Advancements in AI-Driven Approaches for Grid Stability Monitoring

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***Abstract*—In the age marked by growing penetration of intermittent renewable energy sources, distributed energy resources, demand-side management and power electronics-based generation, alongside the trend of grid smartification, power system stability monitoring has become more complex and challenging than ever before. Traditional stability monitoring methods, based on conventional measurements, analytical modeling and rule-based control, have demonstrated limited real-time capabilities, inability to efficiently handle the massive influx of data, rigidity to adapt to rapidly changing grid dynamics, as well as high implementation and maintenance costs. As a response, artificial intelligence (AI) has emerged as a powerful solution for enhancing grid stability monitoring by enabling real-time analysis, predictive modeling, and automated decision-making. This paper provides a comprehensive overview of the state-of-the-art AI-based approaches that are utilized in voltage, frequency and transient stability assessment, as well as in fault detection and classification. The AI techniques such as machine learning, deep learning, fuzzy logic, reinforcement learning and hybrid AI models, have demonstrated advanced capabilities to anticipate grid disturbances, improve disturbance detection and enhance decision-making processes. Besides the great potential of AI-driven solutions, the paper outlines major challenges such as algorithmic limitations, data quality and availability concerns, model generalization, cybersecurity threats, computational complexity, model robustness, integration and interpretability, that must be addressed for a successful integration of AI-based solutions into grid monitoring systems. Ultimately, continuous advancement of AI-driven grid stability solutions will be instrumental for ensuring resilience and efficiency in the constantly evolving power system landscape.**

Keywords—artificial intelligence, stability monitoring, power system stability, machine learning.

I. INTRODUCTION

One of the key challenges of contemporary power systems in the context of energy transition is maintaining system stability [1]. Power system stability can be formally defined as "the ability of an electric power system, for a given initial operating condition, to regain a state of operating equilibrium after being subjected to a physical disturbance, with most system variables bounded so that practically the entire system remains intact". In the pursuit for preserving the equilibrium state, a paramount challenge is to continuously assess and analyze grid conditions within the power system through the process of stability monitoring, which may be categorized into several types, including voltage stability, frequency stability, rotor angle (transient) stability monitoring, and fault detection and classification.

Historically, stability monitoring has relied on supervisory control and data acquisition (SCADA) systems, phasor measurement units (PMUs), and state estimators that employ physical models and linearized system equations. While effective in steady-state conditions, these systems often lack the responsiveness and accuracy needed for dynamic real-time assessment, especially in the presence of noisy data, complex interactions, and rapidly evolving contingencies [2]. Moreover, the energy transition, characterized by an ever-increasing integration of renewable energy resources, advanced control mechanisms, more complex communication networks, bidirectionality of smart grids and high proliferation of power electronics, has introduced more frequent and new forms of stability issues, posing challenges for traditional stability mechanisms [3]. These factors underscore the urgent need for smarter, more flexible grid monitoring frameworks.

Artificial intelligence (AI), encompassing techniques such as machine learning, deep learning, fuzzy logic, and reinforcement learning, is rapidly emerging as a transformative solution to these challenges. AI algorithms excel at handling large datasets, identifying patterns, learning from historical data, and adapting to non-linear and evolving system behaviors. These capabilities make AI an ideal candidate for enhancing grid stability monitoring in ways that go far beyond the limitations of classical methods. This paper aims to provide a comprehensive overview of the current state and potential of AI-based approaches in grid stability monitoring. It reviews a broad range of techniques that have been proposed and developed in recent literature, highlighting their strengths, limitations, and areas of applicability.

II. AI-BASED METHODS

One of the most attractive features of AI in addition to enabling systems to efficiently learn from data is its ability to adapt to changing conditions in real time. A major branch of AI that analyzes input patterns to classify, predict or cluster data is called Machine learning (ML). Some of the most significant ML algorithms include support vector machine (SVM), Decision Tree (DT), artificial neural network (ANN), extreme learning machine (ELM), and Bayesian networks. While SVM seeks to identify the optimal hyperplane, known as the decision boundary, that best separates input data points into distinct classes [4], DT uses a hierarchy of nested rules to generate predictions by determining optimal thresholds at each decision node [5]. ANN, inspired by neuroscience, models complex input-output relationships using layered neurons and possesses nonlinear activation functions that enable it to learn and fit nonlinear patterns [6]. To accelerate ANN training, the ELM employs a model with a single hidden layer with randomly assigned input weights and biases, in which the output weights are computed analytically without iteration [7]. A Bayesian network is a probabilistic graphical model that represents a set of variables and their conditional dependencies via a directed acyclic graph (DAG) [8]. To improve the performance and generalization abilities of ML algorithms in practical applications, ensemble learning (EL) is proposed, which builds and combines a group of models to

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achieve learning tasks [9]. A Random Forest (RF) is an EL method that constructs multiple DTs during training and outputs the majority vote (for classification) or average prediction (for regression), improving accuracy and robustness over individual trees [10]. Deep learning (DL) models, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), are capable of capturing spatial and temporal correlations in high-dimensional data due to their multi-layered structure, making them well-suited for applications like event detection and sequence prediction in grid operations. However, training a CNN and RNN with back-propagation alone is ineffective without suitable initial weights. This limitation was solved by introducing a greedy layer-wise pretraining approach using Deep Belief Networks (DBNs) [11]. Long Short-Term Memory (LSTM) networks are a specialized type of RNN designed to model temporal sequences and their long-range dependencies more accurately than conventional RNNs by utilizing memory cells for storage of history [12]. In addition to discriminative models, there are methods that learn the underlying data distribution to produce new samples, such as Generative Adversarial Network (GAN), introduced by [13], that consists of a generator which creates realistic data from random noise and a discriminator which distinguishes between real and synthetic data. Through adversarial training, both networks compete until they reach a balanced state, known as Nash equilibrium. An Autoencoder (AE) is an unsupervised neural network consisting of an encoder that compresses input data into a lower-dimensional code and a decoder that reconstructs the original input from this code [14]. A Variational Autoencoder (VAE), a variant of AE, adds a regularization term to enforce that the encoded representations follow a multivariate normal distribution, promoting a smooth and structured latent space for generating more realistic and meaningful outputs [15]. Fuzzy logic and expert systems offer a rule-based, human-interpretable approach to decision-making under uncertainty, which is particularly valuable when precise models are unavailable. Reinforcement learning (RL) introduces the concept of learning optimal actions through trial-and-error interactions with the environment, potentially allowing AI agents to autonomously learn control policies that maximize system stability over time. Hybrid AI models, which combine two or more of these techniques, further expand the potential of AI by leveraging their complementary strengths. For example, combining neural networks with fuzzy logic results in neuro-fuzzy systems that can learn from data while retaining explainability.

III. Applications of AI-Driven Techniques in Grid Stability Monitoring

Whereas AI-based methods may be applied to a big range of power system stability-related applications, this paper primarily focuses on novel AI techniques for voltage stability assessment (VSA), frequency stability assessment (FSA), large-disturbance rotor angle stability, i.e., transient stability assessment (TSA) and fault detection (FD).

A. Voltage Stability Assessment

Voltage stability, is referred to as “the ability of a power system to maintain steady voltages close to nominal value at all buses in the system after being subjected to a disturbance” [16]. Ensuring that the voltage is within acceptable voltage levels under varying operating conditions is a critical feature of power system reliability and is influenced by factors such as changes in power demand, fluctuations in generation output, network topology, and system configuration.

There are numerous methods for voltage stability monitoring in the literature. Most commonly, they are divided into time-domain simulation methods, the Lyapunov function methods and nonlinear dynamic methods [3]. Conventional time-domain simulation methods rely on solving a system of differential/algebraic equations that consists of the dynamic characteristic equations of the generator and the system power flow equation [1], such as [17], where the stability index can be established based on the maximum power transfer to the load. Whereas Lyapunov function method consists of determining a Transient Energy Function corresponding to the critical stability of the system, that is, the critical energy [18], nonlinear system methods mainly include central manifold theory, bifurcation theory and chaos theory. However, the abovementioned methods have several setbacks, such as heavy and time-consuming computation [19], and the difficulty to accurately estimate stability region after failure of power systems as the Jacobian matrix becomes singular near the maximum loading point, so it is numerically difficult to obtain the power flow solution [20].

With the advancement of deep learning technology and algorithms which are capable of learning patterns and relationships in the data, researchers have recently shifted their focus to VSA by using data-driven methods. These methods mostly rely on AI generating databases as input of established networks through a large number of off-line simulations and using intelligent algorithms to construct stable classifiers, which are used for assessing the stability of the system [21]. The data-driven methods generally include ANNs, such as a method that utilizes feed-forward neural networks to estimate voltage stability indices (VSI) from an artificially generated dataset [22], calculating different VSI (such as voltage collapse proximity indicator and voltage stability boundary) from PMU dataset [23], or estimating the voltage stability margin use of existing advanced metering infrastructure of smart meters (AMI) [24]. Furthermore, ANN-based methods involve using imperialist competitive algorithm (hybrid ANN-ICA) to obtain Voltage Stability Margin Index (VSMI) [25], as well as defining the stability index as a ratio of lowest singular value to the minimum singular value for the no-load operating conditions based on Multilayer Perceptron (MLP)-based neural networks based on a power flow model and singular value decomposition of the reduced Jacobian matrix [26]. Recent studies based on CNNs include a two-stage short-term voltage stability event detector comprising a 1D-CNN-based fast voltage collapse detector and a 1D-CNN-based regressor to quantify the severity of the short-term voltage stability event [27], a two-level approach in which the substation level adopts a more detailed system model rather than Thevenin equivalent circuit [28].

Other data-driven approaches are based on SVMs, DTs, such as a fuzzy-tree algorithm-based model for the purpose of evaluating the risk of voltage instability [20], classification and regression tree (CART)-based method which extracts a given time series of electric parameters and takes the morphological similarity distance as the time sequence feature [29], Voltage Stability Load Index-based DT [30], a PMU placement algorithm based on CART to identify the most sensitive buses prior to on-line voltage security assessment [31], a tree using a maximum-entropy-based clustering algorithm on a dynamical voltage pattern according to voltage dynamical entropy for short-term signals [32]), random forests (e.g., a method to predict long-term voltage stability margin as represented by Loadability Margin, by using different Voltage Stability Indices as inputs to an ensemble of ML models that employ RF regression [33]), as well as hybrid methods (a method which calculates the stability index based on conventional impedance matching theorem, calculating the load impedance and estimating the distribution system as an equivalent impedance [34], or a method that employs PMU data to calculate maximum Lyapunov exponent based on phase rectification and MLE to forecast transient profile of power system [35]). Table I. summarizes recent advancements in AI techniques utilized for VSA.

B. *Frequency Stability Assessment*

Frequency stability refers to the ability of a power grid to maintain steady frequency after being subjected to a severe system upset resulting in a significant imbalance between generation and load [9]. Ensuring that the power system maintains a stable frequency in case of disturbances has been a critical aspect of power system operation and control. Traditionally, this stability has been maintained by the inherent inertia of synchronous generators, which can absorb or release energy to counteract frequency deviations [49]. However, the increasing integration of inverter-based renewable energy sources, which lack physical inertia, poses new challenges to frequency stability.

Conventional methods for assessing frequency stability include analyzing the system's inertia and its ability to withstand disturbances without significant frequency deviations. These methods often rely on simplified models and assumptions about the system's dynamic response. They typically involve linearized small-signal models, eigenvalue analysis, and system frequency response (SFR) techniques, which evaluate the ability of the power system to maintain stable operation following load-generation mismatches or sudden losses of generation [50]. These methods assume adequate system inertia and controllable spinning reserves, which are increasingly being compromised due to the integration of inverter-based renewable energy sources such as wind and solar, which lack inherent rotational inertia [49]. As a result, traditional tools are less effective in low-inertia systems, prompting the need for enhanced assessment frameworks.

Recent studies have highlighted the need for more advanced assessment techniques using PMUs, virtual inertia modeling, and model predictive control to better assess and enhance frequency stability [51]. Such improvements allow dynamic tracking of frequency variations and more robust control under rapidly changing operating conditions. Therefore, while conventional assessment methods laid the foundation for operational security, evolving grid architectures necessitate a transition to data-driven, adaptive, and real-time capable stability assessment tools.

TABLE I. SUMMARY OF RECENT AI-BASED METHODS FOR VOLTAGE STABILITY MONITORING.

Ref.	Year	Method/Algorithm	Description	Results	Test model
[36]	2022	Kernel Extreme Learning Machine (KELM)	KELM-based long-term voltage stability assessment using PMU data	Accurate identification of voltage instability with low comp. time and high generalization capability.	IEEE 39-bus system
[37]	2024	SVM, RF, Gradient Boosting (GB)	Used network topology behavior as input formulation to predict voltage conditions in power systems using multiple ML techniques.	Achieved high prediction accuracy with MCC of 0.98 for RF and 0.87 for SVM and GB	Not specified
[38]	2025	Wavelet Transform + Vision Transformer + Transfer Learning	An interpretable transformer model for real-time voltage stability under incomplete data conditions.	Outperformed conventional DL models under data scarcity, noise, and imbalance scenarios.	IEEE test cases
[39]	2025	Adversarial Deep Learning (LSTM + GAT, SNCWGAN-GP)	Resilient STVSA model under adversarial cyber-attacks using LSTM-GAT with adversarial training.	Demonstrated robustness and improved generalization under cyber-attack scenarios.	IEEE 39-bus system
[40]	2024	Recurrent Neural Network + Greylag Goose Optimization	Real-time load margin estimation using RNN with optimal PMU bus selection via Greylag Goose Optimization.	Effective monitoring of voltage/load margin with minimal model parameters and convergence time.	Not specified
[41]	2024	Edge Graph Convolutional Network + Deep Reinforcement Learning	Introduces EGCN-DNN for real-time emergency voltage control to enhance transient stability.	Reduced load shedding time and improved adaptability to grid topology changes.	IEEE 39-bus and IEEE 118-bus systems
[42]	2025	Safe Reinforcement Learning (SRL) + Adversarial RL	SRL for safe control actions and adversarial learning to improve strategy resilience for short-term voltage stability.	Increased robustness and safety in STVS emergency control strategies.	IEEE 39-bus and Guangdong Power Grid
[43]	2024	Adaptive Neuro-Fuzzy Inference System (ANFIS)	A hybrid approach combining ANFIS and voltage stability indicators for predicting voltage collapse points.	Demonstrated accurate prediction of collapse proximity compared to other methods.	IEEE 14-bus and 118-bus systems
[44]	2020	Variational Autoencoder (VAE)	Unsupervised VAE model using PMU data for long-term voltage stability estimation.	Successfully predicted proximity to voltage collapse point using latent features.	Multiple IEEE test systems
[45]	2022	Gated Recurrent Graph Attention Network (GRGAT) + Adversarial Domain Adaptation	A distributed, transferable STVSA model using GRGAT with spatial-temporal learning and adversarial training for topology adaptation.	High accuracy with reduced computation and adaptability across grid changes.	IEEE 39-bus system
[46]	2024	Transformer + Conditional Wasserstein GAN (CWGAN-GP)	Transformer-based DL model (StaaT) for STVSA with class imbalance using GAN to generate minority class samples.	Outperformed CNN, BiGRU, and LSTM under extreme imbalance and noise conditions.	IEEE 39-bus system
[47]	2021	Deep Neural Network (end-to-end)	End-to-end framework using raw voltage and angle measurements for continuous STVSA prediction with minimal feature engineering.	Effective in identifying instability onset; validated feasibility of data-driven STVSA.	Not specified (sliding window approach)
[48]	2022	Weighted Least Square (WLS)-SVM	A comprehensive scheme for online VSA using WLS-SVM factoring in the effect of overcurrent protection	Highly accurate real-time VSA performed by predicting voltage stability index using WLS-SVM	IEEE 39-bus and IEEE 118-bus systems

In this context, AI-based techniques represent a prominent solution due to their inherent features. Some of the proposed approaches are based on ELM predictor that outputs a continuous frequency stability margin index to measure the stability degree [52]. A study by Wang et al. highlighted the improved accuracy and effectiveness of dynamic security assessment using DL techniques, including CNN, LSTM, and RL. LSTM is used in combination with CNN to harness both spatial and temporal measurements in the input data, through a four-dimensional tensor input construction process and learn patterns associated with system instability in [53], where it was proven that LSTM's architecture may enable it to capture sequential dependencies in system frequency variations with a superior accuracy because of the ability to exploit spatial-temporal information. Another study [54] demonstrates how eXplainable AI (XAI) alleviates the issue of AI models' intrinsic black-box character by revealing critical dependencies and influences on the power grid frequency and accurately predicting frequency stability indicators (such as RoCoF and nadir) for three major European synchronous areas. RL methods for maintaining frequency stability in inverter-based grids have been studied, where frequency controllers are trained via Deep Q-Networks (DQNs) [55] and Policy Gradient algorithms [56]. These RL-based controllers are able to adapt to changing grid topologies and disturbances without requiring explicit modeling, showing better adaptability and learning efficiency than rule-based controllers. Moreover, the prominence of RL-based method is demonstrated on an RNN-trained distributed transient frequency controller with stability and safety guarantees using Lyapunov and safety-critical control [57]. The model tested on the IEEE 39-bus system has shown an improved optimality while maintaining stability and safety. Another research [58] has confirmed that frequency stability can be successfully controlled in a setting that involves a diesel generator with ultracapacitor-based ESS, where ANNs were used to emulate the diesel generator's behavior. The ANN-based virtual synchronous generator outperformed PI and adaptive VSM controllers in improving frequency stability. Some studies [59] have proposed various Hierarchical Deep Learning (HDL) based approaches such as RCNN, LSTM, and CNN and introduced a HDL-RCNN architecture for voltage and frequency stability in microgrids with transfer learning and layered control strategies that reduced voltage oscillations to 0.004 p.u. and frequency fluctuation to 0.007 p.u. with high robustness. Furthermore, a recent study [60] tried to incorporate fuzzy logic and arithmetic optimization methods and proposed a self-adaptive Virtual Inertia Control (VIC) with secondary frequency control using fuzzy PID in microgrids. Real-time validation via OPAL-RT showed improved frequency response and system stability.

C. *Transient Stability Assessment*

Transient stability, the capability of synchronous machines within an interconnected power system to maintain synchronism following a disturbance, has traditionally involved time-domain simulations that are computationally intensive and challenging to implement in real-time applications due to the unavailability of certain state variables [61]. Moreover, the extended equal area criterion is only applicable to classical generator models, limiting its practical use.

Recent literature on the TSA suggests a shift towards more data-focused ML methodologies. The generally accepted methodology consists of two stages: offline learning and online application. Whereas the offline phase involves different AI models that are trained from historical databases or artificially generated data, the online phase makes use of the wide-area measurement systems (WAMS) that process the data coming from PMUs and input the processed real-time measurements into the trained AI models [9]. The models subsequently provide key information to the system operators and assist in making control decisions. To achieve this, there have been numerous machine learning approaches in the recent literature, mostly based on CNN, RNN, SVM and Deep Belief Networks (DBN). A CNN-based model that not only assesses power system transient stability but also differentiates between two instability modes, aperiodic and oscillatory, using raw voltage phasor data from PMUs is proposed in [62]. By employing a streamlined end-to-end architecture and training with stochastic gradient descent with warm restarts, the model demonstrates superior accuracy, scalability, and robustness to both noise and missing data across benchmark (IEEE 39-bus) and large-scale (WECC 179-bus) systems. Another study [63] suggests a fast small signal stability assessment using CNN variants (FCN, Time LeNet, Time CNN, Encoder, ResNet) trained on PMU data with remarkable results, matching or exceeding the Prony method in reliability and outperforming it in speed and matched or exceeded in reliability. Recent studies based on SVM approaches mostly focus on addressing false classification in TSA by Aggressive SVM and Conservative SVM [64], improving feature extraction of SVM using pinball loss and SMO [65], enhancing SVM algorithm's characteristic vectors with Mahalanobis distance [66], as well as reducing misclassification likelihood in TSA by using Multi-layer SVM (ML-SVM) Employed Genetic Algorithm (GA) to identify valuable feature subsets. The results have shown improved interpretability, reduced false alarms and missed detections [64], higher accuracy and precision in transient state evaluation [66].

With regards to the most optimal method, there have been conflicting opinions based on different studies. Studies such as [67] suggested that SVM has multiple advantages over ANN, such as less number of tuning parameters, less susceptibility to overfitting, and the complexity is dependent on number of support vectors rather than dimensionality of transformed input space. Nevertheless, a comparative analysis of ANN and SVM for online TSA considering uncertainties [68], has assessed TSA under various uncertainties like load, fault type, and location and found that ANN outperforms SVM in classification and computational performance. Therefore, an optimal approach may be similar to the one developed in [69], which is a hybrid approach of SVM-based CNN for TSA based on time-domain analysis parameters that can minimize operational workload and improve efficiency of TSA. An alternative proposal [70], based on ELM combines several major AI techniques (SVM, DT, LR, KNN) in a flexible framework combining ML algorithms for dynamic transient stability prediction, including instability time achieved a prediction error of 0.03s for instability time; and a system accuracy that could reach up to 100% and validated the approach on the IEEE 39-bus system. The potential of ELM for TSA was also proven by successful prediction of TSA indicators using Stacking Ensemble Deep Belief Network (SEDBN) combined with AFO (Aptenodytes Forsteri Optimization) to minimize control cost [71]. The method achieves effective control under constraints with improved robustness and generalization.

D. Fault Detection and Classification

Fault detection and classification (FDC) play a crucial role in preserving the reliable and secure operation of contemporary power systems, mainly in fast service restoration in the event of various contingencies. Traditional methods often rely on threshold-based relay settings or phasor analysis, which may not be effective under evolving grid conditions or high-penetration renewables. Moreover, the evolving complexities of power grids propelled by the renewables' integration and demand side response necessitate more sophisticated solutions. Due to AI's superior performance in classification and pattern recognition even under noisy, faulty or incomplete data, several techniques have been suggested in the literature. The most prominent examples are ELM and SVM, which are used to classify transmission line faults with over 99% accuracy on simulated datasets [72]. Moreover, studies on medium-voltage systems [73] have demonstrated that CNNs combined with Park transform techniques can achieve accurate fault localization. Additionally, VAEs have proven effective for anomaly detection in photovoltaic systems, achieving classification accuracies exceeding 92% [74]. Table II. summarizes recent advancements in AI-based methods for FDC.

IV. CHALLENGES OF AI-BASED METHODS IN STABILITY MONITORING

Despite numerous benefits outlined in the previous sections, the implementation of AI-driven techniques still faces a number of potential challenges. Apart from algorithm-specific limitations, major challenges include data quality and availability, model interpretability, model generalization and adaptation, model robustness and integration.

A. Algorithm-specific Limitations

There have been numerous drawbacks associated with AI-based methods in the context of power system stability assessment. For instance, it is found that ANNs require extensive training time and complex design process, may achieve poor generalization for extrapolation tasks, as well as be prone to overfitting the data [68]. SVMs often suffer from the assumption of linear separability, which is rare in real-world TSA problems, in addition to being less interpretable than some other techniques such as DTs [80]. Furthermore, their performance highly depends on the choice of kernel and tuning. Whereas DTs have a high tendency to overfit data and are sensitive to small changes in input data [81], RFs' main limitation tends to be the computational burden and the absence of explicitly optimized decision margin [10]. Overall, the main algorithmic drawbacks often are the possibility of overfitting with limited training data and the feature selection-dependent performance.

B. Data Quality and Availability

AI models often require large, high-quality labeled datasets. Real-time power system data is often incomplete, noisy, or imbalanced, which negatively impacts model performance [9]. Thus, the data errors caused by sensors, communication failures, or cyber-attacks, require preprocessing such as denoising, imputation, and feature correction. GANs and autoencoders are explored for data completion, but their reliability varies [21].

C. Model Interpretability

Deep learning models (e.g., DNNs, LSTMs) often operate as black boxes, meaning that their decision logic is hard to interpret [82]. This hinders adoption in critical applications where operators need transparency and trust in automated decisions, such as stability control and protection systems [9].

D. Model Generalization and Adaptation

A major setback of the deep learning models often is their lack of generalization capability, i.e. the need for retraining in case of any change of environment occurs, such as topology, load profile, DER mix etc. Due to this phenomenon, models may practically become obsolete [21]. Transfer learning is suggested as a mitigation method [9] but still requires more research effort and exploitation in real-world stability monitoring applications.

E. Model Robustness and Integration

AI systems are sensitive to input and sensor anomalies, adversarial attacks and communication delays. These factors may lead to false predictions or unstable control actions in real-time systems [82]. Moreover, data corruption as a result of cyberattacks is another pressing concern that needs to be addressed in the future. Finally, the potential practical barrier is also the ability of AI to integrate with physical infrastructure due to potential communication constraints, lack of edge-computing readiness, and untested scalability in real grids [82].

TABLE II. SUMMARY OF RECENT AI-BASED METHODS FOR FAULT DETECTION AND CLASSIFICATION

Ref. no.	Year	Method/Algorithm	Description	Results	Test model
[75]	2024	Multi-layer SVMs	Proposes an end-to-end imbalanced fault diagnosis method using transfer learning and oversampling techniques with ML-SVMs.	Outperformed 8 oversampling-based algorithms in robustness and recognition rates.	CWRU, IMS, PHM 2010, TTWD datasets
[76]	2024	Optimized SVM (IPSO-SVM)	Multi-classifier disruption prediction model for EAST using diagnostic signal-specific sub-classifiers weighted via improved PSO.	Achieved a true positive rate of 93.9% and false positive rate under 4.99%.	EAST tokamak disruption dataset
[73]	2024	CNN + Park Transform + PFPT Sine Fitting	Park transform and CNN for classifying and locating faults using 3D voltage waveforms.	93.1% fault classification accuracy, efficient under noisy conditions.	MV Distribution Network
[77]	2024	Teager-Kaiser Energy Operator + Autoencoder (LSTM)	Combined TKEO with LSTM-based autoencoder to detect PMU-based power system events	Accurately detected single and multiple events in real and simulated PMU data.	Modified WECC 179-bus system, New England ISO
[74]	2024	VAE + Anomaly Detection	Used VAE with multiple detectors (IForest, LOF, EE, 1SVM) to detect PV system faults	Accuracy up to 92.99% in MPPT/IPPT modes	GCPV test setup using GPVS-Faults
[78]	2022	Gaussian Naive Bayes + ML Classifiers	Simulated faults in PSCAD; compared GNB, KNN, SVM, DT, RF, ABC for classification accuracy	Noise-resilient fault classification using frequency and time-domain features	220kV, 100km TL in PSCAD
[72]	2023	ELM	Used ELM for fast FD/FC on simulated data from two TL systems.	>99% accuracy and low computational cost	2 Simulink TL models
[79]	2024	ELM + Identity Feature Vector	Used DWT + ELM to classify 12 types of disturbances (single and combined).	99.75% average accuracy; robust against noise.	Synthetic dataset

V. CONCLUSION

The examined literature highlights a major shift in power system stability monitoring, driven largely by the adoption of AI techniques. The analyzed AI-based methods cover a broad spectrum of stability monitoring applications, including frequency, voltage and transient stability assessment, as well as fault detection and classification. Across all domains, data-driven approaches, such as support vector machines, decision trees, random forests, neural networks, ensemble and hybrid frameworks, consistently outperform traditional approaches, particularly in noisy or imbalanced datasets. While challenges remain, such as explainability, real-time implementation, generalization, model robustness and cybersecurity, the collective evidence suggests that AI-driven solutions can substantially improve power system resilience, efficiency, and adaptability, ultimately supporting the transition toward smarter, greener, more efficient and autonomous grids.

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