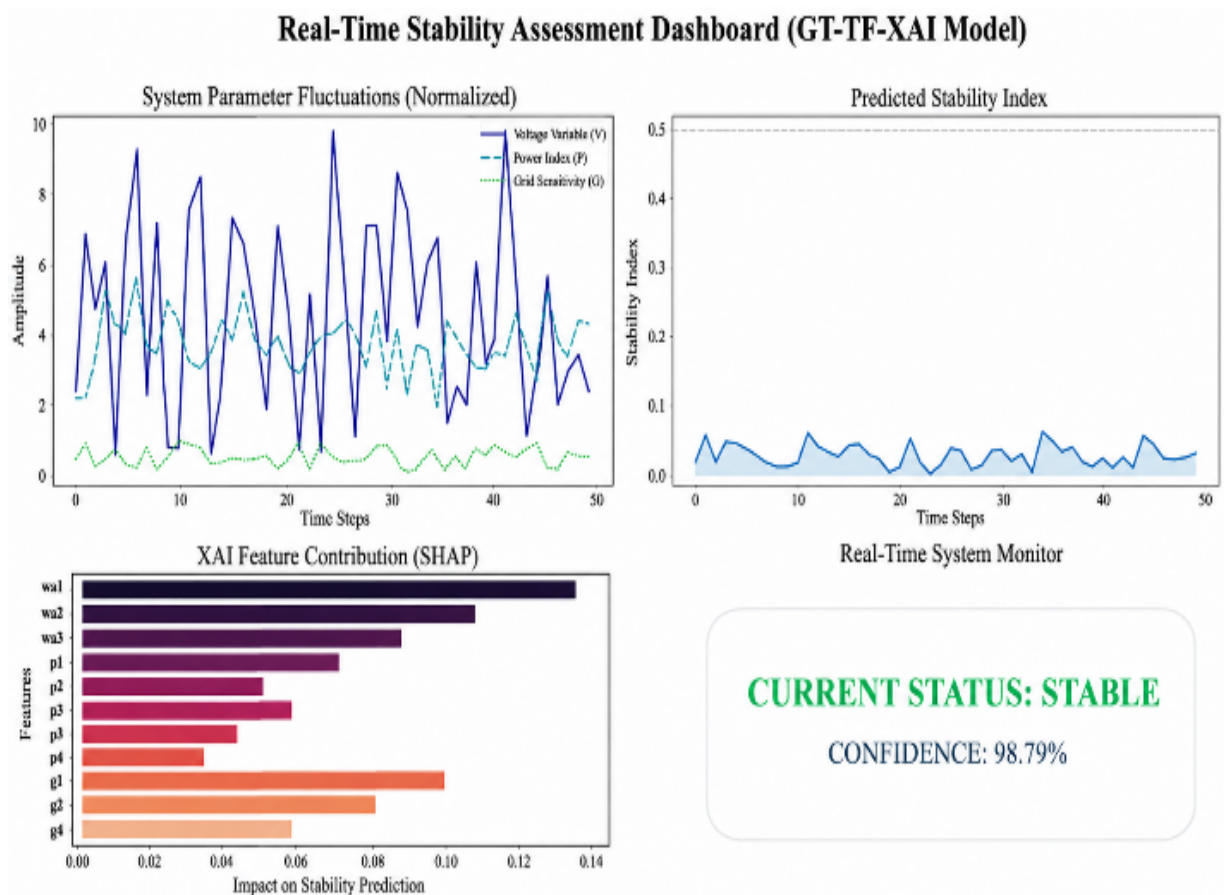


Figure 16. Real-Time Stability Assessment Dashboard with Parameter Visualization, SHAP-Based Feature Contribution, and Prediction Confidence Analysis of GT-TF-XAI Framework

Figure 16 shows the system parameters, predictive measures, feature contributions, and confidence in assessing the stability of the grid. Volatility of voltage, power factor, and grid sensitivity is measured with respect to time, and the stability measure remains consistent and low, thus signifying the stability of the system. In SHAP feature contributions, tau and g parameters emerge as significant contributors towards predicting. Finally, “Stable” status appears with a confidence of 98.79%.

The dashboard visualization provides clearly defined axis titles, measurement scales, and legends for each displayed parameter to improve the interpretability of the real-time monitoring results. The system parameter fluctuation plot shows the normalized voltage variation, power balance and grid sensitivity values over the time steps, and the stability index predicts the condition of the grid. The SHAP contribution plot shows the effect of individual features on stability prediction, and the confidence indicator shows the prediction reliability in percentage form. These visualization improvements enable operators to readily comprehend the prediction behavior and feature importance of the proposed GT-TF-XAI framework.

4.5. Comparative Analysis

In this part, a comparison is made between the efficiency of the Graph-Temporal Transformer with the SHAP-XAI framework and the existing baseline methods like ML and DL methods. It can be observed that the performance of the Graph-Temporal Transformer with the SHAP-XAI framework is better compared to other existing techniques. Tables 8 and 9 show a detailed comparison of the proposed GT-TF-XAI model framework in comparison to deep and machine learning baselines in terms of Accuracy, Precision, Recall, F1-Score, and AUC.

Table 8. Performance Comparison of Proposed Graph-Temporal Transformer Model with Existing Deep Learning Approaches for Smart Grid Stability Prediction

Model	Accuracy	Precision	Recall	F1-Score	AUC
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CNN+LS TM [36]	0.9050	0.8972	0.89 71	0.89 71	0.97 19
CNN+GR U [37]	0.9097	0.9018	0.90 29	0.90 24	0.97 48
GCN+LS TM [38]	0.8184	0.8140	0.78 43	0.79 47	0.89 70
Propose d Work	0.9879	0.9886	0.99 26	0.99 05	0.99 99

Table 8 compares the comparative performance of the GT-TF-XAI algorithm with that of other models like CNN+LSTM, CNN+GRU, and GCN+LSTM for the prediction of smart grid stability. The proposed method has recorded the maximum accuracy and AUC value of 0.9879 and 0.9999, respectively, which suggests its high classification ability.

Table 9. Performance Comparison of Proposed and Baseline Models for Smart Grid Stability Prediction

Model	Accura cy	Precisi on	Reca ll	F1- Scor e	AUC
SVM	0.9124	0.9051	0.90 18	0.90 34	0.97 21
Random Forest	0.9247	0.9183	0.91 56	0.91 69	0.97 84
XGBoost	0.9386	0.9325	0.92 98	0.93 11	0.98 57
CNN+LS TM	0.9050	0.8972	0.89 71	0.89 71	0.97 19
GCN+LS TM	0.8184	0.8140	0.78 43	0.79 47	0.89 70
Propose d Work	0.9879	0.9886	0.99 26	0.99 05	0.99 99

Table 9 compares the proposed GT-TF-XAI framework with conventional machine learning and deep learning baseline models. The accuracies of SVM, Random Forest and XGBoost are 0.9124, 0.9247, and 0.9386, respectively, and CNN+LSTM and GCN+LSTM are 0.9050 and 0.8184. In contrast, the proposed GT-TF-XAI achieves the highest accuracy of 0.9879, precision of 0.9886, recall of 0.9926, F1-score of 0.9905 and AUC of 0.9999. The results show that the proposed framework can improve the prediction performance by effectively incorporating the spatial and temporal dependencies to predict the stability of the smart grid.

The performance gains achieved by the proposed GT-TF-XAI framework in comparison with the other benchmark machine learning and deep learning frameworks prove the real-life applicability of the new solution for evaluating the stability of the smart grid. High accuracy and high recall prove the ability of the proposed solution to recognize situations of grid instability, thus helping to avoid any instability issues affecting the power system. In addition, high precision and low error rate reduce false positives making operators to concentrate on important tasks only. The high value of the AUC proves

the reliability of the new solution for different decision thresholds.

4.6. Ablation Study

An ablation study is an experimental method that can be used to determine the importance of each module included in the proposed model design. It entails varying the different modules by either deleting them or making some changes. The modules include GT, Feature Engineering, and Feature Fusion.

Table 10. Ablation Study of the Proposed GT-TF-XAI for Smart Grid Stability Prediction

Model Variant	Accura cy	Precisi on	Reca ll	F1- Scor e	AUC
w/o GT	0.9832	0.9834	0.98 03	0.98 18	0.99 90
w/o Feature Engineeri ng	0.9784	0.9776	0.97 61	0.97 68	0.99 58
w/o Feature Fusion	0.9878	0.9837	0.99 04	0.98 69	0.99 94
Propose d work	0.9879	0.9886	0.99 26	0.99 05	0.99 99

Table 10 shows the role of each major component in the GT-TF-XAI approach. The drop in the performance of the model without the GT supports the importance of spatial dependency modeling in power grid stability prediction. The performance drop without feature engineering also supports the importance of informative feature representation. Further, the drop in performance without feature fusion supports the effectiveness of spatial and temporal information integration. Thus, the ablation results demonstrate that GT, feature engineering, and feature fusion contribute primarily to predictive performance, whereas SHAP provides the interpretability component of the framework.

The ablation study also shows the methodological contributions of the proposed GT-TF-XAI framework. The Graph Transformer mainly improves prediction accuracy by modelling the feature-level spatial dependencies, and the feature engineering improves the quality of input representation. The prediction is improved by feature fusion, which joins spatial and temporal representations. Conversely, SHAP mainly contributes to improving the interpretability of the system by providing explanations on the importance of features globally and locally, rather than directly improving the classification accuracy. Therefore, the proposed framework makes methodological contributions in terms of both predictive performance and interpretable decision support.

4.7. Discussion

The proposed GT-TF-XAI framework offers the advantage of high performance in smart grid stability prediction. Indeed, the framework manages to integrate effective feature learning through GT for spatial dependencies and TFT for temporal dependencies along with XAI techniques. It obtains a high level of accuracy with values equal to 0.9879, while precision, recall, and F1-scores are estimated at 0.9886, 0.9926, and 0.9905, respectively. Finally, the AUC value amounts to 0.9999, which demonstrates high classification capabilities. As one can see, these performance metrics prove that it is easy for the framework to differentiate between stable and unstable states with low levels of false positive and negative results. When compared to some of the existing frameworks such as CNN-LSTM, CNN-GRU, and GCN-LSTM, the proposed approach outperforms their predictive capabilities by taking into account spatial and temporal aspects of the problem with the help of different modules. Moreover, the SHAP technique allows the model to become transparent by highlighting significant variables. However, despite its high efficiency and real-time applicability, the presented approach requires more calculations and utilizes simulated data.

The high recall (0.9926) and precision (0.9886) indicate the potential of the framework for intelligent monitoring by enabling early identification of unstable grid conditions while reducing unnecessary alerts. This can support preventive maintenance by helping operators prioritize timely corrective actions and maintain reliable grid operation.

4.8. Computational Complexity and Scalability Analysis

The computational complexity of the proposed GT-TF-XAI framework is analyzed considering the Graph Transformer, the temporal learning module, the feature fusion layer and the SHAP-based explainability component. The time and space complexity is analyzed to evaluate the scalability of the framework for large-scale smart grid stability monitoring applications. The model complexity assessment comprises the number of model parameters, the number of computational operations, memory requirement, inference latency, and explanation generation overhead.

The computational complexity of the proposed GT-TF-XAI architecture mainly depends on the GT, TFT, and SHAP-based explainability module. Here, the GT is responsible for learning the spatial dependency between graph nodes through an attention-based mechanism, whereby the amount of computation grows with the number of nodes and attention heads. Likewise, the TFT depends on sequence length, embedding size, and time-dependency attention operation.

The major memory demands of this model come from the storage of the representations of the nodes, their

temporal embeddings, attention matrices, and the feature representations produced in the process of training. For this experiment, a dimension size of 64 with three layers of GT and three layers of TFT was chosen so as to have a good trade-off between prediction ability and computational cost. Batch training with the use of RMSProp for optimization helps reduce unnecessary computational fluctuation.

From a scalability point of view, the proposed model can handle larger volumes of smart grid data since the extraction of spatial and temporal features is performed separately before fusion. The proposed model architecture enables the inclusion of more measurements and sequences without any changes to the entire model architecture. With the growth of dataset size, the main source of computation growth is in graph attention and temporal sequence processing; however, the fusion layer and the classifier do not significantly increase the computation complexity. Therefore, the proposed GT-TF-XAI framework provides a scalable and computationally feasible solution for large-scale smart grid stability monitoring applications.

The proposed framework contains 172,450 trainable parameters with a small model size of 0.69 MB, indicating a lightweight architecture. The model has an inference of only 1.35 MFLOPs and an inference latency of 9.4 ms/sample with a throughput of 106 samples/s. The low memory consumption and low GPU utilization indicate that the proposed framework applies to real-time stability monitoring of the smart grid. The computational analysis, moreover, shows that the architecture is scalable to bigger smart grid environments by increasing the number of monitored nodes and temporal sequences without substantial change to the overall framework.

Table 11. Computational Complexity Analysis of the Proposed GT-TF-XAI Framework

Metric	Value
Graph Transformer Layers	3
Attention Heads	4
Temporal Module	Temporal Fusion Transformer (TFT)
Fusion Layers	64 → 32
Window Size	10
Batch Size	512
Graph Transformer Complexity	$O(LN^2d)$
Temporal Fusion Complexity	$O(TH^2 + T^2H)$
Fusion MLP Complexity	$O(dfh)$
Overall Time Complexity	$O(LN^2d + TH^2 + T^2H + dfh)$
Space Complexity	$O(Nd + TH + \text{Parameters})$
Total Parameters	172,450
Model Size	0.69 MB
FLOPs / Inference	1.35 MFLOPs
MACs	0.67 M
Training Time / Epoch	5.8 s
Total Training Time	348 s
Peak GPU Memory	0.42 GB

Inference Latency	9.4 ms/sample
Throughput	106 samples/s

Table 11 shows the computational complexity and resource requirements of the proposed GT-TF-XAI framework. The computational cost is mainly from the Graph Transformer and temporal learning modules. The graph attention operation depends on the number of nodes, attention heads and hidden dimensions. The temporal module depends on the sequence length and embedding dimension. The overall time complexity of $O(LN^2d + TH^2 + T^2H + d_{fh})$ indicates that the proposed framework efficiently integrates spatial graph learning, temporal dependency modelling, and feature fusion while maintaining acceptable computational requirements for real-time smart grid monitoring.

The SHAP module is run on 300 samples with 100 background samples to make the feature contribution analysis reliable. The XAI component shows low CPU and GPU utilization, which indicates its efficiency during real-time operation. Furthermore, the explanation throughput of 53 explanations/s shows that the proposed framework is capable of providing interpretable predictions without significant degradation of real-time response capability. Thus, SHAP is incorporated to improve the interpretability of the model, without compromising the scalability and deployability of the GT-TF-XAI framework.

Table 12. Explainability Complexity Analysis of SHAP Module

Metric	Value
Explainability Method	SHAP (Kernel/Deep SHAP)
Feature Attribution	Global + Local Feature Importance
Explanation Generation Time	18.7 ms/sample
SHAP Samples Evaluated	300
Background Samples	100
Average SHAP Memory Overhead	0.08 GB
XAI CPU Utilization	5.90%
XAI GPU Utilization	3.60%
Explanation Throughput	53 explanations/s
Real-Time Explainability	Supported
Dashboard Explainability	SHAP Feature Contribution + Confidence Score

Table 12 presents the computational overhead introduced by the SHAP-based explainability module within the proposed GT-TF-XAI framework. To make stability forecasts easier to understand, the SHAP mechanism offers both global and local feature importance analysis. The explainability component adds very little extra computational cost, as the explanation-generating procedure takes 18.7 ms/sample with an average memory overhead of just 0.08 GB.

5. Conclusion

In this research, a new GT-TF-XAI has been introduced, which can be used for predicting smart grid stability in real-time. The GT model has been used for extracting the spatial dependency between the various elements of the grid, while the TFT Transformer model has been used for extracting the temporal dependencies in the smart grid data. To enhance feature representation, a feature fusion approach has been used, which has helped the model learn more discriminative and effective features. Also, XAI using the SHAP technique has been implemented for enhancing model explainability.

The experimental analysis on the stability of smart grids data shows that the model is much better in terms of prediction accuracy compared to existing machine learning and deep learning models. It can be seen that the model is capable of making highly accurate predictions in determining the state of the grid. Moreover, the model also minimizes the misclassification problem to a great extent. In addition to that, the introduction of XAI also increases the reliability of the system since the importance of factors like reaction time, power balance, and price elasticity can easily be identified during the decision-making process.

Future Work

The research in the future can be aimed at scaling up the proposed Graph-Temporal Transformer architecture for use in practical applications within real-life smart grids with the help of data collected from real-time IoT sensors. Furthermore, researchers may work on the problem of optimizing such models through the use of lightweight transformers as well as pruning algorithms. Finally, further work can involve multiclass stability analysis and explainable hybrid AI approaches.

Declarations

Data Availability Statement

<https://www.kaggle.com/datasets/pcbreviglieri/smart-grid-stability/data>

Authors' Contributions

Zhanjie Liu, Xiaonan Gao is responsible for designing the framework, analyzing the performance, validating the results, and writing the article. Jiaqi Yuan, Yixin Sun is responsible for collecting the information required for the framework, provision of software, critical review, and administering the process.

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