Smart Grid Stability Prediction Using Machine Learning

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Abstract. The increasing integration of renewable energy sources and prosumer-driven energy exchange has made smart grid stability a critical challenge for modern power systems. This study presents a comparative machine learning framework for predicting grid stability using a synthetic dataset derived from a four-node Decentralized Smart Grid Control (DSGC) model. Five complementary training approaches—standard learning, correlation-based feature selection, k-means–assisted enrichment, mutual-information–driven selection, and principal component analysis (PCA)—were systematically evaluated using a broad range of classifiers. Tree-based models demonstrated consistently superior performance, with XGBoost and LightGBM achieving up to 98.9% accuracy under PCA- and mutual-information–enhanced pipelines. These findings highlight the strong discriminative potential of machine learning for stability assessment and demonstrate that data-driven approaches can serve as efficient, interpretable, and computationally scalable tools for supporting reliable energy management in next-generation smart grids.

Keywords: Smart grid stability, machine learning, feature selection

1 Introduction

The increasing penetration of renewable energy resources and the emergence of prosumer-based energy exchange have fundamentally reshaped modern power systems. Unlike traditional grids designed for unidirectional power flow, smart grids operate with highly dynamic and bidirectional interactions, making real-time stability assessment substantially more challenging. These fluctuations in supply–demand balance, pricing elasticity, and consumer response times require advanced analytical tools capable of capturing nonlinear dependencies within high-dimensional operational data [1, 2].

Machine learning (ML) has become a key enabler in this domain due to its ability to extract meaningful patterns from complex datasets and outperform classical deterministic approaches. Recent studies demonstrate that tree-based algorithms achieve superior performance on structured smart-grid datasets, often surpassing deep learning models both in accuracy and computational efficiency [2-4]. Additionally, feature selection and dimensionality-reduction techniques have proven effective for improving model

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robustness and reducing the computational overhead of real-time decision-support systems . Similar data-driven strategies have also been successfully applied in other safety-critical domains, including ECG-based cardiac disease classification, psychiatric decision support, and EEG-based emotion or autism detection, where high-accuracy machine learning and deep learning models are used to assist clinical decision-making [5-8].

From a system modeling perspective, the Decentralized Smart Grid Control (DSGC) framework introduced by Schäfer et al. establishes a mathematical foundation for evaluating stability under varying load and pricing conditions [9]. Moreover, deep learning–based approaches have been explored for power-system anomaly detection and stability prediction, particularly through convolutional architectures and temporal feature extraction methods [10-11]. However, most prior work focuses on single-pipeline models or compute-intensive architectures, leaving a gap in comprehensive comparisons across diverse ML strategies within a unified experimental framework.

To address this gap, the present study proposes a comparative machine learning framework that evaluates five complementary training pipelines—standard learning, correlation-based selection, k-means–assisted feature enrichment, mutual-information-based filtering, and principal component analysis (PCA)—using a synthetic dataset generated from the DSGC model. A broad set of classifiers, including ensemble models, kernel-based methods, and tree-based algorithms, are systematically examined. Experimental results show that tree-based models such as XGBoost and LightGBM achieve up to 98.9% accuracy, particularly when combined with PCA or mutual-information-based feature selection.

Overall, this study provides three major contributions:

(i) a comprehensive, multi-pipeline evaluation of ML techniques for smart grid stability prediction;

(ii) an empirical analysis of how dimensionality reduction and feature selection influence accuracy and model efficiency; and

(iii) evidence that lightweight, interpretable ML models can provide near-optimal performance for real-time grid stability monitoring in next-generation smart energy systems.

2 Related Works

The prediction of smart grid stability has been widely studied across different modeling paradigms, ranging from physics-based formulations to data-driven machine learning approaches. Early work by Schäfer et al. introduced the Decentralized Smart Grid Control (DSGC) model, a differential-equation-based framework that captures the dynamic interplay between demand response, pricing elasticity, and frequency deviations under varying operating conditions [9].

Gil-Vera applied supervised learning techniques to classify grid stability conditions and reported substantial improvements over conventional threshold-based mechanisms [1]. Similarly, Gupta et al. proposed a convolutional neural network (CNN) architecture capable of extracting temporal–spatial features from power system measurements, achieving high accuracy in online stability classification [11]. Deep learning has also been utilized for cyber-physical grid security, where He et al. employed neural architectures for detecting false data injection attacks in real time [10], underscoring the broader applicability of advanced learning frameworks within smart grids.

Despite the success of deep learning, several studies emphasize that tree-based machine learning algorithms remain highly competitive—often outperforming deep networks on structured, tabular datasets common in grid-monitoring applications. Grinsztajn et al. demonstrated that methods such as Random Forests and Gradient Boosting Machines generalize better and require significantly fewer computational resources compared to deep neural architectures [2]. Comparative evaluations in power systems, including fault classification and stability prediction tasks, reinforce similar findings [4]. Ensemble-based methods have further been shown to improve reliability in sustainability analysis, renewable integration, and power quality prediction, as illustrated by Durairaj et al. using Random Forests [12].

Temporal modeling approaches have also been considered. Oyucu et al. evaluated hybrid RNN–LSTM frameworks for smart grid stability estimation, demonstrating their capacity to model time-dependent behaviors in dynamic energy systems [13]. However, such deep architectures typically involve long training times and extensive hyperparameter tuning, limiting their practicality in real-time or resource-constrained environments.

Comparable observations regarding the trade-off between model complexity, interpretability, and predictive performance have also been reported in other application domains, such as EEG- and EMG-based neurological disorder analysis, suicide-risk prediction from hemogram values, and multimodal medical decision support systems [5, 14].

In summary, the literature indicates three major trends:

(i) DSGC-based analytical models provide foundational insight but are limited by simplifying assumptions;

(ii) deep learning models achieve strong performance but introduce high computational cost; and

(iii) tree-based and ensemble ML methods offer an effective balance of accuracy, interpretability, and efficiency.

These gaps and insights motivate the need for a unified comparative evaluation of diverse ML pipelines—including feature selection, clustering-assisted processing, and dimensionality reduction—toward scalable and high-accuracy smart grid stability prediction. The present study addresses this need.

3 Methodology

The proposed framework evaluates multiple machine learning strategies for predicting smart grid stability using a synthetic dataset generated from the Decentralized Smart Grid Control (DSGC) model. The overall workflow is designed to assess how preprocessing, feature selection, and dimensionality reduction influence model performance.

3.1 Dataset and Preprocessing

The dataset contains 60,000 samples derived from simulated stability outcomes of a four-node grid topology. Each observation includes twelve numerical features—response times ($\tau 1$–$\tau 4$), nominal power values (p1–p4), and price elasticity coefficients (g1–g4)—alongside a binary label indicating stable or unstable behavior. An initial visualization of the three most informative features ($\tau 1$, p1, g1) reveals the distribution of stable and unstable samples, as shown in Fig. 1.

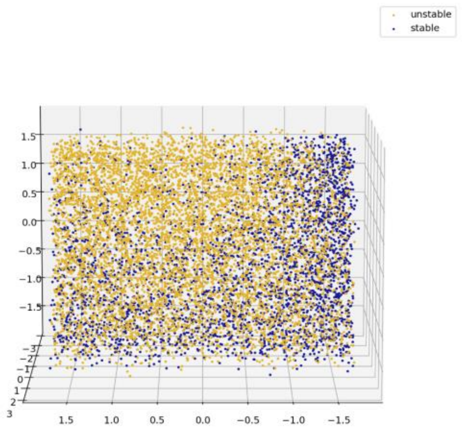

Fig.1. Three-dimensional scatter plot of $\tau 1$, p1, and g1 showing the distribution of stable and unstable samples.

All features are continuous with no missing values; therefore, standard z-score normalization is applied. The dataset is split into 90% training and 10% testing for all experiments to maintain comparability across approaches.

3.2 Machine Learning Pipelines

To understand the impact of different preprocessing strategies, five pipelines are examined:

Baseline Learning. Models are trained directly on the normalized dataset without feature reduction. This pipeline provides a reference point for all subsequent methods.

Correlation-Based Selection. Weakly correlated power features (p1–p4) are removed based on Pearson correlation analysis to evaluate the influence of redundant variables.

K-Means–Assisted Enrichment. Unsupervised clustering (k=2) is applied to the training set, and cluster labels are added as an auxiliary feature to capture latent structural patterns.

Mutual Information Filtering. Only the most informative features—$\tau 1, g1, and\ p1$—are retained based on mutual-information scores, enabling an assessment of extreme dimensionality reduction.

Principal Component Analysis (PCA). Data are projected into a lower-dimensional subspace using three principal components determined by explained variance. This tests the effect of geometric compression on model accuracy.

Across all pipelines, a diverse set of classifiers—logistic regression, support vector machines, discriminant analysis, k-nearest neighbors, tree-based models, boosting methods, bagging, and ensemble voting—is evaluated to identify the most effective modelling strategy. As seen in Fig. 2, the two- and three-dimensional PCA projections highlight the distribution of stable and unstable samples.

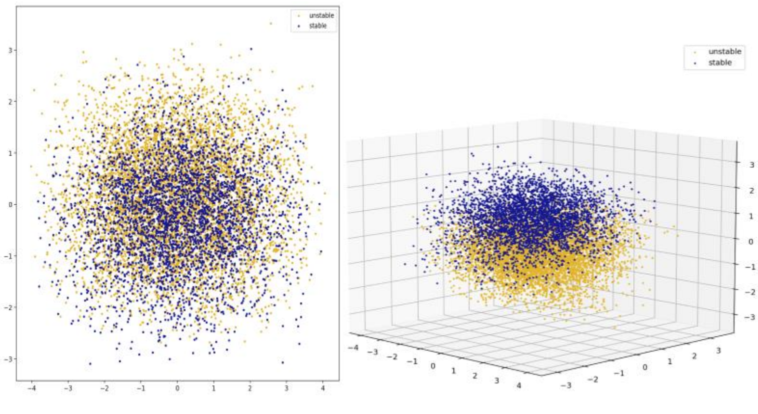

Fig.2. Two- and three-dimensional PCA projections showing class-level separation.

3.3 Evaluation Strategy

All models are assessed using accuracy, precision, recall, and F1-score. Experimental results show that tree-based models, particularly XGBoost and LightGBM, consistently outperform other algorithms across all pipelines. The best performance, reaching up to 98.9% accuracy, is achieved under PCA- and mutual-information–enhanced configurations.

This unified framework enables a systematic comparison of preprocessing techniques and demonstrates the strong discriminative capability of machine learning for smart grid stability prediction.

4 Result and Discussion

Experimental findings from the five machine learning pipelines reveal clear performance patterns shaped by feature relevance, data geometry, and model complexity. The comparative behavior of the strongest classifiers under each pipeline is summarized in Table 1, which provides a consolidated view of accuracy trends across preprocessing strategies.

Table 1. Accuracy (%) of best-performing classifiers across preprocessing pipelines

Pipeline	LightGBM	XGBoost	Random Forest	SVC
Baseline	97.0	96.8	95.2	96.2
Correlation	97.8	97.5	96.1	96.8
K-Means	98.0	97.6	96.0	96.7
MI Filter	98.7	98.8	97.9	89.0
PCA	98.9	98.7	97.8	97.5

Tree-based algorithms demonstrate high performance from the outset, achieving 92–97% accuracy in the baseline pipeline. These results indicate strong inherent separability in the DSGC-generated feature space, enabling nonlinear models to capture stability boundaries effectively. Linear methods, in contrast, perform considerably worse, reflecting their limited capacity to model nonlinear interactions between response times, elasticity coefficients, and power variables.

Correlation-based feature selection yields moderate improvements. Removing weakly informative power features ($p1 - p4$) enables LightGBM and Random Forest to reach up to 97.8% accuracy, suggesting that feature redundancy introduces mild noise without fundamentally altering classification geometry. Support Vector Classifiers also display slight performance gains, while linear and distance-based models fluctuate by approximately ±1–2%.

The k-means–assisted pipeline introduces unsupervised structure by injecting cluster labels as an auxiliary feature. Tree-based classifiers rise to approximately 98.0%, and SVC shows modest improvement, indicating partial alignment between latent cluster structure and stability outcomes. Linear models remain largely unchanged, reaffirming their limited responsiveness to nonlinear geometric cues.

Mutual-information filtering produces a more distinct shift by preserving only the three most informative features ($\tau1, g1, p1$). This aggressive reduction decreases performance for linear and probabilistic models, but tree-based methods remain exceptionally robust. LightGBM and XGBoost achieve 98.7–98.9% accuracy, illustrating their adaptability to compact feature spaces that retain strong discriminative power.

Principal Component Analysis (PCA) emerges as the most effective preprocessing strategy. By projecting the dataset into a subspace that captures the dominant variance directions, PCA enhances class separation while reducing noise. LightGBM achieves the highest accuracy of 98.9%, followed by XGBoost at 98.7%, and SVC at 97.5%. These gains highlight PCA's ability to balance dimensionality reduction with expressive representational capacity.

Overall, the comparative findings indicate that tree-based models consistently provide the most reliable performance; dimensionality reduction—especially PCA—substantially reinforces nonlinear models; and the DSGC-derived dataset exhibits an intrinsically strong discriminative structure that enables high accuracy without deep neural architectures.

As shown in Table 2, the PCA-enhanced LightGBM model achieves highly balanced class-level performance, correctly predicting 989 out of 1000 samples, with only 11 total misclassifications. This confirms that the reported 98.9% accuracy reflects genuine separability rather than class imbalance.

Table 2. Confusion matrix of the best-performing model (LightGBM with PCA, 98.9% accuracy)

Heading level	Predicted Stable	Predicted Unstable
Actual Stable	495	5
Actual Unstable	6	494

5 Conclusion

The experimental evaluation of five machine learning pipelines demonstrates that data-driven approaches provide highly effective and computationally efficient tools for smart grid stability prediction. Tree-based models consistently outperform other classifier families across all preprocessing strategies, with the highest accuracy of 98.9% obtained when combined with PCA or mutual-information–based feature selection. These findings highlight the strong discriminative structure of the DSGC-derived dataset and confirm that nonlinear, ensemble-based algorithms are well suited for capturing the underlying dynamics of stability behavior.

Dimensionality reduction plays a key role in enhancing performance, particularly for high-capacity models. PCA effectively compresses the feature space while improving class separability, whereas mutual-information filtering shows that even minimal yet highly informative subsets of features can sustain near-optimal accuracy. The comparative analysis across pipelines further illustrates how preprocessing choices influence model stability, robustness, and generalization.

The overall results indicate that machine learning methods especially gradient-boosted decision trees offer a practical and scalable foundation for real-time stability monitoring in modern smart grids. Future work may extend this framework to multinode or large-scale grid topologies, incorporate temporal modeling for dynamic operation conditions, and explore hybrid architectures that integrate ML predictions with physical-grid simulation models.

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