Feature transformation with ensemble learning for power grid stability in sustainable energy and industry systems

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ABSTRACT

Power grids today operate under unpredictable and rapidly changing conditions, making reliable stability prediction increasingly important. This study evaluates two hybrid learning frameworks that integrate deep feature transformation with ensemble classification. In the first framework, an autoencoder (AE) is used for feature encoding before classification with extreme gradient boosting (XGBoost), while the second applies a TabTransformer (TT) followed by the same classifier. For comparison, conventional ensemble models, including random forest and standalone LightGBM, are also assessed. The models are tested on a large public dataset using stratified cross-validation and standard performance metrics. Results show that the AE-XGBoost hybrid achieves the highest performance, with a test accuracy of 97.73% and an F1-score of 0.98 for both stable and unstable states. LightGBM also performs strongly, offering consistent accuracy (95.8%) and good interpretability. In contrast, TT-XGBoost, despite its architectural novelty, achieves lower accuracy (89.4%) and struggles with unstable states. These findings highlight that model effectiveness depends not only on architectural complexity but also on the synergy between feature transformation and classification. The results provide practical insights for building dependable, confidence-aware predictive systems to support smart grid decision-making.

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1. INTRODUCTION

Modern electric grids are undergoing rapid transformation due to the increasing integration of renewable energy sources, dynamic load patterns, and decentralized generation. These developments introduce significant uncertainty and operational complexity, making conventional rule-based control strategies inadequate for maintaining real-time stability [1]-[3]. As a result, there is a growing shift toward predictive, data-driven decision support systems that leverage real-time telemetry and operational data from the generation, transmission, and distribution layers to manage grid behavior proactively.

In this context, machine learning (ML) has emerged as a powerful tool for grid stability prediction and situational awareness. Ensemble learning methods such as random forest, gradient boosting, and optimized variants like LightGBM have shown robustness and scalability in classifying complex power system states under diverse operating conditions [4], [5]. These approaches are particularly effective for tasks such as fault diagnosis, load forecasting, and dynamic stability assessment, especially when handling large-scale, imbalanced, or noisy datasets [6], [7]. Deep learning (DL) further extends the capabilities of ML by capturing non-linear and high-dimensional relationships in grid signals [8]. Autoencoders, for example, have been used for unsupervised feature compression and anomaly detection by preserving essential dynamic patterns of the grid [9]. Similarly, attention-based architectures such as TabTransformer have recently gained prominence for their ability to capture inter-feature dependencies and contextual information in structured tabular data [10], [11].

Despite these advancements, several challenges remain. Many existing models face issues such as low interpretability, imbalanced learning outcomes, and poorly calibrated probability estimates, all of which are critical limitations in high-stakes grid control environments. In addition, hybrid frameworks that combine the strengths of deep representation learning and ensemble decision models are still underexplored in grid stability applications. To address these gaps, this study proposes and evaluates two hybrid architectures that integrate deep feature transformation with ensemble learning to improve the reliability of binary grid stability classification. The first approach employs an autoencoder-based encoder coupled with an Extreme Gradient Boosting (XGBoost)t classifier, while the second applies TabTransformer for feature attention, followed by the same gradient boosting classifier [12]. These hybrid models are systematically benchmarked against conventional ensemble baselines using a publicly available grid stability dataset. The evaluation considers not only accuracy and F1-score but also class balance, interpretability, and confidence calibration [13], [14], which are key metrics aligned with real-world operational needs. This work contributes toward the development of smarter, more dependable ML-based frameworks tailored for next-generation power grid resilience [15].

2. METHOD

2.1. Dataset description

This study uses the publicly available “smart grid stability” dataset from Kaggle, which contains 60,000 records. Each record represents an operational state of an electric power grid with 12 continuous input features grouped into three layers:

- Generation layer: four internal damping coefficients (τ1 to τ4)
- Transmission layer: four power output readings (p1 to p4)
- Distribution layer: four phase angle indicators (g1 to g4)

The dataset provides two target outputs: a continuous stability index (stab) and a categorical label (stabf) indicating whether the grid state is "stable" or "unstable."

This study focuses on the binary classification task using stabf. All features are continuous, and the dataset contains no missing values. Before training, input features were normalized using standard scaling. The dataset covers diverse grid conditions, offering a robust basis for evaluating predictive models [16], [17]. Figure 1 illustrates the mapping of the generation (τ1–τ4), transmission (p1–p4), and distribution (g1–g4) features to their respective layers in the electric grid, leading to a binary stability outcome.

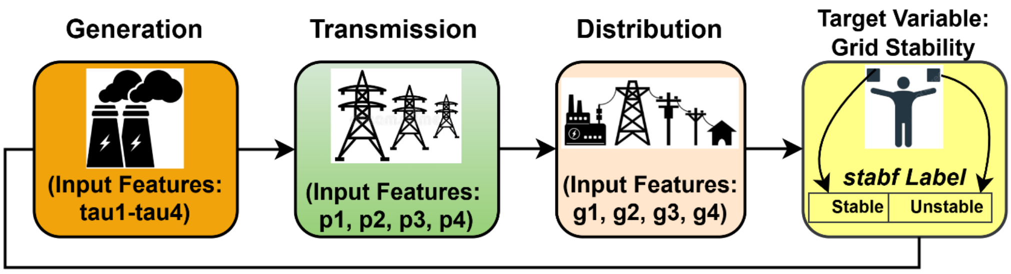

Figure 1. Schematic representation of the dataset's feature groups

2.2. TabTransformer with extreme gradient boosting (TT-XGBoost)

This hybrid model combines TabTransformer for deep feature transformation with XGBoost for classification. TabTransformer captures inter-feature dependencies through attention, while XGBoost provides robust gradient-boosted classification for stability prediction [18].

2.2.1. Feature transformation using TabTransformer

TabTransformer applies multi-head self-attention to capture dependencies among input features. Although originally designed for mixed-type data, in this study, it is adapted for continuous features by embedding each variable into a dense vector space [19], [20] as in (1).

$$E_i = Embedding(C_i),\ \forall_i \in \{1, \dots, d\} \tag{1}$$

The feature embeddings are passed through multi-head attention layers to model relationships among variables as presented in (2).

$$Attention(Q, K, V) = Softmax\left(\frac{Q_i K_i^T}{\sqrt{d_k}}\right)V \tag{2}$$

Where, $Q = XW^Q$, $K = XW^K$, and $V = XW^V$ represent the query, key, and value matrices. The final enriched representation is obtained as given in (3).

$$Z = Concat\ (head_1, \cdots, head_h)W^0 \tag{3}$$

The matrix Z encodes contextual information among features and is forwarded to the XGBoost classifier (see in section 2.4).

2.2.2. Workflow

During training, input features are embedded and transformed by the TabTransformer to produce enriched vectors Z, which are then used to train the XGBoost classifier. At inference, a new instance x′ is converted into its enriched form z′, and the trained XGBoost model predicts its stability class. This pipeline combines attention-based feature encoding with the predictive strength of XGBoost [21]. The overall workflow is shown in Figure 2.

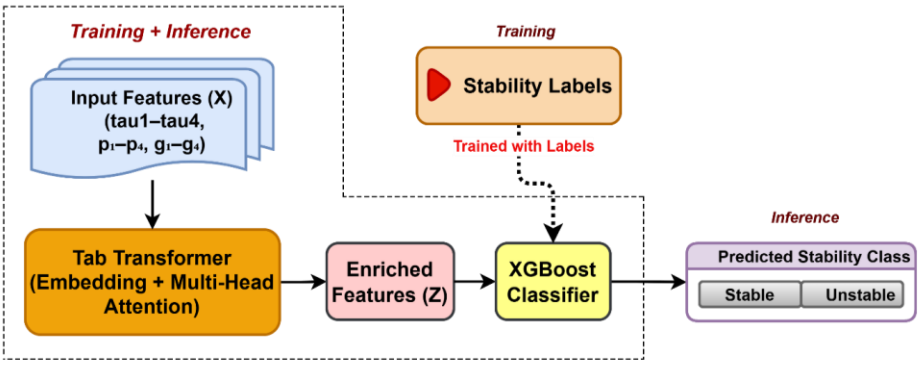

Figure 2. Architecture of the TT-XGBoost hybrid model showing training and inference phases

2.3. Autoencoder with extreme gradient boosting (AE-XGBoost)

This hybrid model combines an Autoencoder for feature compression with XGBoost for classification. The Autoencoder reduces redundancy in the input data while retaining its essential structure, producing compact representations that improve learning efficiency [22].

2.3.1. Feature extraction using autoencoder

The autoencoder is trained to reconstruct its input while compressing it into a lower-dimensional latent space. This process reduces noise and redundancy, producing compact feature vectors that capture the essential characteristics of the grid data [23], [24]. The model is optimized by minimizing the reconstruction loss, as shown in (4).

$$L_{AE} = \frac{1}{n}\sum_{i=1}^{n} \|x_i - \hat{x}_i\|^2 \tag{4}$$

After training, the decoder is discarded, and only the encoder is retained to generate compressed features for classification.

2.3.2. Workflow

During training, the autoencoder learns compact feature representations from the input matrix X. These compressed vectors Z are then used to train the XGBoost classifier. At inference, for a new sample x′, the encoder generates its compressed representation z′, which is classified using the trained XGBoost model. This hybrid approach improves prediction by reducing feature noise and focusing on meaningful patterns, while retaining the interpretability and efficiency of XGBoost [25]-[27]. The overall process is shown in Figure 3.

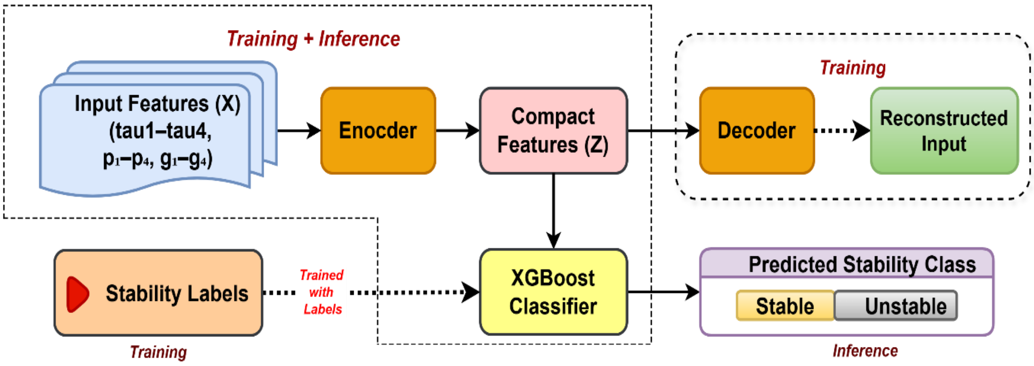

Figure 3. Architecture of the AE-XGBoost hybrid model

2.4. XGBoost classifier

XGBoost is a gradient-boosted ensemble of decision trees, widely recognized for its scalability and interpretability. In this study, it serves as the decision layer for both hybrid models (TT-XGBoost and AE-XGBoost). The learning process is defined by the objective function as shown in (5).

$$\mathcal{L}^{(t)} = \sum_{i=1}^{n} \ell\left(y_i, \hat{y}_i^{(t-1)} + f_t(z_i)\right) + \Omega(f_t) \tag{5}$$

Where ℓ is a differentiable loss function (e.g., logistic), f_t is the tree added at iteration t, and $\Omega(f_t)$ penalizes model complexity. Predictions are updated as given in (6).

$$\hat{y}_i^{(t)} = \hat{y}_i^{(t-1)} + \eta f_t(z_i) \tag{6}$$

Where η is the learning rate controlling the step size. To summarize the end-to-end process, Algorithm 1 outlines the unified workflow of the proposed hybrid AE-XGBoost and TT-XGBoost models for grid stability prediction. This formulation is applied consistently across both hybrid models to ensure a unified classification framework.

Algorithm 1. Hybrid AE-XGBoost and TT-XGBoost workflow for grid stability prediction
Input: smart grid dataset (12 features, stability label)
Output: predicted stability state (stable/unstable)

1. Load and normalize the dataset; split into training and testing sets.
2. For AE-XGBoost:
   - Train Autoencoder to extract compressed features (Z_AE).
3. For TT-XGBoost:
   - Use TabTransformer to embed features and apply attention to obtain (Z_TT).
4. Train XGBoost classifier using Z_AE and Z_TT features separately.
5. Evaluate all models (RF, LightGBM, AE-XGBoost, TT-XGBoost) using accuracy, F1, MCC, and ROC-AUC.
6. Compare results to identify the most accurate and computationally efficient model.
7. Deploy the selected model for real-time grid monitoring and decision support.

3. RESULTS AND DISCUSSION

The proposed hybrid models were compared with widely used machine learning techniques. Performance was evaluated using accuracy, precision, recall, and F1-score, as shown in Table 1. AE-XGBoost clearly outperforms all other models, achieving 97.73% accuracy with excellent precision, recall, and F1-scores across both classes. LightGBM also performs strongly, maintaining a good balance between accuracy and interpretability. In contrast, TT-XGBoost records the lowest accuracy (89.42%) and struggles particularly with unstable states (Class 1), reflected in its lower recall and F1-score. To gain deeper insights, composite indicators such as Matthews correlation coefficient (MCC), balanced accuracy, and ROC AUC were also computed (Table 2). AE-XGBoost again leads across all three measures, followed closely by LightGBM, while TT-XGBoost shows weaker reliability and balance.

Figure 4 provides a consolidated comparison of all models across key metrics, including validation accuracy, test accuracy, precision, recall, F1-score, and ROC AUC. The AE-XGBoost model shows consistently superior performance, followed closely by LightGBM. Meanwhile, TT-XGBoost lags slightly due to higher sensitivity to continuous feature scaling.

Table 1. Performance metrics of hybrid and baseline models for grid stability prediction

Model	Validation accuracy	Test accuracy	Precision		Recall		F1-score	
			Class 0	Class 1	Class 0	Class 1	Class 0	Class 1
Random forest	0.9446	0.9386	0.94	0.93	0.96	0.9	0.95	0.91
LightGBM	0.9574	0.9584	0.96	0.95	0.97	0.93	0.97	0.94
TT-XGBoost	0.89225	0.8942	0.91	0.87	0.93	0.84	0.92	0.85
AE-XGBoost	0.9773	0.9773	0.98	0.97	0.98	0.97	0.98	0.97

Table 2. Comparative performance of hybrid models based on composite evaluation metrics

Metric	RF	LightGBM	TT-XGBoost	AE-XGBoost
MCC	0.8669	0.9101	0.7706	0.9507
Balanced accuracy	0.9298	0.9532	0.8827	0.9756
ROC AUC score	0.9885	0.9939	0.9652	0.9981

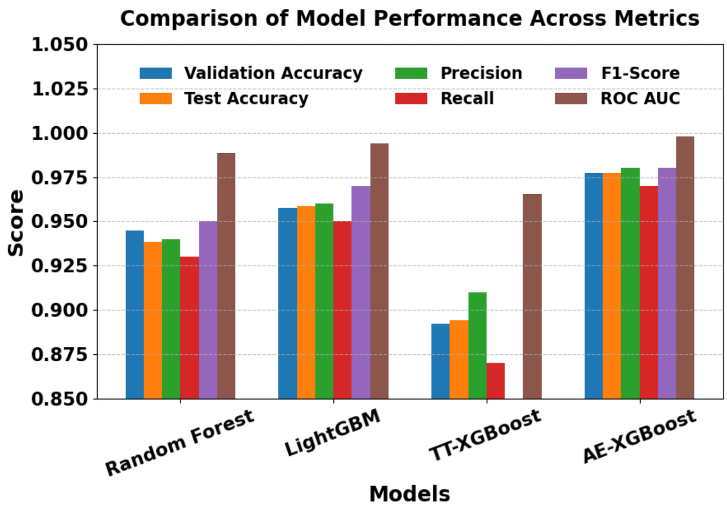

Figure 4. Summary comparison of model performance across key metrics

In addition to accuracy, runtime and computational efficiency were evaluated to assess practical feasibility. The AE-XGBoost model required moderately higher training time because of the autoencoder pretraining step, but once trained, it delivered fast and stable inference suitable for real-time use. LightGBM showed the shortest runtime and lowest resource usage, making it ideal for quick deployment in control applications. TT-XGBoost, on the other hand, involved higher computational cost due to its attention layers, which increased latency during both training and prediction. Overall, the results show that AE-XGBoost provides the best trade-off between accuracy and response time, supporting its use in operational smart-grid environments.

From a deployment point of view, both hybrid models can be adapted for real-time use in smart-grid control centers. AE-XGBoost, due to its compact feature representation, supports faster inference with low latency, making it suitable for near real-time stability monitoring. LightGBM is even lighter and can be used for continuous, low-delay decision-support tasks. In contrast, TT-XGBoost, while technically advanced, introduces higher processing latency and is better suited for offline analysis or periodic retraining scenarios. This reduced performance is mainly due to its sensitivity to continuous feature scaling and the absence of categorical variables, which limits the effectiveness of its attention mechanism in capturing distinct feature relationships.

Beyond numerical performance, these results carry practical implications. AE-XGBoost's accuracy and reliability make it well-suited for real-time stability monitoring, where errors can have serious consequences. LightGBM, while slightly less accurate, offers faster training and better interpretability, making it attractive for routine control tasks. TT-XGBoost, despite its architectural novelty, shows weaker consistency and would require further refinement before practical deployment. These differences highlight that model selection depends on operational priorities: accuracy and robustness for critical monitoring, versus efficiency, and explainability for everyday decision support.

Figure 5 shows the confusion matrices of the four models. In Figure 5(a), random forest performs reasonably well but misclassifies several unstable cases. Figure 5(b) illustrates LightGBM, which reduces errors and achieves a more balanced classification. Figure 5(c) presents TT-XGBoost, where the model struggles with unstable conditions, leading to lower recall. Finally, Figure 5(d) shows AE-XGBoost, which delivers the highest accuracy with very few misclassifications.

Figure 6 presents the ROC curves of the four models. In Figure 6(a), random forest shows fair discrimination but struggles with unstable states. Figure 6(b) displays LightGBM, which produces a smooth and consistently high curve, reflecting strong classification ability. Figure 6(c) shows TT-XGBoost, where the dip in the curve highlights difficulty in separating stable from unstable conditions. Finally, Figure 6(d) illustrates AE-XGBoost, which achieves a near-perfect curve with an AUC close to 1.0, confirming excellent class separation.

To further interpret model behavior, Figure 7 shows the feature importance plots. In Figure 7(a), random forest identifies key variables but with less consistency than other models. Figure 7(b) illustrates LightGBM, which emphasizes phase angles and power outputs, highlighting their role in stability prediction. Figure 7(c) presents the standalone XGBoost model, where importance is spread across features but still highlights the main influencing variables. Finally, Figure 7(d) displays the TabTransformer, which distributes attention more evenly, but this broad focus may weaken its ability to capture the most critical patterns.

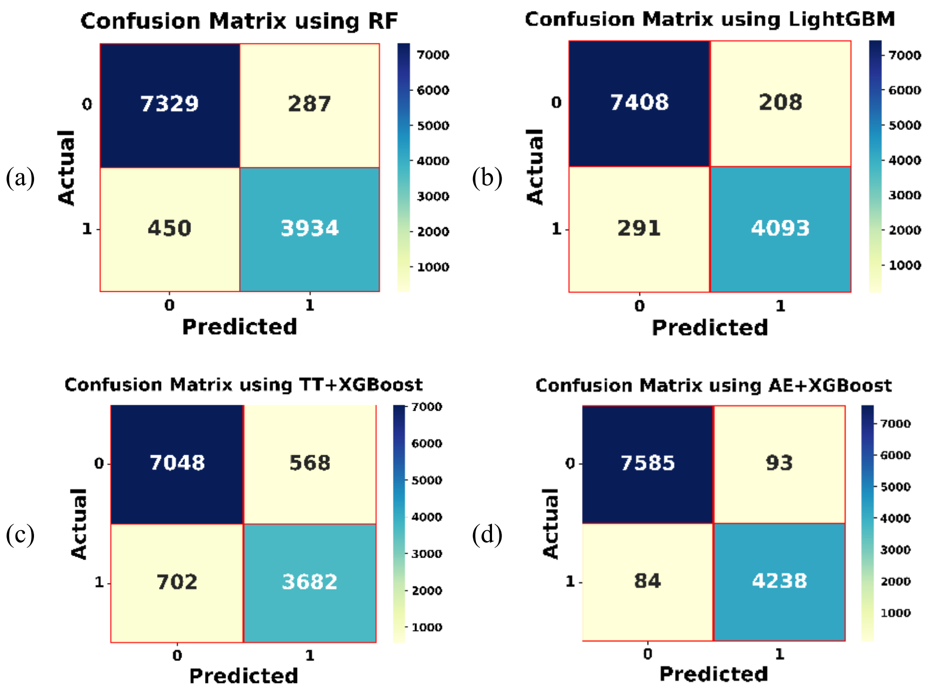

Figure 5. Confusion matrices of the four models: (a) random forest, (b) LightGBM, (c) TT-XGBoost, and (d) AE-XGBoost

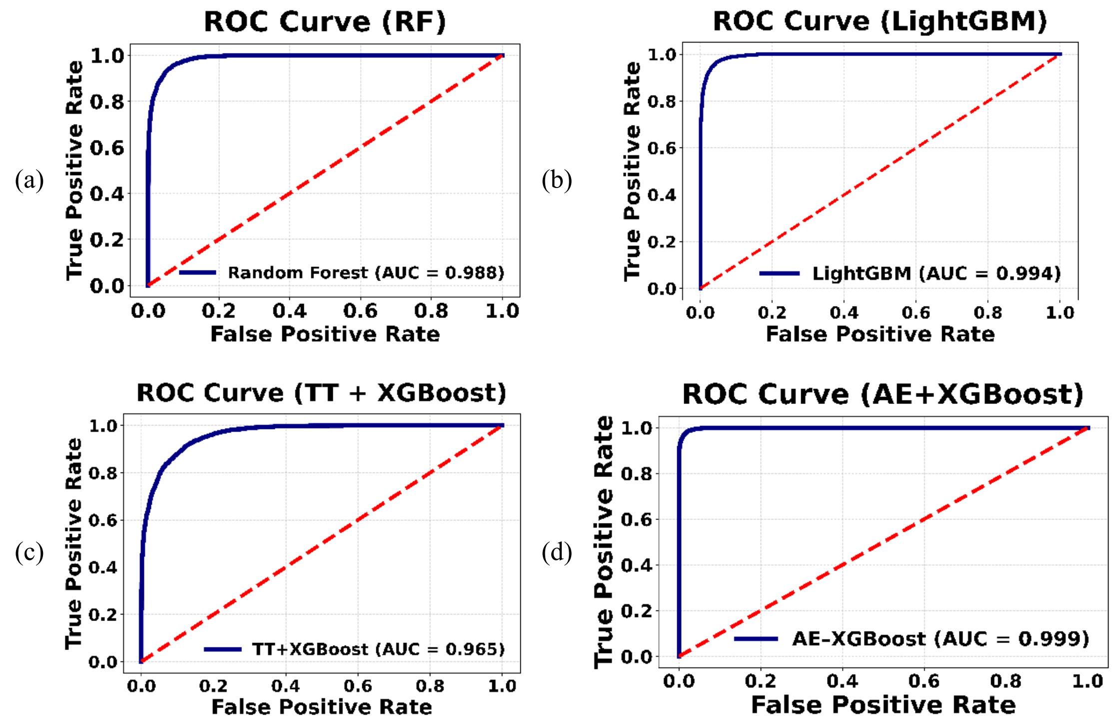

Figure 6. ROC curves of: (a) random forest, (b) LightGBM, (c) TT-XGBoost, and (d) AE-XGBoost

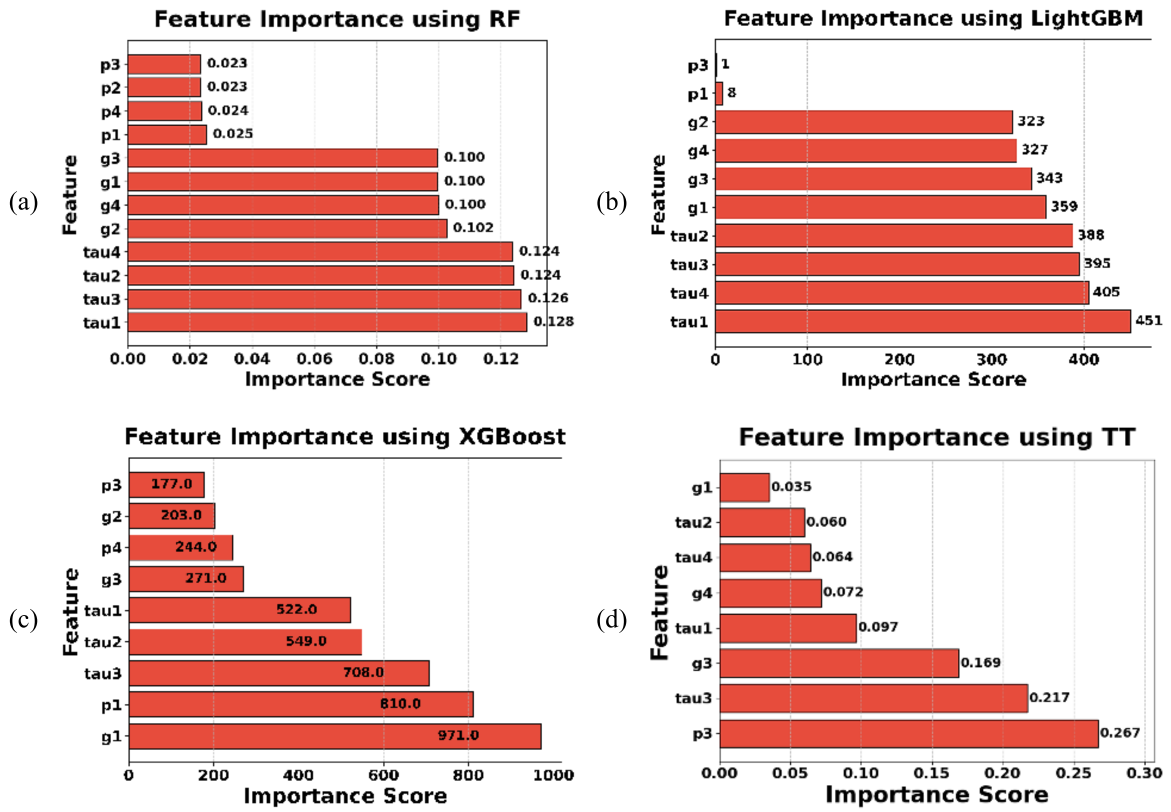

Figure 7. Feature importance plots showing the key variables identified by (a) random forest, (b) LightGBM, (c) standalone XGBoost, and (d) TabTransformer

4. CONCLUSION

This study evaluated hybrid machine learning models for predicting grid stability, focusing on accuracy, reliability, and interpretability. The autoencoder–XGBoost (AE-XGBoost) model achieved the best overall performance, with strong precision and balanced metrics, while LightGBM offered fast and consistent results. TT-XGBoost, though innovative, showed lower stability under certain conditions. AE-XGBoost is suited for high-accuracy, real-time monitoring, whereas LightGBM is faster and ideal for low-latency control tasks. Together, they offer complementary options depending on system needs. These models can also support renewable forecasting, early fault detection, and load balancing, and can be integrated with SCADA systems or digital twins for continuous monitoring and adaptive decision-making. Future work will focus on real-time integration and combining AE and TT features to further improve robustness and adaptability under evolving grid conditions.

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AUTHOR CONTRIBUTIONS STATEMENT

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors state no conflict of interest.

DATA AVAILABILITY

The data used in this study are publicly available on the Kaggle platform and can be accessed at: https://www.kaggle.com/code/mineshjethva/power-grid-stability-with-deep-learning.

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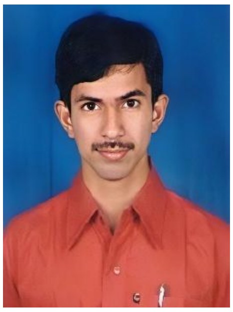

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