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DECENTRALIZED ENERGY DEMAND FORECASTING FOR ELECTRIC VEHICLES VIA BLOCKCHAIN AND FEDERATED LEARNING

[1]*V. MadhuMohan*, *MCA Student, Department of MCA*

[2] *Shaik Haseena, M.Tech, (Ph.D), Assistant Professor, Department of MCA*

[12]*Dr KV Subba Reddy Institute of Technology, Dupadu, Kurnool*

ABSTRACT

The many benefits that electric vehicles (EVs) provide over traditional gas-powered vehicles are the main reason for their increasing use. However, because of the higher energy consumption and peak load, integrating EVs into the grid can be challenging. We suggest a blockchain-based federated learning system for predicting EV energy consumption that makes use of several linear regression techniques. The blockchain network stores the data collected from EVs. The data is stored in encrypted storage, and only those with the right credentials may decode it. A federated learning approach is used to train a machine learning model using data from EVs. A model is trained on each EV, and the parameters of the model are then dispersed throughout the blockchain. In order to quantify and minimise communication delays and optimise system performance, we use a novel technique to the analysis of BCFL communications overhead and latency concerns. The outcomes of the deployment confirm how well our approach predicts the energy needs of EVs. A massive real-world dataset including more than 60,000 transactions at EV charging stations in Boulder, Colorado, was utilised to train the BCFL model. Since all of the models had R2 values over 0.91, which indicates a high degree of accuracy in predicting energy usage, the findings demonstrate the framework's dependability.

I. INTRODUCTION

The development of intelligent transportation networks, which contribute to the reduction of harmful greenhouse gas emissions, is largely dependent on the quick growth and broad acceptance of electric cars. The necessity to accommodate EVs' charging needs has increased in tandem with the number of EVs on the road in recent years. To reduce the burden on power networks and save money, it is thus essential to predict the demand for charging electric cars with high accuracy. Given the increasing demand for electricity and the expanding number of EV installations, it is critical to forecast the charging demand for electric vehicles. This gives the business and its clients important information about the charging needs of their vehicles based on variables like mileage and usage trends. The EV charging demand forecast [1] allowed consumers to plan their trip lengths and choose other charging stations before their battery runs out.

Federated Learning (FL) is a decentralised machine learning method where many devices or nodes work together to build a common model without exchanging personal information. Due to its capacity to provide accurate predictions and secure user privacy, this approach has gained widespread adoption, making FL a great choice for applications in industries including banking, healthcare, and energy. Numerous modern applications have also been made in industries including finance, healthcare, and energy. Federated learning has also been used in a number of modern contexts in recent years.

Predicting the energy consumption for electric vehicles (EVs) utilising charging stations as participating nodes is one exciting use of FL in the energy industry. This approach reduces energy use and data transmission expenses to a centralised

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server while offering more precise energy estimates and safeguarding user privacy. FL may also significantly lower the amount of data storage needed.

FL in the energy sector has also been proposed to be facilitated by block chain technology, which provides a safe and decentralised platform for data exchange. In order to ensure secrecy among linked nodes and thwart hacking efforts, participating charging stations transmit their local model to the blockchain network, which aggregates all models into a single, global model.

The main driving force behind this study is the challenge of integrating electric vehicles into the grid, specifically the requirement to manage peak loads and rising energy demands, securely store this data using blockchain technology, and use machine learning to improve forecasts of the relationships between energy supply and demand. As part of a broader endeavour to advance EV Charging Solutions while maintaining efficiency and security, the model's efficiency is increased via the optimisation of BCFL communication overhead/latency. The contributions of this study are as follows:

• The use of machine learning methods, namely Blockchain-Based Federated Learning (BCFL), to forecast energy use in EV charging stations.

• Meeting increasing energy needs while preserving user privacy and security.

• Energy consumption may be correctly estimated by employing techniques like Decision Tree, LASSO Regression, Random Forest, Ridge Regression, and MLP Neural Network; these algorithms are extensively tested on publicly accessible datasets.

• In-depth analysis of delay and communication overhead in BCFL frameworks for predicting energy consumption at EV charging stations. We examine its intricate dynamics, paying special attention to measuring and reducing communication delays that affect system performance. Our innovative method stands out as providing crucial information for refining BCFL frameworks for practical energy sector applications, resulting in more robust yet effective prediction models.

This is how the remainder of the paper is structured. The relevant work is covered in Section II, while background information on the blockchain and smart contracts is given in Section III. The suggested system is presented in Section IV, its performance assessment is covered in Section V, and the paper is concluded in Section VI.

II. LITERATURE SURVEY

"Recurrent neural network model with deep learning LSTM for predicting demand for electric vehicle charging,"

G. Balraj, A. A. Victoire, J. Shanmuganathan, and A. Victoire,

Electric cars' rapid expansion and uptake have made them a key part of smart transport networks, which helps to reduce greenhouse gas emissions that harm the environment. Since the number of electric cars (EVs) has surged in recent years, there is an urgent need for these vehicles to be charged. As a result, forecasting the demand for electric car charging is crucial to reducing the strain on electric networks and providing lower charging charges. In order to estimate the demand for electric vehicle charging, a new deep learning (DL)-based long-short term memory (LSTM) recurrent neural network predictor model is attempted to be developed in this research study. The standard arithmetic optimisation method (AOA) is used to optimise the parameters of the novel deep long-short term memory (DLSTM) neural predictor model. The empirical mode decomposition (EMD) is used to decompose the input time series data while preserving its properties. This study's innovative EMD—AOA—DLSTM neural predictor overcomes the disappearing and expanding gradients of basic recurrent neural learning. Its superiority is evaluated using Georgia Tech's EV charging dataset in Atlanta, Georgia,

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USA. The optimal outcomes of 97.14% prediction accuracy, mean absolute error of 0.1083, and root mean square error of 2.0628×10^{-5} are obtained throughout the simulation. Additionally, it was determined that the mean square error was 4.25516×10^{-10} and the mean absolute error was 0.1083. When compared to earlier methods from prior publications, the findings demonstrate the effectiveness of the prediction metrics calculated using the new deep learning LSTM neural predictor for the dataset under consideration.

"Decentralised data-based communication-efficient learning of deep networks,"

B. A. Y. Arcas, D. Ramage, S. Hampson, E. Moore, and H. B. McMahan

Distributed machine learning has often been implemented via heterogeneous networks in recent years, such as a wide area network that connects data centres and edge clusters or a local area network within a multi-tenant cluster. Modern machine learning techniques find it difficult to conduct effective training in these heterogeneous networks due to the large variation in connection speeds across worker nodes. Low-speed connectivity are a problem for both centralised and decentralised training methods. In this research, we offer a decentralised method, called NetMax, that greatly accelerates the training process by allowing worker nodes to interact across high-speed lines. These are some of the new features that NetMax has. First, rather than using a central master node (also known as a parameter server), it uses a unique consensus approach that enables worker nodes to train model copies on their local dataset asynchronously and communicate with one another to synchronise their local copies. Second, with a well calibrated probability, each worker node chooses one peer at random to share information with each iteration. Peers with fast connectivity are specifically chosen with a high likelihood. Third, the overall convergence time is intended to be minimised by the peer selection probability. Furthermore, we demonstrate NetMax's convergence analytically. We test NetMax on heterogeneous cluster networks and demonstrate that it outperforms the state-of-the-art decentralised training methods Prague, Allreduce-SGD, and AD-PSGD by 3.7×, 3.4×, and 1.9×, respectively.

"Demand reshaping for electric vehicle charging using Federated Learning,"

Z. Zhang, J. Zhang, S. Lin, and M. Dedeoglu,

Electric vehicle (EV) owners may encounter lengthy delays for charging during peak hours in metropolitan locations due to the time-consuming nature of EV charging, despite EVs' efficient power use. Heterogeneous EV charging demand may be reshaped to improve user experience and charging station profitability. This research suggests a demand reshaping framework where EV customers are free to choose where they want to charge and each charging station posts the hourly rates in advance. The ideal charging rates should reduce the amount of time customers must wait to be charged and increase the revenue generated by charging stations. In order to estimate the hourly charging demand at various charging stations, charging stations train a deep neural network model. The trained neural network is then used to quantitatively calculate the ideal pricing. We demonstrate how financial incentives might enhance quality of service by temporarily and geographically smoothing out peak demand for EV charging. As a result, charging stations profit from improved service quality, while EV consumers gain from shorter charging times.

"An analysis of intelligent energy management systems for the transportation of electric vehicles in the future,"

A. Yassine and Z. Teimoori,

Because of its capacity to lower car emissions, electric vehicles, or EVs, have garnered attention in recent years. One essential component of this technology to better adapt for all-purpose transportation use is the development of an intelligent system to control EV charging needs. In order to regulate charging schedules, EVs must be connected to the Smart Grid (SG) so they can communicate with charging stations and other energy resources. Artificial Intelligence (AI)

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techniques can help the system, but they can also pose security and privacy risks. To guarantee data security, privacy preservation techniques have been established in recent years. Blockchain technology and federated learning (FL) are two new approaches to information security issues. As a result, a thorough literature assessment is suggested in this article to examine current EV energy management issues and solutions as well as suggest possible future research avenues for EV charging/discharging coordination applications.

"A review of deep learning techniques for forecasting power loads and renewable energy in smart microgrids,"

N. Javaid, N. Ashraf, S. Aslam, H. Herodotou, S. M. Mohsin, and S. Aslam,

Recently, microgrids have become a key component of smart grids that integrate energy storage devices, load control techniques, and distributed renewable energy sources (RESs). Because RESs are intermittent, smart microgrids face a number of difficulties, including supply and demand balance, power quality, and dependability. Forecasting power output from renewable energy sources (RESs), such solar panels and wind turbines, is thus increasingly crucial for the power grid's continuous and effective functioning. It also aids in achieving the best possible use of RESs. Another essential component of smart microgrids that aids in power production planning and energy trading with the commercial grid is energy demand forecasting. Promising approaches for forecasting consumer needs and energy output from RESs include models based on machine learning (ML) and deep learning (DL). This book offers a thorough analysis of the current DL-based methods that have been developed for electric power load forecasting as well as wind turbine and solar panel power forecasting. In order to help future researchers find relevant datasets for their work, it also covers the datasets used to train and test the various DL-based prediction models. Although there are some relevant studies on energy management in smart grid applications, they are mostly concerned with a particular producing application, like wind or solar. Furthermore, none of the investigations examine the production and load side forecasting techniques at the same time. Lastly, despite their importance in DL-based forecasting techniques, the datasets utilised for forecasting have not been taken into account in prior studies. Due to its data-centered approach and presentation of DL-based applications for load and energy production predictions in both the residential and commercial sectors, our survey work is thus fundamentally unique. Comparing the various DL techniques covered in this manuscript shows that the effectiveness of these forecasting techniques depends heavily on the volume of historical data; therefore, handling big data requires a lot of data storage devices and devices with high processing power. Lastly, this paper highlights a number of unresolved research issues and prospects in the field of smart microgrid forecasting for renewable energy.

III. SYSTEM ANALYSIS & DESIGN

EXISTING SYSTEM

Federated learning algorithms' decentralised nature and privacy-protecting capabilities have made them more and more popular in machine learning [2]. To depict intricate connections or high-dimensional data, they make use of deep neural networks in federated learning frameworks [3]. The Federated Averaging Algorithm was thoroughly introduced by McMahan et al. [2], and it forms the basis of many further research studies in Federated Learning.

In order to create a decentralised and privacy-preserving demand reshaping mechanism, Dedeoglu et al. [4] offer a novel method for demand reshaping of electric vehicle (EV) charging demand through federated learning-based demand reshaping that combines federated learning with a deep reinforcement learning algorithm. Simulation studies provide strong evidence of efficacy when compared to the conventional centralised learning approach, but they ignore the possible communication cost and

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delay that federated learning introduces, which might be important in practical applications. Forecasting energy demand is crucial for efficient management of charging stations and grid stability as more EVs hit the market. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs), two deep learning approaches, have been used in a number of studies to forecast the energy consumption at EV charging stations [5, 6]. These centralised methods, however, might result in data leaks and privacy issues.

These issues are addressed by combining deep neural networks with federated learning for EV energy demand prediction. For example, Saputra et al. [7] suggested a deep neural network-based federated learning method to forecast EV charging station energy use trends. Their method protected the privacy of local data while enabling the stations to work together to build a global model.

By integrating blockchain networks, EV charging stations may take part in training and testing the model while preserving data confidentiality and integrity [8]. Blockchain technology has been suggested as a safe and decentralised way to manage the federated learning process.

Wang et al. [9] suggested a blockchain-based federated learning system for the internet of cars that would protect locally-applied model updates using homomorphic encryption and the consortium blockchain. Comparing the suggested approach to the conventional centralised learning approach, the simulation experiments provide compelling proof of its efficacy. It does not, however, address the possible effects of the latency and communication cost that federated learning introduces, which might be important considerations in practical applications.

Blockchain technology has the potential to establish dependable local energy markets, as shown by Mengelkamp et al. [10]. They created a distributed energy management system based on blockchain technology that would enable secure and open energy exchange amongst people. Additionally, this study set the stage for further blockchain research aimed at forecasting the energy requirements of electric vehicles.

A federated learning method for smart grid demand forecasting was introduced by Tun et al. [11]. In light of the increasing significance of energy management systems in electric vehicles (EVs), authors highlighted the advantages of this kind of learning, including privacy protection and decentralised computing. Zinkevich et al. [12] employed parallel stochastic gradient descent (SGD) to create a decentralised machine learning model called "one-shot parameter averaging." This architecture used a final communication cycle to produce suboptimal central models, after which local models were trained using local data sets by SGD optimised trainers. Important considerations such as data distribution across nodes and the use of one-shot parameter averaging on non-SVM ML systems were overlooked.

Disadvantages

• Data complexity: In order to identify Energy Demand Forecasting, the majority of machine learning models now in use must be able to properly read massive and complicated information.

• Data availability: In order to provide precise predictions, the majority of machine learning models need a lot of data. The accuracy of the model may degrade if data is not accessible in large enough amounts.

• Inaccurate labelling: The accuracy of the machine learning models that are now in use depends on how well the input dataset was used for training. Inaccurate labelling of the data prevents the model from producing reliable predictions.

PROPOSED SYSTEM

• The use of machine learning methods, namely Blockchain-Based Federated Learning (BCFL), to forecast energy use in EV charging stations.

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• Meeting increasing energy needs while preserving user privacy and security.

• Energy consumption may be correctly estimated by employing techniques like Decision Tree, LASSO Regression, Random Forest, Ridge Regression, and MLP Neural Network; these algorithms are extensively tested on publicly accessible datasets.

• In-depth analysis of delay and communication overhead in BCFL frameworks for predicting energy consumption at EV charging stations.

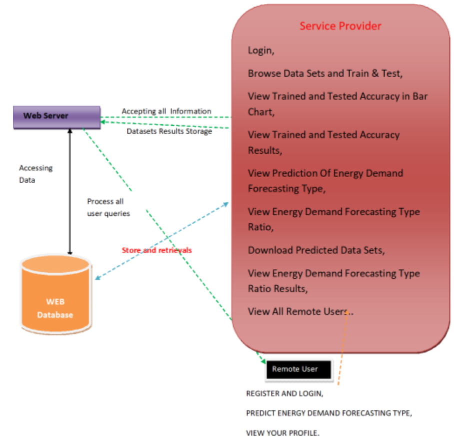
We examine its intricate dynamics, paying special attention to measuring and reducing communication delays that affect system performance. Our innovative method stands out as providing crucial information for refining BCFL frameworks for practical energy sector applications, resulting in more robust yet effective predictive models.

Advantages

- Using several linear regression techniques, this study suggests a Blockchain-based Federated Learning (BCFL) strategy to forecast the energy consumption at EV charging stations. The proposed system displays an overview of the suggested BCFL architecture.
- Electric car charging stations at various charging stations make up the network concept. Electricity from the electrical grid powers each charging station, which in turn powers EVs. Every charging station gathers its own local dataset, which includes information about the station, including its name, the energy used, the effective charging time, and the start and end times of charging. The charging history of every electric car at a certain charging station is viewable in a related log file.

SYSTEM ARCHITECTURE

Architecture Diagram



IV. IMPLEMENTATION

Modules

Service Provider

The Service Provider must use a working user name and password to log in to this module. Following a successful login, he may do several tasks including browsing data sets and training and testing. See the Bar Chart for Trained and Tested Accuracy, the Results of Trained and Tested Accuracy, the Energy Demand Forecasting Type Prediction, the Energy Demand Forecasting Type Ratio, and the Predicted Data Sets for Download. View All Remote Users and the Results of the Energy Demand Forecasting Type Ratio.

View and Authorize Users

The administrator may see a list of all registered users in this module. Here, the administrator may see the user's information, like name, email, and address, and they can also grant the user permissions.

Remote User

A total of n users are present in this module. Before beginning any actions, the user needs register. Following registration, the user's information will be entered into the database. Following a successful registration, he must use his password and authorised user name to log in. Following a successful login, the user will do tasks like REGISTERING AND LOGINING, Forecast the Type of Banking Enabled by Robotic Things

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Type of Energy Demand Forecasting Prediction Examine your profile.

ALGORITHM

Logistic regression Classifiers

The relationship between a collection of independent (explanatory) factors and a categorical dependent variable is examined using logistic regression analysis. When the dependent variable simply has two values, like 0 and 1 or Yes and No, the term logistic regression is used. When the dependent variable contains three or more distinct values, such as married, single, divorced, or widowed, the technique is sometimes referred to as multinomial logistic regression. While the dependent variable's data type differs from multiple regression's, the procedure's practical application is comparable.

When it comes to categorical-response variable analysis, logistic regression and discriminant analysis are competitors. Compared to discriminant analysis, many statisticians believe that logistic regression is more flexible and appropriate for modelling the majority of scenarios. This is due to the fact that, unlike discriminant analysis, logistic regression does not presume that the independent variables are regularly distributed.

Both binary and multinomial logistic regression are calculated by this software for both category and numerical independent variables. Along with the regression equation, it provides information on likelihood, deviance, odds ratios, confidence limits, and quality of fit. It does a thorough residual analysis that includes diagnostic residual plots and reports. In order to find the optimal regression model with the fewest independent variables, it might conduct an independent variable subset selection search. It offers ROC curves and confidence intervals on expected values to assist in identifying the optimal classification cutoff point. By automatically identifying rows that are not utilised throughout the study, it enables you to confirm your findings.

Naïve Bayes

The supervised learning technique known as the "naive bayes approach" is predicated on the straightforward premise that the existence or lack of a certain class characteristic has no bearing on the existence or nonexistence of any other feature. However, it seems sturdy and effective in spite of this. It performs similarly to other methods of guided learning. Numerous explanations have been put forward in the literature. We emphasise a representation bias-based explanation in this lesson. Along with logistic regression, linear discriminant analysis, and linear SVM (support vector machine), the naive bayes classifier is a linear classifier. The technique used to estimate the classifier's parameters (the learning bias) makes a difference.

Although the Naive Bayes classifier is commonly used in research, practitioners who want to get findings that are useful do not utilise it as often. On the one hand, the researchers discovered that it is very simple to build and apply, that estimating its parameters is simple, that learning occurs quickly even on extremely big datasets, and that, when compared to other methods, its accuracy is rather excellent. However, the end users do not get a model that is simple to use and comprehend, and they are unaware of the value of this method.

As a consequence, we display the learning process's outcomes in a fresh way. Both the deployment and comprehension of the classifier are simplified. We discuss several theoretical facets of the naive bayes classifier in the first section of this lesson. Next, we use Tanagra to apply the method on a dataset. We contrast the outcomes (the model's parameters) with those from other linear techniques including logistic regression, linear discriminant analysis, and linear support vector machines. We see that the outcomes are quite reliable. This helps to explain why the strategy performs well when compared to

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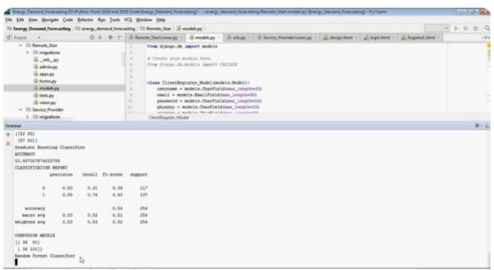
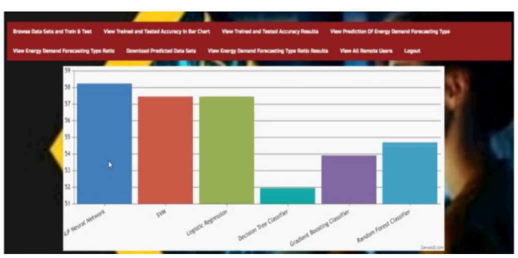
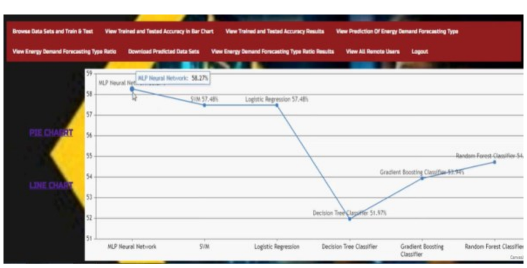
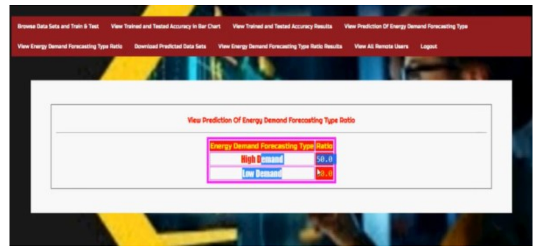
others. We employ a variety of tools (Weka 3.6.0, R 2.9.2, Knime 2.1.1, Orange 2.0b, and RapidMiner 4.6.0) on the same dataset in the second section. Above all, we make an effort to comprehend the outcomes.

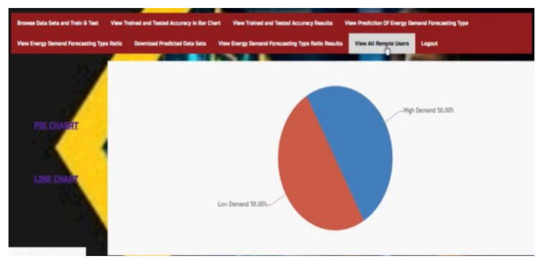
V. SCREEN SHOTS

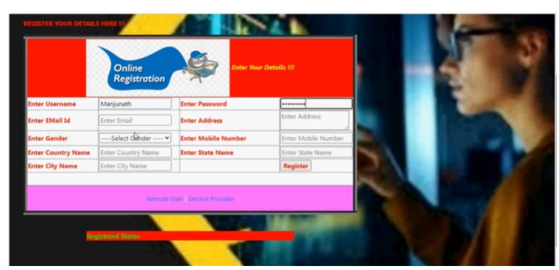


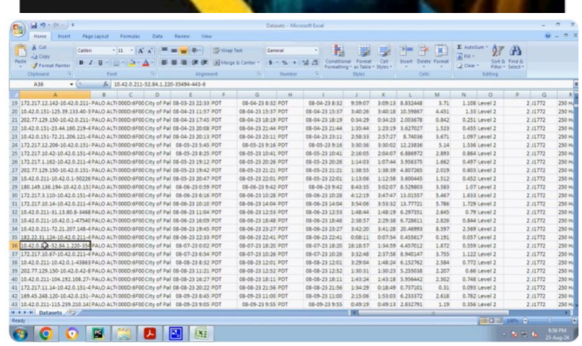












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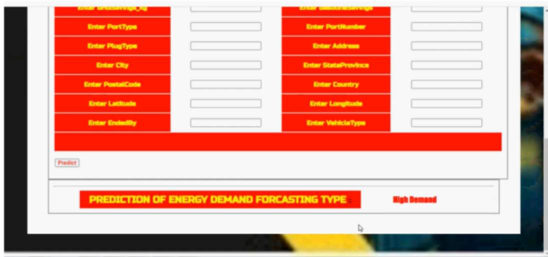

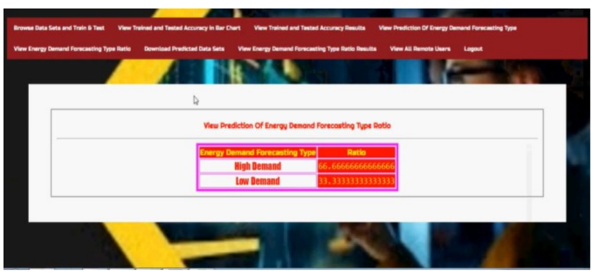

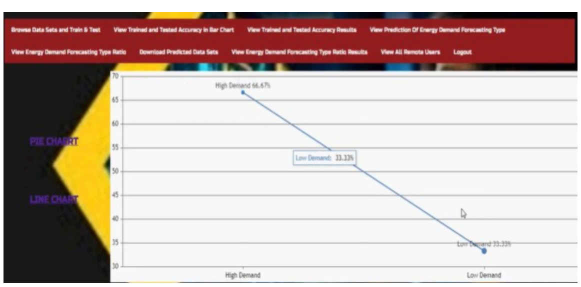

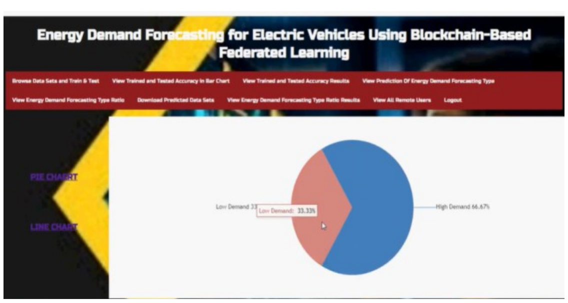

VI. CONCLUSION

In order to predict energy usage at electric vehicle (EV) charging stations, this article explores the use of machine learning methods, specifically focussing on Block chain-Based Federated Learning (BCFL). In addition to meeting rising energy needs, our suggested BCFL structure ensures user privacy and data security. Its performance was assessed using real-world data. Participants in the study estimated energy use using Decision Tree, LASSO Regression, Random Forest, Ridge Regression, and MLP Neural Network estimation methodologies. A careful analysis showed that the Random Forest algorithm produces better MSE and MAE performance results, and that the block chain-based Federated Learning Architecture properly anticipates the energy consumption of EV charging stations. This model also earned the greatest R2, demonstrating exceptional prediction accuracy. All models had R2 values over 0.91, although the MLP Neural Network did not perform well. The findings highlight the advantages of using block chain technology for safe and accurate energy demand forecasts, underscoring the BCFL framework's potential to improve smart grid management and encourage the expansion of EV infrastructure.

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