International Journal of Scientific Research and Engineering Development-– Volume 7 Issue 3, May-June 2024

Available at www.ijsred.com

RESEARCH ARTICLE OPEN ACCESS

Survey on Advanced Machine Learning Techniques for Predicting Smart Grid Stability

Abdulaziz Salihu Aliero[1]

[1]School of Computer Applications, Lovely Professional University,Punjab,India

[1]Department of Information and Communication Technology,
Kebbi State University of Science and Technology Aliero, 1144 Nigeria

abdulaziz.12306122@lpu.in, abdulaziz.salihu@ksusta.edu.ng

--************************--

***Abstract*:**
Smart grids transform the electricity sector into an intelligent, digital energy network, integrating information, telecommunication, and advanced power technologies. Artificial Intelligence (AI) is a key driver, enabling intelligent decision- making and response to sudden changes in customer energy demands, power supply disruptions, or renewable energy output fluctuations in a smart grid. This paper survey advanced ma- chine learning algorithms for predicting smart grid stability using ad at a set from simulations. The XG Boost classifier outperformed other models with high accuracy demonstratingpromisingperformance.In future as the smart grid involves vast data, the ML models can be improved over time and new predictive models can be deployed. So everything hinges on data and data is the key to unlock ML. Hence, AI and ML can be used to boost the performance of smart grids.

***Keywords*— sustainability prediction, machine learning, artificialintelligence,comparativeanalysis,smartgridtechnology**

--************************--

I. INTRODUCTION

The need for energy worldwide is rising quickly. Thus, in order to make the energy systems more effective, adaptable, and sustainable, they must be updated and evolved. The term “smartgrid”referstotheintegrationofdigitalcommunication and information technology with traditional electrical grid infrastructure. A smart grid is a network of self-sufficient systems that allow the integration of conventional and non-conventional power generation sources to the electrical grid, reducing the need for labour while providing consumers with safe, dependable, high quality, and sustainable electricity [1], [2]. With the use of digital communication systems, smart metres, smart appliances, renewable energy resources, and energy efficient resources, smart grids allow for the two-way flow of data and electricity.With the use of digital communication systems, smart metres, smart appliances, renewable energy resources, and energy efficient resources, smart grids allowfor the two-way flow of data and electricity. Power systems are more secure, reliable, and efficient when there is two-way communication between electricity producers and consumers as well as bidirectional power flow[3],[4].Advanced control, communication, and metering technologies are integrated and linked into the smart grids. This lead to results in the production of massive volumes of multi-type, high-dimensional data. It takes coordination, storage, and collecting to handle such vast volumes of data. The data processing capabilities of the current technology are severely limited. Artificial Intelligence (AI)approachesmustthereforebeusedinsmartgridapplica- tions.Artificialintelligence(AI)toolsofferaneffectivemeans of analysing data, drawing conclusions from it, and makingthe right decisions to guarantee that the grid is operating as planned. AI has the power to completely transform the energy sector. Artificial Intelligence (AI) has the potential to function as the central nervous system of the smart grid, gathering and analysing vast quantities of data from numerous smart sensors and making prompt choices to improve the grid’s stabilityanddependability.AIiscrucialtousingthevastamount ofdatathatcouldbevaluableandproducinginsightsthat can be put into practice. Conventional methods require vast amounts of intricate data, which lengthens computation times and often reduces accuracy. AI and machine learning (ML) provide a simple way to overcome this problem [5], [6]. With the use of artificial intelligence (AI) and machine learning (ML), suppliers may better analyse customer behaviour and determinetheirpreciseelectricityneeds.Additionally,thiswill make it possible to generate the appropriate kind of billing data. Customers will be able to obtain pricing and energy usage information through the integration of AI and ML with smart grids, enabling them to actively respond to requests to reduceenergyuseduringperiodsofpeakenergydemand.This will ultimately lead to smart grids operating more efficiently. By integrating Information and Communication Technologies (ICTs) into smart grids, producers and consumers can take an activeroleinensuringthatthesystemcontinuestooperate as planned. Establishing communication between the utility producing the electricity and itscustomers is necessary to turn thegridsmart.Theprincipalgoalsforthedeploymentofsmart grids are

- Enhancingthemanagementofdemand
- Boostingenergyefficiencyand
- Encouraging a self-healing grid for increased resilience and dependability

Demand response (DR) is a concept that has been developedto further modernise smart grids as a result of technological advancements.Increasedcustomercontrolandcostreductions are made possible by DR. Customers are given the option to voluntarily shift or cut back on their electricity use duringpeak hours in exchange for a variety of incentives, such as discounted prices. DR programmes are being used by utilities andoperatorstobalancethesupplyanddemandofpowerin a changing market. DR analysis's primary goals include: lowering the overall amount of power generated; decreasing the overall amount of electricity consumed encouraging the use of clean, green energy and getting rid of line overloading. DR is one of the most important concepts in smart grids. By adjusting their electricity use in reaction to fluctuations in the price of electricity over time, DR enables end-use customersto significantly contribute to the functioning of the smart grid [7], [8], and [9]. It is anticipated that customer consumption patternswillshiftifthetarifforconsumptionratecontinue to fluctuate. Additionally, in DR, users receive incentives to encourage them to use less electricity during periods when market prices are high or the smart grid's dependability is in doubt.Inordertoattainalowpeakloadcurveandlowerpower costs,demandresponse(DR)isimplementedatboththeutility andconsumerlevels[10],[11],[12].Itispossibletoanticipate customer electricity use and automate demand response (DR) withtheintegrationofnewer,moresophisticatedtechnologies like artificial intelligence (AI) and machine learning (ML) with smart grids [13], [14], [15]. Large amounts of data are involved in the smart grid, therefore new prediction models may be implemented and the ML models can be enhanced over time. Thus, data is everything, and data is the key to unlockingmachinelearning.Thus,smartgridperformancecan be increased with the application of AI and ML.

A. *Motivationandcontribution*

Over the next few decades, it is anticipated that energy consumption will rise very high as a result of the world's growing population, industrialization, and expanding global economy. With this increase in electricity demand the traditional grid can not handle it, consumer data can be combined with smart grid technology to create an effective electricity distributionnetwork.Themotivationbehindsmartgridsis to address the limitations and challenges of traditional power grids. The power system is becoming more complicated, and traditional grids are not resilient or scalable enough to handle it,suchastheintegrationofrenewableenergysourcesand the growing scale of the grid [30], [31]. Furthermore, finding patternsandstandardsintheproductionprocessandextracting knowledge from aggregated data are the driving forces behind machine learning and deep learning. In the industrial sector, these methods are crucial, especially for smart manufacturing and the smart grid paradigm. ML and DL can increase output, findproductflaws,andforecasthowlongmachinerywill last with the help of diagnostic, descriptive, prescriptive, and predictiveanalytics.ApplicationsforMLandDLtechnologies can also be found in smart grids, secure IoT architectures, transportation, logistics and supply chains, and electric machine condition monitoring. The use of ML and DL technologies is becoming more widespread and promising, with advantages including increased general quality, dependability, andsafetyinavarietyofdomains[32],[33],[34].However, smart grids aim to improve energy efficiency, interaction, security, and stability analysis in the power system [35]. They are designed to be self-healing, adaptable, and capable of integratingvarioussystems,suchasinformationsystems,

thermal energy systems, and transportation systems [36]. Smart grids enable customers to send information to the grid station and improve communication between the grid station and customers, allowing for real-time information exchange and demand management [33]. Additionally, smart grids facilitate the incorporation of renewable energy sources and assist inthe growth of the electrical market more effective, reliable,and persistent energy network.

In light of the above, the primary contributions of this survey can be summed up as follows: An overview of ML, DL, and SG has been explored to get in-depth knowledge behindthemandreviewtheapplicationsofMLandDLin SGsystems,whichincludeloadforecasting,gridstability,load optimization, and anomaly detection.

B. *Paper organization*

Thepaper'sorganizationisdelineatedasfollows:Section I comprises the introduction, succeeded by literature review of smartgridsinSectionII,propose methodologyinSectionIII,acomprehensivereview and discussion of existing literature, exploration ofchallengesandfutureprospects and lastly the paperend with conclusions.

II. LITERATUREREVIEW

AIhasbeengainingahugemomentumandhasbeenmaking a tremendous impact in the recent world. The transition of traditional electric grid system to the smart grid can be achieved through the integration of AI and ML techniques with the existing conventional methods. With the emergence of AI and ML the reliability and the resilience of smart grids can be improved. AI techniques can be applied to load forecasting, power grid stability assessment, faults identification and security issues with the power and smart grid systems.Theimplementationofseveralmachinelearningtechniquesto improve the responsiveness, efficiency, security, stability, and reliabilityofsmartgridshasbeenevaluatedbyAzadetal.[16]. Additionally, some of the difficulties in putting ML solutions for smart grids into practice have been covered. In order to examine the impact of customer schedulable loads and the an- ticipateddailyelectricitypriceprofileonaggregatorrevenues, Zheng et al. [43] have created machine learning models based on past data. Compared to other ML classification and regres- sion algorithms, K-Nearest Neighbour (KNN) and Gaussian progressregressionhavedemonstratedconsistentperformance andyieldedcorrectresults,whichiswhytheywereselectedfor theirstudy.Bomfim[17]haslookedintohowmachinelearning has evolved in the context of smart grids. He gave a summary of studies that have using machine learning (ML) to study smart grids. These studies were conducted by quantitatively describing journal articles and newspaper articles that were registeredintheIEEEXploreLibrarydatabase.According to his poll, the electrical network's safety and dependabilityas well as energy management and forecasting are the two main areas of research on smart grids. You et al. [18] have demonstrated how AI may be able to reduce the amount of timeneededformodelcreationandnumericalcomputation

when compared to traditional simulation-based techniques. Thebenefitsofmachinelearningtechniquesinidentifyingand analysing features for the design of contemporary industrial systems, including smart grids, have been demonstrated by Gunel and Ekti [19]. They gave a quick overview of thesmart grid's applications and talked about machine learning algorithms.Vermaetal.[20]havedescribedhowtheadventof forecasting techniques like artificial neural networks (ANNs), deep learning techniques, etc. has expanded the scope of planningandoperatingsmartgrids.Inthisstudy,asurvey ofworkspertainingtoseveralcomponentsofthesmartgrid is presented. The works are categorised according to the computational intelligence techniques that were employed to solve the planning or operation problem. A thorough and understandable overview of the most recent developments in AI approaches for stability analysis and control in smart grids hasbeenprovidedbyShietal.[21].Theyhavegivena broad synopsis of artificial intelligence, covering its defini- tions, background, and current approaches. Following that, they provided a thorough analysis of AI applications for smart grid security assessment, stability assessment, fault detection, and stability control. The application of AI-based methodshas produced outstanding outcomes. Furthermore, they have talked about the main obstacles that arise when implementing AI-based solutions, including the need for a large amount of data,unevenlearning,theinterpretabilityofAI,problemswith learning transfer, the resilience of AI to poor communication quality, and the resilience against adversarial examples or attacks. Additionally, they have offered viable ways to get beyond these barriers to close the knowledge gap between academiaandindustry,whichwillpromoteAIapplicationsfor smartgridstabilitycontrolandanalysis.Giventhecomplexity, unpredictability, and volume of data related to smart grids, artificial intelligence techniques can be utilised to support the advancement and success of smart grids. The application of AI-based methods has produced outstanding outcomes. Fur- thermore, they have talked about the main obstacles that arise whenimplementingAI-basedsolutions,includingtheneedfor a large amount of data, uneven learning, the interpretability of AI,problemswithlearningtransfer,theresilienceofAItopoor communication quality, and the resilience against adversarial examples or attacks. Additionally, they have offered viable waystogetbeyondthesebarrierstoclosetheknowledge gap between academia and industry, which will promote AI applications for smart grid stability control and analysis. Artificial intelligence (AI) approaches can be used to support thedevelopmentandsuccessofsmartgridsinthefuture,given their complexity, ambiguity, and vast volume of data. Zhanget al. have provided a summary of the potential applicationsof deep reinforcement learning (DRL), reinforcement learning (RL),anddeeplearning(DL)insmartgridsintheirstudy[22]. Additionally, they have given a summary of the most current developmentsinthestudyoftheirusesinsmartgridtechnolo- gies. AI 2.0 is rapidly growing as a result of the decliningcosts for processing power, an abundance of data, and the accessibility of improved AI algorithms. Since smart grids are the power systems industry's newest trend, their performance shouldimprovewhenartificialintelligenceisincorporated

with current technologies. Compared to traditional electrical systems, the introduction of smart grids promises more ef- fective and efficient electricity generation, transmission, and consumption. DR, a key idea in smart grid technology, pro- motescustomerinvolvementinenergyconservation.Retaining the equilibrium between supply and demand for electricity requirespreciseforecastingofelectricityconsumption.To do this predicting, machine learning (ML) based predictive modelscanbeused.Userstatisticsaresenttotheserverbythe smartmetresintegratedintothesmartgrids.Predictivemodels for processing the data from smart metres can be createdusing machine learning techniques. Ali and Choi [23] have presented an extensive analysis of the most recent AI methods that enable rapid and real-time demand response. Due to the recent rapid advancements in AI, the energy sector has been using expert systems, ANN, and fuzzy logic for demand-side management (DSM) and energy management in residential areas, smart homes that leverage DR programmes, and overall homes. A crucial component of the smart grid's cost-effective reliability improvement is distributed resistance (DR). The fieldofDRresearchhasdrawnmoreattentionthroughouttime.

High complexity, extensive data use, and real-time decision-making are all part of disaster recovery. The use of AI andML is essential to making demand side response possible.The research paper [24] by Antonopoulos et al. is a summary of the artificial intelligence techniques applied in disaster recovery. Their research is grounded in a methodical analysis of more than 160 publications, 40 businesses and business ventures, and 21 significant projects. They have demonstrated the growing demand in the disaster recovery industry for AI- based solutions. Artificial intelligence (AI) techniques have produced tools for prediction, effective real-time control of networked systems, and decision-making for use in disaster recovery. load prediction and estimation are essential to the operation of the power system; AI and ML techniques have been used in load forecasting in DR. Artificial Intelligence techniques have also been used to forecast electricity costs. Thus, the grid operators are able to preserve the equilibriumof the grid's operations thanks to the uses of AI in DR. An enormousamountofdataonelectricityusefromtheclientside is generated by the installation of many smart metres and can be analysed. To build dependable and energy-efficient smart grids, probabilistic load forecasting (PLF) must be developed.

AmethodknownasBayesiandeeplearninghasbeenused by Yang et al. [25] to tackle this difficult issue. They have suggested creating a brand-new multitask PLF framework based on Bayesian deep learning in order to measure the uncertainties that are shared by various customer groupswhile taking their differences into consideration. They have developed a clustering-based pooling technique to boost data amountandvariety,whichlowersoverfittingandenhancesthe prediction performance of the model. Their suggested model performed better than the traditional methods, as shown bythe test results that were collected. For the creation of future smart grids, energy load forecasting is crucial. Traditional statisticalandmachinelearningmethodshaveahighdegreeof overfitting and forecasting error. For the purpose of managing energyconsumptioninsmartgrids,MohammadandKim have presented an energy load forecasting (ELF) model based on deep neural network architectures in their paper [26]. Research has been done on the effectiveness and applicability of deep recurrent neural networks (deep-RNN) and deep feed-forward neural networks (deep-FNN). A multi-size trainingset was used to replicate both designs. The architectures' performances with different combinations of hidden layersand activation functions have also been evaluated, and the simulationresultshavebeencomparedintermsofmeanabso- lute percentage error. They have deduced that their proposed model has performed better than the current load forecasting models based on the experimental data. A precise deep neural network technique for short-term load forecasting (STLF) has been introduced by Kuo and Huang [27]. Five additional widely used AI algorithms—Random Forest (RF), Support Vector Machine (SVM), Decision Tree (DT), Multi-layer Perceptron (MLP), and Long Short Term Memory network (LSTM)—have been compared to see how well the suggested load forecasting model performs. Their model yielded very good forecasting accuracy, with Mean Absolute Percentage Error(MAPE)andCumulativeVariationofRootMeanSquare Error (CV-RMSE) of 9.77 and 11.66, respectively. In smart grids, precise and effective price forecasting is crucial to preventing the detrimental effects of price dynamics. Two clevermethodsforapplyingmachinelearningtotheElectricity Price Forecasting (EPF) problem have been put out by Atef and Eltawil [28]. To forecast the hourly price, they initially used a Support Vector Regression (SVR) model, which they compared to the outcomes of a deep learning model. TheSVR model has fared worse than the deep learning strategy, with average root mean square error values of 0.416 and 1.1165, respectively. A reinforcement learning-based decision support system has been developed by Lu et al. [29] to help chooseelectricitypricingschemes,withthegoalofminimising the amount of unhappiness that each smart grid end user experiences with power payments and usage. The decision issuewasdescribedasatransitionprobability-freeMarkovde- cision process (MDP) with an enhanced state framework. The computational and prediction performance was then enhanced by solving the problem using a batch Q-learning algorithm integrated with a kernel approximator. From a continuous high-dimensional state space, their suggested technique may extractthehiddenfeaturesunderlyingthetime-varyingpricing schemes. The test findings are quite encouraging. As a result,a precise predictive policy tailored to each user can be created to lessen their discontent with cost and energy use. With artificial intelligence (AI) shaping the electric power systems of the future, computational intelligence technologies are a useful tool for resolving planning or operational issues in smart grids. Likewise in the current smart electricity grid, the electricity is obtained from the grid and also sold to the grid, and in the future smart grid Electricity is generated from the grid and sold between customers as well as the grid [37] as illustrated in Figure1. There are several types of smart grid whichinclude:Advancedmeteringinfrastructure,Distribution Automation,Renewableenergyintegration,Demandresponse, Energy storage integration, Electric vehicles, and microgrids. Thesmartgridiswellpoisedtofundamentallychangeour

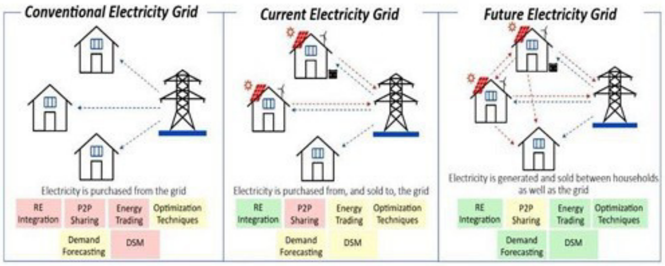

Fig. 1: An illustration of a standard, modern, and prospective electrical grid
[37]

lives with the help of machine learning and deep learning models. Smart grid has several uses for deep learning and machine learning. They can be applied to evaluate and extract usefulinformationfromthevastamountsofdatagenerated in an Internet of Things-based grid system [38]. To efficiently analyze the data and make the right judgments to operate the grid,MLmethodsaremadepossible[39].Thesemethods can be applied to anomaly detection, adaptive control, sizing, consumption, price, power generation, future optimal schedule, and detecting network intrusions in the event of a data leak [40]. In the future, deep learning and big data may be essential tools for resolving issues with the smart grid. It can improve the smart grid's responsiveness, efficiency, security, stability, and dependability.

A. *Whysmartgridareimportant*

The current electricity grid infrastructure was established over a century ago, primarily to meet the relatively straightforward electricity needs of that era. This grid system comprisedpowerlinesandsubstations,facilitatingthetransmission of electricity from coal and fossil fuel-powered plants to residential and commercial properties. The power generation process was localized, with power plants strategically located within communities to cater to modest energy demands. Consequently, the grid was designed to deliver electricity from utilities to individual customer premises.

However,thecontemporaryenergylandscapepresentschallenges that the traditional grid structure struggles to address. The grid's inherent limitation lies in its one-way directional flow,whichimpedesitsabilitytoadapttothedynamicenergy demands characteristic of the 21st century. For instance, disruptions such as power line failures can lead to inadequate energy supply from power plants precisely when demand peaks. Moreover, the current grid predominantly relies on a singular power source, lacks granularity in usage data, and consequently, poses challenges in effective energy management.

To remedy these shortcomings, historical approaches involved the construction of additional power plants. However, the contemporary approach emphasizes sustainability and reduced reliance on fossil fuels, advocating for the adoption ofa smart grid infrastructure.

Likewise, traditional electric power grids encounter intrinsiceffectiveness,lackreal-timesurveillancecapabilities,

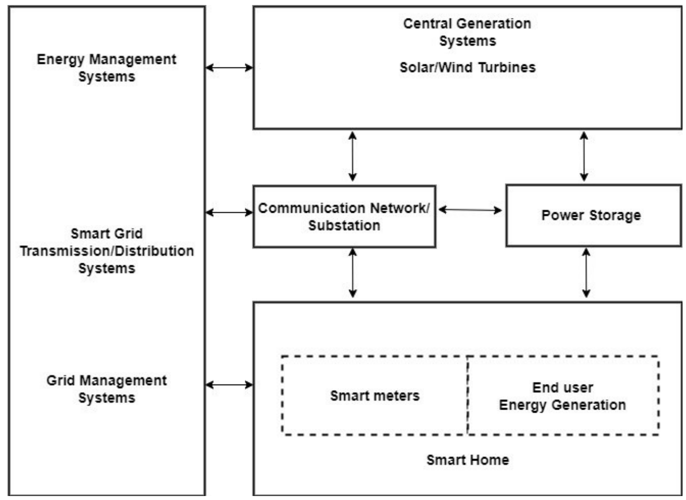

Fig.2:SmartGridArchitecture

and are susceptible to various external challenges. Smartgrids represent a paradigm shift, incorporating contemporary technologies and digital communication strategies to optimize energy production, distribution, and utilization. Within this context,) machine learning (ML) and Deep Learning (DL models have emerged as compelling tools for addressing challenges across various sectors within smart grids [41]. The adoption of machine learning methods within smart grids has gainedsignificanttraction,especiallyinareasthatincludeload balancing, fault detection, energy management, and cybersecurity. Researchers have leveraged algorithms such as support vectormachines(SVM),decisiontrees,andensemblemethods to predict energy demand patterns. Additionally, clustering algorithmshavebeenemployedtogroupconsumerswithsimilar energy consumption profiles, aiding in personalized energy management strategies [42]. For demand forecasting, deep learning models such as long short-term memory networks (LSTMs) and recurrent neural networks (RNNs) have demonstrated superior capabilities in capturing complex temporal relationships. These models have been successfully applied to predictshort-termandlong-termenergyconsumptionpatterns, enabling utilities to optimize resource allocation and grid operations.

B. *SmartgridArchitecture*

A smart grid is a computerized electrical system that improvesthesustainability,efficiency,andconsistencyofenergy delivery through the use of digital technologies to provide a moreintelligentandresponsiveenergyinfrastructure.Traditional grids are not capable of two-way communication, but the infrastructure of the new smart grid, as shown in Figure2, has distributed delivery systems and sophisticated controls. A smart grid's architecture combines several different parts and technologies as follows:

- **Smart Metering:** Smart meters, facilitating bidirectional communicationbetweenutilitiesandcustomers,areubiquitous within smart grid infrastructures. With the utilization of these meters, energy usage can be monitored in real time, improving demand responsiveness, billing accuracy, and outage management.
- **Communication Networks:** Powerful communication networks are necessary for information sharing amongst the various smart grid components. This covers both conventional and wireless communication technologies, including cellular networks, WiFi, and fiber optics.
- **Sensors:** The grid is equipped with sensors that gather information on voltage, current, and temperature, among other characteristics. By enabling utilities to promptly detect and resolve problems.
- **Grid Management Systems:** The smart grid is monitoredandcontrolledbysophisticatedsoftwareandcontrol systems. Utilities can use these systems to detect and address defects, optimize the distribution of energy, and instantly balance supply and demand.
- **Solar panels and wind turbines:** The advent of the smartgridheraldsaparadigmshiftintheutilization of renewable energy sources. Power generation is now diversified across multiple sources, resulting in a more robust and efficient system. Renewable resources like wind and solar energy, being sustainable and increasingly prevalent, play a pivotal role in modern electric power generation. However, the intermittency inherentin these renewable sources introduces complexities to conventional grid operations. Thesmartgridinfrastructurefacilitatestheintegration of renewable energy sources by providing essential data andautomationcapabilities.Thisenablessolarpanelsand wind farms to contribute energy to the grid and optimize itsutilization.Thegrid'scapacityforcommunicationand electricity management enhances its intelligence, paving thewayforreducedrelianceonfossilfuelsinthefuture.
- **Cybersecurity Measures:** Considering smart grids primarily rely on digital technology and communication networks, strong cybersecurity defenses are essential to thwartingcyberattacksandguaranteeingtheconfidentiality and integrity of grid data.
- **ElectricVehiclesIntegration:**Smartgridsaremade to facilitate the integration of electric vehicle charging infrastructure in response to the growing popularity of electricvehicles.Toeffectivelyhandletheincreasedload, there's a need for intelligent charging stations and grid control technologies.
- **Grid Storage Systems:** Batteries and other energy storage devices are essential for balancing changes in supply and demand. They store extra energy at times of low demand and release it during moments of high need.
- **Analytics and Data Management:** Through advanced analytics, the vast quantities of data produced by smart grid components undergo processing and analysis. Utilities can forecast system behavior, maximize grid performance,andmakewell-informeddecisionswiththeaidof this data-driven strategy.

III. PROPOSEDMETHODOLOGY

Inthispart,thesuggestedmethodologyhasbeenexplained.

DatasetusedThedatasetthathasbeenusedcorresponds to an augmented version of the ―Electrical Grid Stability Simulated Dataset, created by Vadim Arzamasov (Germany) and donated to the University of California (UCI) Machine Learning Repository. The dataset contains the simulation results of grid stability.

Performance comparison based on training time and prediction time taken by each model The training time is a representation of the length of the time period taken by a classifier from the beginning of the model training to the moment it is ready to perform the task of classification. The prediction time is the duration taken by a classifier to predict the outcome. The training time and the prediction time for each classification algorithm have been extracted. Table VI depicts the performance comparison of the models based on training and prediction times.

Havingpresentedinthepreviousstudythetrainingtimeand the prediction time for Logistic Regression is the minimum at 0.043sand0.001srespectively.ThetrainingtimeforXGBoost classifier is 11.135s and its prediction time is 0.047s. SVM takes the maximum time for training. The training time is 102.53swhichisoveraminute.Thepredictiontimefor SVM is 4.931s. The prediction time for KNN is 16.097swhich means KNN takes the most time for predicting the outcome among the other algorithms. Its training time is however0.395s.NBhasatrainingtimeandpredictiontimeof 0.078s and 0.031s respectively. DT takes 1.117s for training and 0.016s for predicting. The training time and prediction time for RF classifier are 19.022s and 0.447s respectively. SGD classifier is quite fast in predicting the outcomes. Its predictiontimeis0.005s.ThetrainingtimeforSGDis0.771s. Gradient Boosting classifier has a training and prediction time of 31.067s and 0.071s respectively.

CONCLUSION

MLandDLhavegreatpotentialforsmartgridapplications, but there are still several challenges that need to be resolved. These include the intelligibility of black-box models, the robustness of algorithms in the face of adversarial attacks,andthesmoothintegrationofAI-drivensolutionsintoexisting grid infrastructure. Furthermore, winning over stakeholders and getting these technologies widely adopted depends on guaranteeing the security and privacy of critical grid data.

Moreover, the research indicates that enhancing the accuracy, scalability, and efficacy of smart grid management is crucial in domains such as load forecasting, grid stability prediction, load optimization, and anomaly detection. Preprocessingdata,modelcorrectness,scalabilityforhugenetworks, and real-world data validation are among the challenges. Subsequent investigations ought to concentrate on enhancing the resilience of models, including real-time data streams, and evaluating models using field data.

TheapplicationofAIandMLtechniquesinsmartgridsprovides powerful technical support to the digital power systems. In this paper an analysis of nine ML classification algorithms namely,SVM,LogisticRegression,KNN,NB,DT,RF,SGD, XGBoost and Gradient Boosting has been performed basedon six evaluation metrics namely, accuracy, recall, precision, F1-score, AUC-ROC and AUC-PR for predicting smart grid stability from a dataset that has been obtained from the UCI machine learning repository. XGBoost classifier has attained an accuracy of 97.5, recall of 98.4, precision of 97.6, F1-score of 97.9, AUC-ROC of 99.8 and AUC-PR of 99.9 outperforming all the other classification algorithms that have beenimplemented.Thestabilityofsmartgridisanessentiality for enabling efficient power distribution. ML plays a vitalrole in predicting the stability of a smart grid. As part of the future work, other ML models can be deployed for predicting the stability of the smart grids and enhancing their reliability. Also,implementationoftheMLmodelscanbeusedtoachieve stability using the Field Programmable Gate Array (FPGA)

REFERENCES

[1] C. Wietfeld, A. A. Cardenas, H. Chen, P. Popovski and V. W. S.Wong, "Smart Grids",*IEEE Wireless Communications*, vol. 24,no.2,pp.8-9,April2017.

[2] LuisM.Camarinha-Matos,–Collaborativesmartgrids–Asurvey on trends‖, *Renewable and Sustainable Energy Reviews*, vol.65,pp.283-294, Nov.2016.

[3] R. Morello, C. De Capua, G. Fulco and S. C. Mukhopadhyay, "ASmart Power Meter to Monitor Energy Flow in Smart Grids: TheRole of Advanced Sensing and IoT in the Electric Grid of theFuture", *IEEE Sensors Journal*, vol. 17, no. 23, pp. 7828-7837,Dec. 2017.

[4] T.SamadandA.M.Annaswamy,"ControlsforSmartGrids:Architectures and Applications",*Proceedings of the IEEE*, vol.105,no.11,pp.2244-2261,Nov.2017.

[5] B. K. Bose, "Artificial Intelligence Techniques in Smart Grid andRenewableEnergySystems—SomeExampleApplications",*Proceedings of the IEEE*, vol. 105, no. 11, pp. 2262-2273, Nov.2017.

[6] E. Hossain, I. Khan, F. Un-Noor, S. S. Sikander and M. S. H.Sunny, "Application of Big Data and Machine Learning in SmartGrid, and Associated Security Concerns: A Review", *IEEE Access*,vol. 7,pp.13960-13988,Jan.2019.

[7] S.Gupta,R.Kambli,S.WaghandF.Kazi,"Support-Vector-Machine-Based Proactive Cascade Prediction in Smart Grid UsingProbabilisticFramework",*IEEETransactionsonIndustrialElectronics*, vol. 62,no.4,pp.2478-2486,April2015.

[8] S.Ghosh,X.A.SunandX.Zhang,"Consumerprofilingfordemand response programs in smart grids", in *Proc. IEEE PESInnovativeSmartGridTechnologies*,Tianjin,China,2012,pp.1-6.

[9] A.AlmalaqandG.Edwards,"AReviewofDeepLearningMethods Applied on Load Forecasting", in *Proc. 2017 16th IEEEInternational Conference on Machine Learning and Applications(ICMLA)*,Cancun,Mexico,2017,pp.511-516.

[10] J. S. Vardakas, N. Zorba and C. V. Verikoukis, "A Survey onDemand Response Programs in Smart Grids: Pricing Methods andOptimizationAlgorithms",*IEEECommunicationsSurveys&Tutorials*, vol.17,no.1,pp.152-178,July2014.

[11] S. Bahrami, M. H. Amini, M. Shafie-khah and J. P. S. Catalão, "ADecentralizedElectricityMarketSchemeEnablingDemandResponseDeployment",*IEEETransactionsonPowerSystems*,vol. 33,no.4,pp.4218-4227,July2018.

[12] S. C. Chan, K. M. Tsui, H. C. Wu, Y. Hou, Y. Wu and F. F. Wu,"Load/PriceForecastingandManagingDemandResponseforSmartGrids:MethodologiesandChallenges",*IEEESignalProcessingMagazine*,vol. 29,no.5,pp.68-85,Sept.2012.

[13] FahadJaved, Naveed Arshad, Fredrik Wallin, IanaVassileva, ErikDahlquist, –Forecasting for demand response in smart grids: An analysis on use of anthropologic and structural data and short termmultiple loads forecasting‖, *Applied Energy*, vol.96, pp.150-160,Aug. 2012.

[14] RenzhiLu and SeungHo Hong, –Incentive-based demand responseforsmartgridwithreinforcementlearninganddeepneuralnetwork‖,*AppliedEnergy*, vol.236,pp.937-949,Feb. 2019.

[15] Muhammad QamarRazaaand Abbas Khosravi, –A review on artificial intelligence based load demand forecasting techniques forsmartgridandbuildings‖,*RenewableandSustainableEnergyReviews*, vol.50,pp.1352-1372,Oct.2015.

[16] S. Azad, F. Sabrina and S. Wasimi, "Transformation of Smart GridusingMachineLearning,"in*Proc.201929thAustralasianUniversities Power Engineering Conference (AUPEC)*, Nadi, Fiji,2019,pp.1-6.

[17] T. S. Bomfim, "Evolution of Machine Learning in Smart Grids," in*Proc. 2020 IEEE 8th International Conference on Smart EnergyGridEngineering(SEGE)*,Oshawa,ON,Canada,2020,pp.82-87.

[18] Shutang You, Yinfeng Zhao, MirkaMandich, Yi Cui, Hongyu Li,Huangqing Xiao, Summer Fabus, Yu Su, Yilu Liu, Haoyu Yuan,Huaiguang Jiang, Jin Tan and Yingchen Zhang, "A Review onArtificialIntelligenceforGridStabilityAssessment,"in*Proc.2020 IEEE International Conference on Communications, Control,and Computing Technologies for Smart Grids (SmartGridComm)*,Tempe,AZ,USA,2020,pp. 1-6.

[19] K.GünelandA.R.Ekti,"ExploitingMachineLearningApplications for Smart Grids" in *Proc. 2019 16th InternationalMulti-Conference on Systems, Signals & Devices (SSD)*, Istanbul,Turkey, 2019,pp.679-685.

[20] P. Verma, K. Sanyal, D. Srinivasan, K. S. Swarup and R. Mehta,"ComputationalIntelligenceTechniquesinSmartgridplanningand operation: A Survey", in *Proc. 2018 IEEE Innovative SmartGrid Technologies - Asia (ISGT Asia)*, Singapore, 2018, pp. 891-896.

[21] ZhongtuoShi,WeiYao,ZhoupingLi,LingkangZeng,YifanZhao,Runfeng Zhang,YongTangandJinyuWen,‗Artificialintelligence techniques for

stability analysis and control in smartgrids:Methodologies,applications,challengesandfuturedirections ',*AppliedEnergy*,vol.278,pp.115733-115744,Nov.2020.

[22] DongxiaZhang,XiaoqingHanandChunyuDeng,–Reviewonthe research and practice of deep learning and reinforcement learninginsmartgrids‖,*CSEEJournalofPowerandEnergySystems*,vol.4, issue.3,pp.362 –370,Sept.2018.

[23] Syed SaqibAli and Bong Jun Choi, –State-of-the-Art Artificial Intelligence Techniques for Distributed Smart Grids: A Review‖,*Electronics*, vol.9,pp.1030-1055,June2020.

[24] IoannisAntonopoulos,ValentinRobu,BenoitCouraud,DesenKirli,SonamNorbu,AristidesKiprakis,DavidFlynn,SergioElizondo-GonzalezandSteveWattam,–Artificialintelligenceand machine learning approaches to energy demand-side response: Asystematic review‖, *Renewable and Sustainable Energy Reviews*,vol.130,pp.109899-109934, Sept.2020.

[25] YandongYang,WeiLi,T.AaronGulliverandShufangLi, –BayesianDeepLearning-BasedProbabilisticLoadForecastingin SmartGrids‖,*IEEETransactionsonIndustrialInformatics*,vol.16,issue.7 ,pp.4703 –4713,July2020.

[26] Faisal Mohammad and Young-Chon Kim, –Energy load forecasting model based on deep neural networks for smart grids‖,*InternationalJournalofSystemAssuranceEngineeringandManagement*,vol.11,pp.824–834,Sept.2019.

[27] Ping-HuanKuoand Chiou-JyeHuang, –A High Precision Artificial Neural Networks Model for Short-Term Energy LoadForecasting‖,*Energies*,vol.11,pp.213-226,Jan.2018.

[28] S. Atef and A. B. Eltawil, "A Comparative Study Using DeepLearningandSupportVectorRegressionforElectricityPriceForecasting in Smart Grids," in *Proc. 2019 IEEE 6th InternationalConference on Industrial Engineering and Applications (ICIEA)*,Tokyo, Japan,2019,pp.603-607.

[29] T. Lu, X. Chen, M. B. McElroy, C. P. Nielsen, Q. Wu and Q. Ai,"A Reinforcement Learning-Based Decision System for ElectricityPricingPlanSelectionbySmartGridEndUsers,"*IEEETransactions on Smart Grid*, vol. 12, no. 3, pp. 2176-2187, May2021.

[30] B. Ibrahim, L. Rabelo, E. Gutierrez-Franco, and N. Clavijo-Buritica,"Machine learning for short-term load forecasting in smart grids,"*Energies*, vol. 15, no. 21, p. 8079, 2022.

[31] S. Tiwari, A. Jain, N. M. O. S. Ahmed, Charu, L. M. Alkwai, A. K. Y.Dafhalla, and S. A. S. Hamad, "Machine learning-based model forpredictionofpowerconsumptioninsmartgrid-smartwaytowardssmartcity," *Expert Systems*, vol. 39, no. 5, p. e12832, 2022.

[32] T. Kotsiopoulos, P. Sarigiannidis, D. Ioannidis, and D. Tzovaras, "Ma-chinelearninganddeeplearninginsmartmanufacturing:Thesmartgridparadigm," *Computer Science Review*, vol. 40, p. 100341, 2021.

[33] T. Mazhar, H. M. Irfan, I. Haq, I. Ullah, M. Ashraf, T. A. Shloul, Y. Y.Ghadi, Imran, and D. H. Elkamchouchi, "Analysis of challenges andsolutions of iot in smart grids using ai and machine learning techniques:A review," *Electronics*, vol. 12, no. 1, p. 242, 2023.

[34] M. Massaoudi, H. Abu-Rub, S. S. Refaat, I. Chihi, and F. S. Oueslati,"Deep learning in smart grid technology: A review of recent advance-mentsandfutureprospects,"*IEEEAccess*,vol.9,pp.54558–54578, 2021.

[35] J.Jiao,"Applicationandprospectofartificialintelligenceinsmartgrid,"in *IOP Conference Series: Earth and Environmental Science*, vol. 510,no. 2.IOP Publishing, 2020, p. 022012.

[36] A. Ghosh and A. KOLE, "A comparative analysis of enhanced ma-chine learning algorithms for smart grid stability prediction," *AuthoreaPreprints*, 2023.

[37] S. K. Fasogbon and S. A. Shaibu, "Energy grid optimization using deepmachine learning: A review of challenges and opportunities," 2023.

[38] E. Hossain, I. Khan, F. Un-Noor, S. S. Sikander, and M. S. H. Sunny,"Application of big data and machine learning in smart grid, andassociatedsecurityconcerns:Areview,"*IeeeAccess*,vol.7,pp.13960–13988,2019.

[39] V. Garg and B. Agarwal, "Survey of literature on machine intelligenceanddeeplearningforsmartgridapplications,"in*20198thInternationalConference on Power Systems (ICPS)*.IEEE, 2019, pp. 1–5.

[40] S. Azad, F. Sabrina, and S. Wasimi, "Transformation of smart gridusing machine learning," in *2019 29th Australasian Universities PowerEngineering Conference (AUPEC)*.IEEE, 2019, pp. 1–6.

[41] X. Fang, S. Misra, G. Xue, and D. Yang, "Smart grid—the new andimproved power grid: A survey," *IEEE communications surveys &tutorials*, vol. 14, no. 4, pp. 944–980, 2011.

[42] A. E. Ezugwu, A. M. Ikotun, O. O. Oyelade, L. Abualigah, J. O.Agushaka,C.I.Eke,andA.A.Akinyelu,"Acomprehensivesurveyof clustering algorithms: State-of-the-art machine learning applications,taxonomy, challenges, and future research prospects," *Engineering Ap-plications of Artificial Intelligence*, vol. 110, p. 104743, 2022.

[43] Y. Zheng, S. Suryanarayanan, A. A. Maciejewski, H. J. Siegel, T. M. Hansen and B. Celik, "An Application of Machine Learning for a Smart Grid Resource Allocation Problem," in Proc. 2019 IEEE Milan PowerTech, Milan, Italy, 2019, pp. 1-6.

