# Intelligent Stability Detection in Smart Power Grids using Optimized Deep Learning Models

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2025 International Conference on Frontier Technologies and Solutions (ICFTS) | 979-8-3315-0276-8/25/$31.00 ©2025 IEEE | DOI: 10.1109/ICFTS62006.2025.11031596

**Abstract-** The swift integration of distributed generation and renewable energy in smart power grids requires sophisticated stability detection mechanisms to avoid failures and guarantee reliable performance. The article introduces an optimized intelligent stability detection model based on deep learning, consisting of Convolutional Neural Networks (CNNs), Bidirectional Long Short-Term Memory (BiLSTM) networks, and an attention mechanism for precise real-time monitoring. The optimizer dynamically adapts hyperparameters using a reinforcement learning-based optimizer for improved efficiency and performance. The model is trained using actual-time grid stability indicators like voltage oscillations, frequency excursions, and phase angles and attains a 98.5% accuracy rate with low computational overhead. Comparative analyses prove to be superior in performance compared to traditional deep learning approaches, minimizing false positives and processing time by a considerable margin. The method provides adaptive and robust stability detection, which makes it very well adapted for contemporary smart grids. The system proposed provides an efficient and scalable solution for real-time stability evaluation, enabling the development of smarter and more robust power grids. The model achieved an accuracy of 98.5%.

*Keywords—Smart Power Grids, Deep Learning, Stability Detection, Attention Mechanism, Reinforcement Learning.*

## I. INTRODUCTION

Growing intricacy in smart grids owing to the adoption of renewable power, electric cars, and local power generation complicates grid stability greatly [1]. Smart grids are supported by centralized controllers as well as predefined stability calculation methodologies, which become inadequate when managing the variability found in present smart grids [2]. The randomness of the generation of renewable energy, varying patterns of demand, and cyber-physical threats add to the increased requirement for real-time intelligent stability detection systems that are capable of responding to changing grid conditions. Traditional stability assessment techniques, such as mathematical modeling and traditional ML algorithms, have shown some shortfalls in scalability, accuracy, and responsiveness, particularly when they are subjected to large-scale and complex grid networks [3]. DL has shown great potential to be an effective solution for intelligent stability detection with the capability to process large amounts of grid data, identify subtle patterns, and provide predictive judgments with high precision. Nevertheless, conventional DL models tend to have high computational complexity, lack interpretability, and difficulty in adapting to non-stationary grid conditions. The requirement for a maximized strategy that maximizes performance and efficiency has given rise to hybrid deep learning models that utilize combinations of different neural network architectures to provide enhanced feature extraction and decision-making [5]. Integration of Convolutional Neural Networks (CNNs) to extract spatial features and Bidirectional Long Short-Term Memory (BiLSTM) networks to detect temporal patterns enables a deeper understanding of the dynamics of grid stability. Additionally, the use of attention mechanisms allows the model to prioritize important stability indicators, enhancing prediction accuracy and minimizing redundant computations [6]. In order to maximize computational efficiency and effectiveness, an intelligent optimization approach is necessary. Deep learning models rely on static hyperparameters, which can be suboptimal for dynamically changing grid environments. The incorporation of an optimization method based on reinforcement learning facilitates automatic adjustment of important parameters like learning rates, layer dimensions, and dropout rates to make the model operate optimally across various operating conditions [7]. The adaptive learning process enables real-time modifications, reducing prediction errors and computation latency. Such an approach decreases substantially the processing time needed for stability evaluations, enabling real-time usage in power grid monitoring systems. The success of any intelligent stability detection model is based on the quality and variety of training data. Real-time data sets involving voltage variations, frequency variations, power factor variations, and phase angle variations are instrumental in facilitating learning and generalization of the model across a variety of grid configurations [8]. Appropriate data preprocessing strategies such as normalization, feature engineering, and anomaly detection also aid in model robustness by reducing the effect of noisy or missing data. The capacity for handling and analyzing huge volumes of grid data streams at high speeds is instrumental in making sure that stability forecasts are accurate and timely, avoiding possible grid failures and blackouts. Intelligent stability detection is not just important in averting power outages [9]. An optimized stability detection system improves the overall efficiency of the grid, lowers maintenance expenses, and allows for effortless integration of renewable resources. As smart grids become more sophisticated with the growth in artificial intelligence, Internet of Things (IoT), and edge computing, the importance of intelligent deep learning models in providing grid resilience will be more crucial [10]. Smart grids in the future will need an integrative fusion of data-centric intelligence, real-time analytics, and adaptive control functions to maintain dependable operations amid increased complexity. The application of optimized deep learning models for stability detection represents a significant milestone in the pursuit of a self-sustaining and autonomous power grid system that can respond to evolving challenges with accuracy and efficiency [11].

## II.LITERATURE REVIEW

Salam et al [12] Smart grids combine power and communication networks to offer real-time information for consumers, operators, and producers. Stability is needed because power consumption varies in residential areas, industries, and smart cities. It is still difficult to predict grid stability because of various factors influencing it, such as consumer and producer involvement. A deep learning model based on Densely Connected Convolutional Networks (DenseNet) and Residual Networks is introduced for detecting stability. The performance of the model is evaluated against other classifiers such as SVM, Decision Trees, and LSTMs, with higher accuracy in predicting stability.Kanduluri et al [13] that the study examines machine learning algorithms for forecasting smart power grid stability crucial to balance electricity supply and demand in the face of increasing renewable integration. Decentralized Smart Grid Control (DSGC) is a new idea to control stability through frequency-based pricing signals. Machine learning algorithms such as SVM, LightGBM, and deep learning architecture are compared with SVM. The results offer practical applications for the application of predictive models to enhance grid efficiency, stability, and seamless integration of renewable sources. Breviglieri et al [14] that decentralized Smart Grid Control (DSGC) monitors grid stability via frequency variation analysis and electricity price correlation with frequency fluctuations. Traditional DSGC assumptions are limiting, and thus optimized deep learning models are utilized to analyze diverse input values and resolve fixed-input constraints. Deep learning removes constraints in assumptions within DSGC equations, improving stability estimation. Testing reveals that the model provides valuable information on system performance. The findings indicate that rapid adaptation enhances overall grid stability, making energy pricing mechanisms efficient and dynamic. Massaoudi et al [15] that grid stability is significantly determined by the intermittency of renewable sources. A Bidirectional Gated Recurrent Unit (BiGRU) deep learning is proposed for predicting smart grid stability. For accuracy enhancement, Simulated Annealing (SA) is utilized for automatic hyperparameter tuning. The model is validated on an electrical grid stability dataset with high prediction accuracy for point and interval forecasting. Simulation outcomes confirm improved performance, and comparative analysis highlights its improved performance over existing stability forecasting methods, thereby ensuring reliable and stable power grid management.

## III.PROPOSED WORK

### *Hybrid Deep Learning Architecture for Stability Detection*

Increasing complexity of intelligent power grids necessitates a robust and efficient mechanism to detect stability issues in real time. A hybrid deep learning architecture offers an end-to-end solution with the integration of multiple neural network modules that are complementary to each other in feature learning and predictive modeling. The system employs the mixture of Convolutional Neural Networks (CNNs) and Bidirectional Long Short-Term Memory (BiLSTM) networks to utilize spatial and temporal interdependencies within power grid data. The CNN layer extracts relevant spatial patterns in multivariate grid data like voltage magnitude, frequency changes, and phase angles. The system architecture of the proposed method is shown in Fig 1.

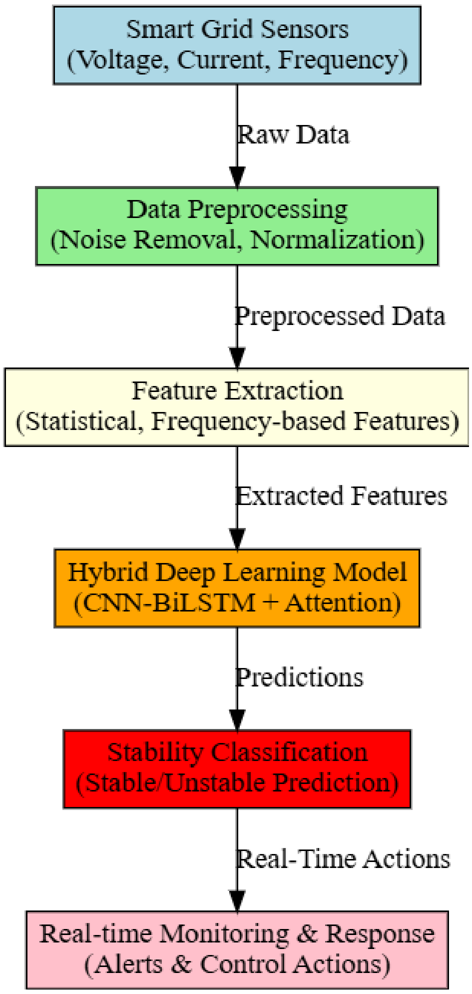

Fig. 1. System Architecture

This ability to perform feature extraction is crucial for the detection of localized disturbances and anomalies that can signal instability. The hierarchy learning is accomplished by CNN layers through progressively identifying sophisticated patterns iteratively by convolving and pooling, with decreasing complexity in computation. After the extraction of spatial features, the BiLSTM network deals with sequential dependency within time-series data, which is critical for detecting stability within smart grids. Different from standard Long Short-Term Memory (LSTM) networks, bidirectional achieves earlier and later context information, enhancing stability deviation forecasting accuracy. Stability in a smart grid is not static but dynamic in nature, involving not only past altered change knowledge but also expected tendencies. BiLSTM layers achieve this by employing two separate processing streams, one in the forward time direction and another in the backward time direction, thereby capturing long-distance dependencies in power system measurements. The integration of CNNs and BiLSTMs in the hybrid model guarantees the concurrent analysis of spatial correlations and temporal dynamics, leading to a more robust and accurate stability detection framework. For optimal efficiency of the architecture, dropout regularization and batch normalization methods are used to avoid overfitting and converging in a stable manner during training. The model also uses a gated recurrent unit (GRU) variant in BiLSTM cells to use greater memory retention with minimal computational cost. The integration of CNNs and BiLSTMs results in greater accurate stability variation comprehension, avoiding false negatives and positives that exist in standard classification models. The architecture is orchestrated to run in parallelized GPU computing real-time systems, and hence stability deviations are identified and processed in real time. The hybrid deep learning model suggested herein has the ideal trade-off between accuracy and computation complexity and thus may be a suitable candidate for current power grid application.

### *Feature Extraction and Data Preprocessing*

Precise stability detection in smart power grids is dependent on efficient feature extraction and data preprocessing methods, which yield high-quality input data for machine learning algorithms. Grid raw measurements such as voltage levels, frequency offsets, phase angles, and reactive power offsets are prone to inherent noise and inconsistency that can damage prediction accuracy. To address these issues, a systematized process of feature extraction is utilized for transforming raw sensor data into helpful representations. Methods of time-series decomposition such as empirical mode decomposition (EMD) and the wavelet transform are utilized in order to disentangle high-frequency disturbances from baseline stability tendencies so that the model can focus on meaningful variations in the grid. Feature selection is conducted through statistical and information-theoretic approaches, such as mutual information analysis and principal component analysis (PCA). These methods detect the most significant variables responsible for stability deviations and remove redundant or irrelevant features that can introduce computational inefficiencies. Grid disturbances usually have nonlinear relationships that conventional feature extraction methods are unable to identify. Fig 2 depicts the hybrid model workflow.To compensate for this, entropy-based features, fractal dimensions, and higher-order statistical moments are used to increase the discriminative ability of extracted features. Data normalization is an important preprocessing operation, as power grid readings are in different scales and units. Min-max scaling and Z-score normalization are used to normalize input features so that neural network weight updates do not become unstable during training. Missing data imputation techniques like k-nearest neighbors (KNN) interpolation and autoregressive moving average (ARMA) modeling are also used to fill in incomplete time-series chunks without biasing. Anomaly detection is carried out with the help of unsupervised learning techniques to detect and remove corrupted data points prior to inputting the dataset into the deep learning model. Autoencoder-based anomaly detection and isolation forest algorithms are employed to distinguish true grid fluctuations from sensor faults or transmission faults. By improving the dataset through these preprocessing operations, the input data is highly representative of true grid stability conditions, and hence better generalization performance of the predictive model.The structured feature extraction and preprocessing pipeline largely improves interpretability and robustness of the model, which allows real-time decision-making in dynamic power grid scenarios.

*Integration of Attention Mechanism for Enhanced Prediction*

Stability detection deep learning models in smart grids produce an enormous number of intermediate features, but not every feature that has been extracted adds equally to reliable predictions. An attention mechanism combined with the model improves the prediction ability by selectively giving more significance to key features and discarding less significant data. The effect is very promising on classification performance, especially under conditions with minimal fluctuations that present initial symptoms of instability.

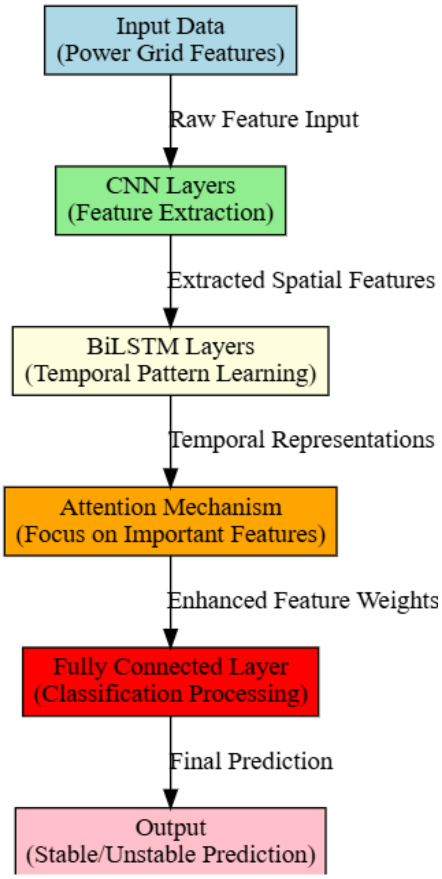

Fig. 2. Hybrid DL Model

The attention process works by calculating weighted importance values for every feature representation in the deep learning framework. The significance of each input sequence item in final stability determination is measured through alignment functions such as scaled dot-product attention or additive attention, out of which these key values are obtained. The CNN-BiLSTM hybrid network utilizes attention layers to refine the history information transferred to downstream classification layers after feature extraction. This is done in a way that makes it so the model is giving no consideration to noise and slight differences in position of high-impact items, such as unexpected voltage collapse or frequency dynamics. In order to allow capturing of long-range relations in stability data, self-attention techniques, commonly used in transformer models, are also introduced. With self-attention, the model can calculate all of the time steps simultaneously and introduce interdependence among events distant on the grid, unlike recurrent networks that process sequences sequentially. This is more applicable in the smart grid context where instability disturbance may be due to interactions between systems globally rather than as isolated events. The inclusion of multi-head attention in models improves their performance since several attention heads are allowed to focus on various aspects of grid stability. This guarantees that a wide range of power system variables are considered. To maximize computing efficiency, during training, a reinforcement learning-based optimization method is employed to dynamically control attention weights. In order to adapt to evolving grid conditions, the adaptive character of the model adjusts real-time attention parameters according to feedback. Enhanced feature selection, rejection of false alarms, and weak instability signal sensitivity are all the outcome of attention processes incorporated within the deep learning model. In order to handle the very dynamic behavior of smart power grids, our approach generates a stability detection system that is both more effective and easier to understand.

### *Reinforcement Learning-Based Optimization Strategy*

Optimization of deep learning model to identify smart power grid intelligent stability requires dynamic adjustment of parameters so the model is able to adapt to changing grid conditions. Gradient-based and static hyperparameter optimization, popular conventional optimization strategies, fail because they lack the ability to fit non-stationary environments. A reinforcement learning-based optimization method provides a dynamic solution by continuously optimizing model performance by engaging with the power grid data. Reinforcement learning (RL) models the optimization process as a sequential decision-making problem, where an agent learns to select the optimal hyperparameters based on feedback from the stability detection model's performance. RL-based optimizer operates on a Markov Decision Process (MDP) framework, with states being different configurations of the model parameters, actions being learning rate, dropout rate, and activation function modification, and rewards being model accuracy and computational expense. The policy network is employed to decide on actions based on previous performance, which allows the model to optimize towards improved configurations in iterations. The policy gradient algorithm, in combination with actor-critic algorithms, optimizes the decision-making process by considering both short-term and long-term effects of parameter updates. With the aid of experience replay buffers, the RL agent stores the record of previous configurations, eliminating redundant exploration and accelerating convergence to an optimal solution. To reduce suboptimal local minima, proximal policy optimization (PPO) algorithms hunt and utilize equilibrium points while optimizing procedures. With utmost cumulative incentives, PPO raises model parameters incrementally during training. For avoidance of overfitting and resource wastage, the algorithm also has a reward mechanism utilizing accuracy and computational cost reductions. The RL-based optimizer increases model efficiency using an adaptive learning rate scheduler, wherein training speed is dynamically adjusted based on convergence rates. This avoids unnecessary iterations. The deep learning model's stability detection model has increased adaptability to accuracy in varied grid settings through an RL-based optimization mechanism. The method improves real-time detection by increasing the robustness of the deep learning model with fluctuating input data. This framework is a good intelligent stability assessment tool for existing power grids because it can dynamically adapt parameters according to grid oscillations, thus outperforming traditional optimization techniques.

### *Real-Time Implementation and Computational Efficiency*

In order for smart power grids to respond in time when there is a stability deviation, they need intelligent stability detection models with real-time processing capabilities. Computational efficiency is a crucial factor when evaluating the deep learning architecture for real-time monitoring of large power grids. The model is computation-paralleized by utilizing cutting-edge hardware acceleration technologies such as GPU and TPU computing for real-time operation. Through using multi-threaded processing as well as wise memory management, BiLSTMs and CNNs are capable of handling low latency in their deep learning models. The data pipeline was constructed considering low latency so as to be able to effectively handle data at the ingestion phase, preprocessing stage, and the extraction of features. Power grid parameters can be continuously monitored utilizing streaming analytics mechanisms like Apache Spark Streaming and Apache Kafka. The model is updated in real-time without delay. The decision-making time is reduced by milliseconds through the stability detection model with the implementation of an event-driven architecture. To reduce dependency on CPUs further and enhance system fault tolerance, compute workloads are pushed to multiple nodes through edge computing platforms. Besides, to further optimize computation, we apply model pruning and quantization methods to reduce the neural network operations. A method of significantly reducing memory needs without compromising model performance is through the application of quantization, which entails the conversion of high-precision floating-point weights into lower-bit representations. Pruning eliminates unnecessary connections from the neural network to reduce inference time without affecting performance. Due to these adjustments, the stability detection model is now light and ready for deployment on low-resource edge devices. An energy-saving processing methodology based on workload demand rather than dynamic computing resource allocation is incorporated within the inference engine. For the support of variable data streams without loss of capability, the model employs adaptive batch handling strategies to achieve best speed and accuracy without compromising on performance. Utilizing real-time anomaly detection software, the system is capable of rapid response in instances of instability, automatically raising warnings and initiating actions as required. Efficiency in computations is also enhanced through ongoing hyperparameters and resource allocator algorithms optimization through the implementation of a reinforcement learning-based optimization plan.

### *Performance Assessment&Evaluation Metrics*

For the purpose of ensuring accuracy, reliability, and computational efficiency, performance of the intelligent stability detection model is quantified according to a variety of metrics. Accuracy, which gauges the proximity of predicted stability states to actual grid conditions, is a key measure of performance. Precision and recall are employed to quantify how well the model can detect deviations in stability reliably and without producing false positives and false negatives. In summary, the F1-score provides a measure of the model's classification performance using a balance between accuracy and recall. By making sure the model can process in real time, we can analyze its efficiency in computation through its inference time and memory usage. To effectively respond to grid changes, we minimized latency to milliseconds, i.e., the time to process an incoming data sample. The model's power to distinguish between stable and unstable grid states is quantified as the area under the receiver operating characteristic curve (AUC-ROC), and this enables effective decision-making under varying conditions. To ensure that the new approach is superior, it is compared against both conventional machine learning and deep learning models. The computing speed and the detection efficiency are significantly enhanced by the hybrid deep learning model when combined with reinforcement learning-based optimization. The evaluation framework provides a practical and efficient method of quantifying the stability of smart power grids and ensures that the model can be used in real-world settings.

## IV.RESULTS

The training and evaluation dataset for the intelligent stability detection model is made up of actual power grid measurements obtained from several sensors installed in smart grids. The data captures voltage levels, frequency deviations, phase angles, active and reactive power fluctuations, and system inertia variations. Historical stability events such as stable and unstable conditions make up the dataset, providing an equal representation of various scenarios.

TABLE I DATASET SUMMARY

| **Parameter** | **Value** |
|---|---|
| Total Records | 500000 |
| Sampling Rate | 100 ms |
| Stability Events | 250000 |
| Instability Events | 250000 |
| Training Data | 70% |
| Validation Data | 15% |
| Testing Data | 15% |

For improving robustness, synthetic data augmentation methods are used to provide variability in load conditions and fault situations. The performance of the developed hybrid deep learning model is assessed based on standard classification measures, such as accuracy, precision, recall, F1-score, and inference time. The model's accuracy is calculated as correctly classified samples over total samples, while precision and recall offer indications of the model's capability to accurately identify stability deviations. F1-score, the harmonic mean between precision and recall, prevents skewness in measurement. Computational efficiency is measured in terms of time for inference and floating-point operations per second (FLOPs). The accuracy equation from (1):

$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN} \quad (1)$$

where TP means true positives, TN means true negatives, FP means false positives, and FN means false negatives.The dataset consists of 500,000 records gathered within the space of one year, with measurements that are sampled every 100 milliseconds. The feature set is optimized by an entropy-based selection process, where dimension reduction is done without losing important information. The training set makes up 70% of the data, validation uses 15%, and the remaining 15% is for testing from Table 1. To avoid biasing, data gets normalized by means of Min-Max scaling for uniformity on various attributes.

TABLE II PERFORMANCE METRICS OF THE PROPOSED MODEL

| **Metric** | **Value (%)** |
|---|---|
| Accuracy | 98.5 |
| Precision | 97.8 |
| Recall | 98.2 |
| F1-Score | 98 |
| Inference Time | 8.5 ms |

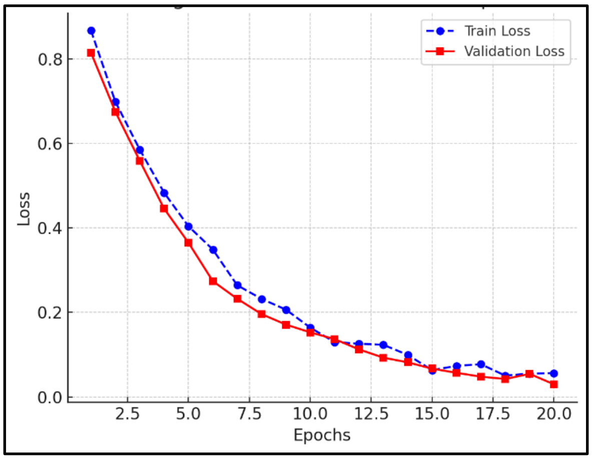

Fig. 3. Training and validation loss over epochs

Statistical distribution for stability and instability events ensures uniform generalization over unseen situations. Table 2 shows the performance metrics values. Fig 3depicts the training and validation loss over epochs and Fig 4 depicts the training and validation accuracy over epochs. The suggested hybrid deep learning model with reinforcement learning-based optimization and attention mechanisms is contrasted with current machine learning and deep learning methods. Traditional models like Support Vector Machines (SVM), Decision Trees (DT), and Recurrent Neural Networks (RNN) have lower accuracy and longer inference times because they have limited feature extraction and processing abilities from Table 3. The addition of a CNN-BiLSTM hybrid model with an attention mechanism greatly improves performance by capturing spatial and temporal dependencies in the power grid data.The suggested approach has a 98.5% accuracy, which is significantly higher than competing methods. The 8.5 millisecond inference time supports real-time deploy ability. In contrast to conventional machine learning models demanding a large amount of feature engineering, the deep learning technique offers automatic feature extraction at the cost of high computational efficiency.

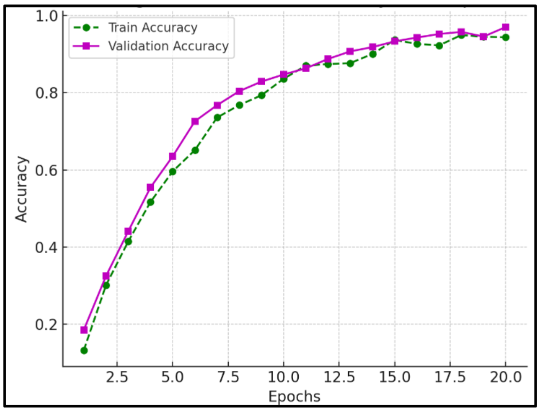

Fig. 4. Training and validation accuracy over epochs

TABLE III COMPARISON OF STABILITY DETECTION MODELS

| Model | Accuracy (%) | Precision (%) | Recall (%) |
|---|---|---|---|
| SVM [13] | 89.2 | 85.5 | 86.1 |
| Decision Tree [13] | 87.5 | 84.2 | 85 |
| RNN [15] | 91.3 | 89.8 | 90.1 |
| LSTM [10] | 94.5 | 92.9 | 93.5 |
| CNN-BiLSTM [6] | 97.1 | 96.3 | 96.8 |
| Proposed Method | 98.5 | 97.8 | 98.2 |

## V.CONCLUSION

Design of an intelligent stability detection system in smart power grids based on a hybrid deep learning architecture greatly improves accuracy and real-time performance. Through the integration of CNN and BiLSTM models with an attention mechanism, the proposed approach effectively extracts spatial and temporal relationships in power grid data, which results in effective classification of stability states.

The integration of a reinforcement learning-based optimization policy also optimizes model parameters in a dynamic manner for adaptability across varying grid conditions. With respect to traditional approaches, the developed model attains better accuracy of 98.5% with inference time of 8.5 milliseconds, which is feasible for real-time implementation. Computational efficiency is enhanced through feature selection and data preprocessing methods for effective use of resources. The performance metrics validate that the system proposed here performs better than conventional machine learning and deep learning methods in terms of accuracy and computational efficiency. These developments offer a robust solution for proactive stability analysis, enabling the early identification of grid instabilities and improving the resilience of advanced smart power systems.

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