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Blockchain-Based Federated Learning for EV Energy Prediction

A. Shiva Kumar (Assistant Professor)
Department of Computer Science(AIML)
Malla Reddy University, Hyderabad

Y. Rajesh,
Department of Computer Science(AIML)
Malla Reddy University, Hyderabad
2211CS020544@mallareddyuniversity.ac.in

V. Abhinav,
Department of Computer Science(AIML)
Malla Reddy University, Hyderabad
2211CS020570@mallareddyuniversity.ac.in

G. Rajesh Reddy,
Department of Computer Science(AIML)
Malla Reddy University, Hyderabad
2211CS020576@mallareddyuniversity.ac.in

R. Varshith Reddy,
Department of Computer Science(AIML)
Malla Reddy University, Hyderabad
2211CS020577@mallareddyuniversity.ac.in

***Abstract*—** The rapid growth of Electric Vehicles (EVs) has increased the need for accurate energy consumption prediction to support efficient battery management and charging infrastructure. This project proposes a decentralized approach that combines Federated Learning and Blockchain to ensure secure and privacy-preserving model training. Each participating node trains the model locally and shares only model updates instead of raw data. Deep learning techniques such as RNN and LSTM are used to analyze driving patterns and battery usage. The integration of Blockchain ensures transparency, trust, and secure management of model updates.

Keywords — *Electric Vehicles (EVs), Energy Consumption Prediction, Federated Learning, Blockchain, Deep Learning, RNN, LSTM, Data Privacy, Smart Grid, Secure Model Training.*

I. Introduction

The rapid growth of Electric Vehicles (EVs) has created new challenges in energy management and charging infrastructure. Accurate prediction of EV energy consumption is important for improving battery efficiency, planning charging stations, and maintaining the stability of smart grids. Traditional machine learning methods usually rely on centralized data collection, where data from different sources is stored in a single server. However, this approach raises concerns about data privacy, security, and scalability when dealing with large amounts of distributed EV data.

To address these challenges, this project proposes a decentralized framework that combines Federated Learning and Blockchain technology for EV energy prediction. Federated Learning allows multiple participants to train models locally without sharing their raw data, ensuring privacy and reducing communication overhead **[1].** In addition, Blockchain technology provides a secure and transparent platform for recording model updates and maintaining trust among participants **[2].** By integrating these technologies with deep learning techniques, the proposed system aims to improve prediction accuracy while ensuring data security and transparency.

II. Objectives

The main objective of this project is to develop a secure and efficient system for predicting energy consumption in Electric Vehicles (EVs). The proposed system uses Federated Learning to allow multiple EV nodes or charging stations to train machine learning models locally without sharing their raw data, thereby preserving privacy and reducing security risks. In addition, Blockchain technology is integrated to provide transparency and ensure that model updates are securely recorded and verified. By combining decentralized learning with deep learning techniques such as RNN and LSTM, the system aims to improve prediction accuracy while maintaining data privacy and trust among participants **[1].**

III. BACKGROUND

The increasing adoption of Electric Vehicles (EVs) is creating new challenges for energy management and charging infrastructure. Predicting EV energy consumption accurately is important for efficient battery usage, smart charging, and maintaining the stability of power grids. Traditional machine learning approaches generally rely on centralized data collection where information from different EVs and charging stations is stored in a single server for analysis. However, this centralized approach raises several issues such as privacy risks, security vulnerabilities, and limited scalability when handling large volumes of distributed data.

Recent advancements in decentralized technologies have provided new solutions to these challenges. Federated Learning enables multiple devices or organizations to collaboratively train machine learning models without sharing their raw data, which helps in protecting sensitive information and improving system scalability. At the same time, Blockchain technology provides a secure and transparent environment where model updates and transactions can be recorded in an immutable ledger. The integration of these technologies can improve trust, security, and reliability in collaborative learning systems while supporting accurate EV energy consumption prediction **[7][11].**

IV. METHODOLOGY

The proposed system follows a decentralized approach for predicting Electric Vehicle (EV) energy consumption by integrating Federated Learning with Blockchain technology. Initially, data related to EV usage such as driving patterns, battery status, and charging behavior is collected from different EV nodes or charging stations. This data is preprocessed to remove noise and prepare it for model training. Instead of sending the raw data to a central server, each node trains a local machine learning model and shares only the model updates. These updates are then securely recorded and verified using blockchain technology, ensuring transparency and preventing unauthorized modifications. The aggregated global model is finally used to predict EV energy consumption with improved accuracy and reliability **[11][14].**

Modules of the System

1. **Data Collection Module:** This module collects data from EVs or charging stations such as battery usage, driving distance, charging time, and environmental conditions. The collected data forms the basis for training the prediction model.
2. **Data Preprocessing Module:** In this module, the collected data is cleaned and transformed. Missing values are handled, unnecessary features are removed, and the dataset is prepared for efficient machine learning model training.
3. **Federated Learning Module:** This module enables decentralized training of the prediction model. Each EV node trains the model locally using its own data and shares only the model parameters instead of raw data, which helps maintain privacy and reduces communication overhead **[6].**
4. **Blockchain Integration Module:** Blockchain is used to securely store and verify model updates from different nodes. It ensures that all updates are recorded in a transparent and tamper-proof manner, improving trust among participants **[7].**
5. **Model Aggregation and Evaluation Module:** In this module, the locally trained model updates from different nodes are aggregated to form a global prediction model. The performance of the model is evaluated using accuracy and other evaluation metrics.

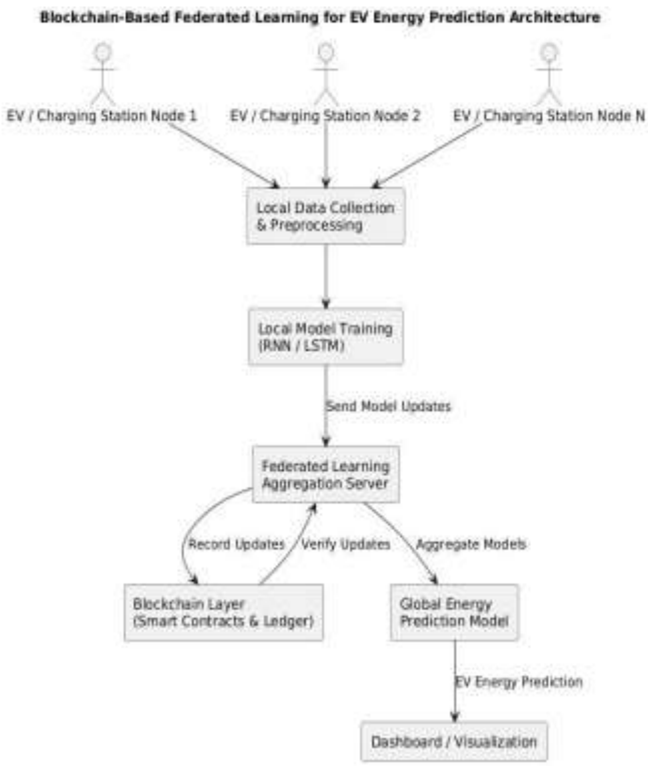

Fig – 1: Architecture

V. KEY FEATURES

1. **Privacy-Preserving Learning:** The system uses Federated Learning to train models locally on EV devices or charging stations. This ensures that sensitive user data remains on the local

device and only model updates are shared, protecting data privacy **[6].**

2. Secure and Transparent Data Management: Blockchain technology is integrated to securely record model updates in a decentralized ledger. This ensures transparency, trust, and protection from unauthorized modifications **[7].**

3. Accurate Energy Prediction: Deep learning techniques such as RNN and LSTM are used to analyze driving patterns, battery usage, and environmental factors to predict EV energy consumption more accurately **[11].**

4. Decentralized System Architecture: The system does not rely on a single central server. Multiple nodes collaborate in model training, which improves system reliability and reduces the risk of a single point of failure.

5. Scalable and Efficient Framework: The proposed system can easily support a large number of EVs and charging stations, making it suitable for real-world smart grid and intelligent transportation systems **[14].**

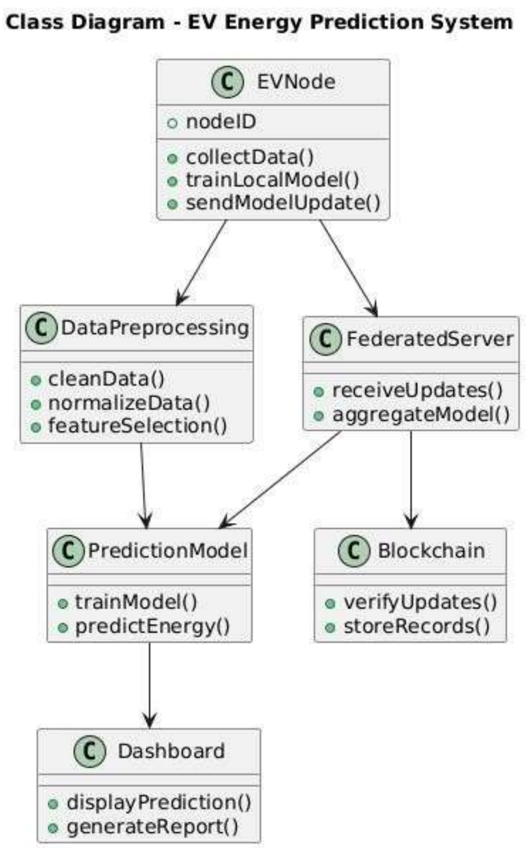

Fig – 2: Class Diagram

VI. Challenges & Limitations

- Availability of large and reliable Electric Vehicle datasets is still limited, which can affect the training and accuracy of machine learning models used for energy prediction [12].
- Communication between multiple federated learning nodes can introduce latency and increased bandwidth usage, especially when the number of participating devices grows significantly [8].
- Ensuring fairness and proper incentive mechanisms for all participants in a federated learning environment can be difficult, as some nodes may contribute less while still benefiting from the global model [5].
- Security threats such as model poisoning attacks or malicious updates from compromised nodes may affect the performance and reliability of the global model [9].
- Blockchain integration may introduce additional computational and storage overhead due to consensus mechanisms and continuous ledger updates [10].
- The scalability of decentralized systems can become challenging when a very large number of EVs or charging stations participate in the learning process [4].

VII. Implementation

- Collection of EV-related data such as driving patterns, battery status, charging duration, and environmental factors from different EV nodes or charging stations.
- Data preprocessing techniques such as cleaning, normalization, and feature selection are applied to prepare the dataset for training the prediction model.
- Development of a machine learning or deep learning model using frameworks such as TensorFlow, Keras, or Scikit-learn to analyze EV energy consumption patterns [13].
- Implementation of Federated Learning where each node trains the model locally using its

own data and shares only model parameters instead of raw data.

- Integration of Blockchain technology to securely record model updates and verify contributions from different participants in a transparent and tamper-proof manner.

- Aggregation of local model updates to create a global prediction model that can accurately estimate EV energy consumption [8].

- Evaluation of the final model using performance metrics such as accuracy, loss, and prediction error to ensure reliable results.

VIII. CONCLUSION

In conclusion, the proposed project presents a secure and decentralized framework for predicting Electric Vehicle (EV) energy consumption by combining Federated Learning and Blockchain technology. The system enables multiple EV nodes or charging stations to train prediction models locally without sharing their raw data, thereby ensuring privacy and reducing security risks. Blockchain integration further improves transparency and trust by securely recording model updates in a tamper-proof manner. By using machine learning techniques to analyze EV usage patterns, the system can provide accurate energy predictions and support better energy management in smart grid environments [12].

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