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A MATHEMATIC APPROACH TO ELECTRIC VEHICLE TRAVEL RANGE PREDICTION USING IOT AND MACHINE LEARNING WITH ROAD CONDITIONS AND CROWDSOURCED CHARGING DATA

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Abstract

Electric vehicle (EV) is increasingly promoted for their environmental and economic benefits but still challenges of range prediction and reliable access to charging infrastructure in long trip journey is necessary. Estimating driving range is complex due to its dependent on multiple factors such as traffic condition, internal load, charging patterns, road conditions, driving behavior and environmental conditions. In this paper proposes a hardware and machine learning collaborative system to predict the EV travel range prediction by incorporating road conditions data. In the proposed system various onboard sensors collect information about road conditions like flat, uphill, downhill with battery parameters which are then processed using ML driven analysis to estimate the travel distance based on the available battery charge and road conditions. The system also allows other users to analyze the road condition for their upcoming trip based on historical available data and the system recommends a travel range. Additionally, the system integrates with IoT enabled charging stations to provide real time updates on station availability along with crowdsourcing mechanism verified by user whether the charging station is public or private. By combining predictive analytics IoT connectivity and user driven data sharing this integrated approach improves trip planning reduces the risk of vehicle stranding and increases charging accessibility for EV users.

Key Words and Phrases: Electric Vehicles, Battery, Machine Learning, Road Condition, Internet of Things, Charging Station.

1 Introduction

EV have emerged as a sustainable alternative to conventional internal combustion engine vehicles and offering zero emissions and environment friendly. But still EV constrained by key challenges among which range prediction and identifying nearest charging station in their journey. Unlike fuel based vehicles where travel distance is largely proportional to fuel levels but in EV range depends on multiple factors such as traffic condition, internal load, charging

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patterns, road conditions, driving behavior and environmental conditions. This issue becomes especially critical in uphill road surface this significantly directly impact on battery energy consumption. Similarly existing nearest navigation to charging system with their real time status is also very important for EV long trip journey.

In this paper, we propose a machine learning and IoT (Internet of things) framework that integrates real time sensing and ML driven analysis and community shared driven data for further used to predict EV travel range and charging station recommendation. By incorporating a) Road condition sensing based on onboard sensor connected (accelerometers, gyroscopes and GPS) capture road conditions. This information is processed locally and shared via vehicle to vehicle (V2V) or cloud platforms to enhance

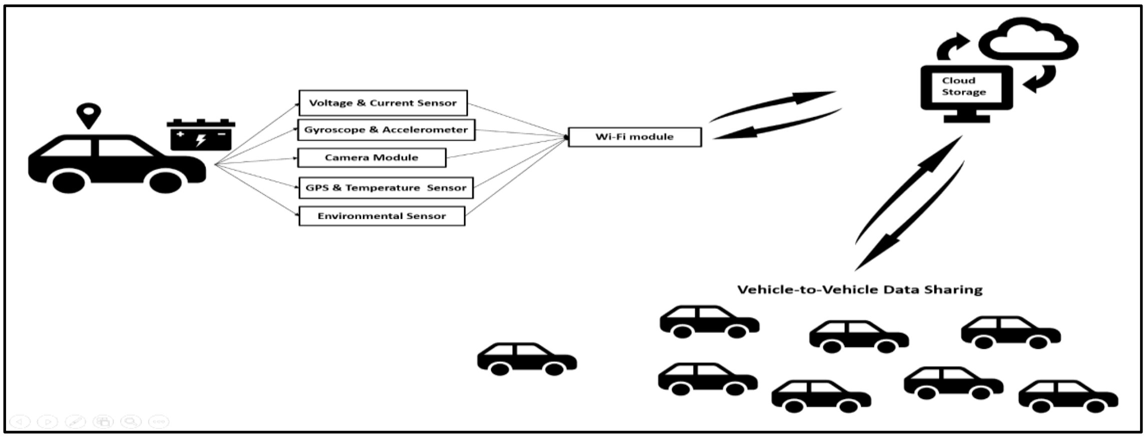

Figure 1. System Overview

prediction accuracy for upcoming routes. b) Crowdsourced charging infrastructure & IoT charging Station: Real time charging station status with crowdsourcing EV charging station data verified by user the type public/private charging station and availability of charging stations and creating a continuously updated and reliable database. This information is shared on the network to assist to other vehicle to trip planning. c) ML enabled range prediction: A central ML system analyzing road condition data based on available historical data and battery metrics and charging availability to generate range predictions optimized travel distances and charging recommendations. This integrated approach improving user confidence in their long trip journey.

Furthermore, the figure 1 shows the system overview of the proposed framework multiple sensors are connected to EV for capturing one or more parameters of EV and transmitting that data to cloud storage and given to machine learning model for further analysis and prediction.

2 Methodology

The proposed system integrates a hardware based sensing platform and a machine learning framework to collaboratively predict EV travel range based on upcoming road condition and charging station available data. The methodology is divided into two major components i.e.

hardware implementation and Machine Learning data processing.

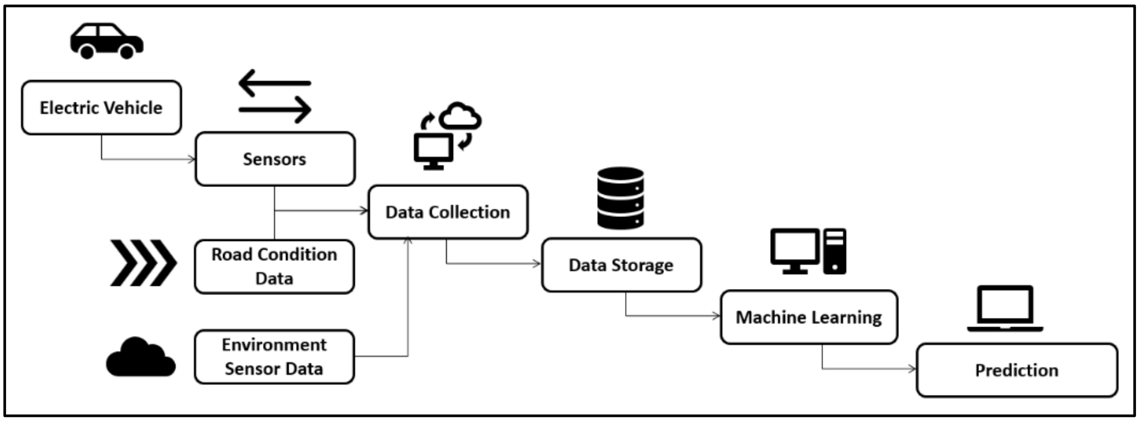

Figure 2 System Flow Diagram

2.1. Hardware Implementation

a) IoT based EV prototype monitoring unit

The EV prototype hardware schematic is shown in figure 3 is designed around the ESP32 [16] microcontroller it is chosen for its low power consumption with inbuilt Wi Fi/Bluetooth connectivity and ability to handle multiple sensor interfaces. The key sensors used in the system are, voltage divider to measures voltage and current of the EV battery pack to monitor power consumption in real time. DHT11 sensor to captures ambient temperature and humidity which is further used to analyze battery effect performance and energy consumption across various road conditions. MPU6050 sensor combines an accelerometer and gyroscope to analyze road conditions like flat, uphill and downhill road surface. GPS NEO6M module is used to records the vehicle location real time and maps the road condition with all other parameter like battery parameters and road conditions with temperature and humidity for cloud/V2V sharing.

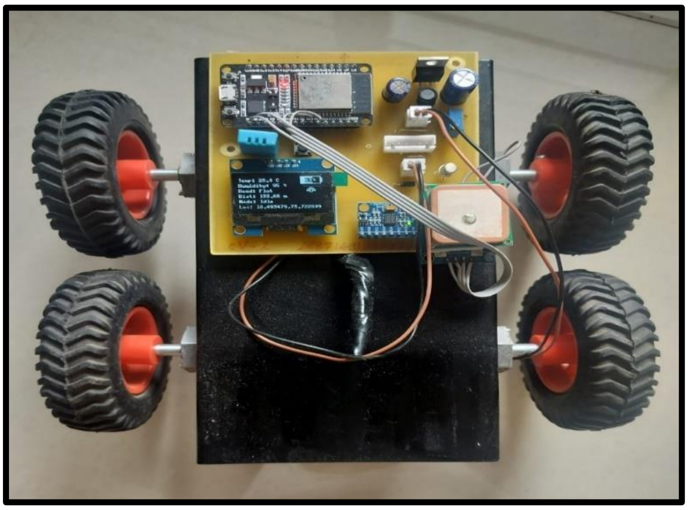

Figure 3 EV prototype hardware

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The developed experimental system setup is IoT based EV monitoring unit connections are as below, the battery charging is detected through GPIO 27 (CHARGING_STATUS pin) which identifies whether the vehicle is connected to a charger. An OLED display for live data visualization such as battery percentage, charging status, road condition, distance travelled based on RPM motor used in prototype EV and network connectivity. The ESP32 [16] connects to the internet using Wi-Fi and periodically transmits the collected data (battery voltage, state of charge, charging status, environmental conditions, road profile, distance and GPS coordinates) to a remote server via HTTP request. Each device is uniquely identified using its MAC address which enabling multi vehicle monitoring on a central server.

b) Charging Station Prototype

An IoT enabled charging station experimental prototype unit schematic shown in figure 4 built using an ESP32 [16] microcontroller. The ESP32 [16] device is equipped with charging pins and indicator LEDs that represent the availability of the charging point. When the station is connected to the internet the Wi-Fi indicator LED glows and will confirming successful connectivity. The charging status GPIO 27 pin is configured as an input to detect whether a charger is plugged in. If the pin reads low then it indicates that a vehicle is connected and charging is ongoing in this case the charging led connected to GPIO 14 will glows. If the pin reads high then it means the station is free available and the LED remains off. Additionally, a Wi Fi connection led is connected to GPIO 15 lights up when the station is successfully connected to the internet and confirming network availability. The ESP32 [16] communicates this charging status Available or Unavailable to a remote server via HTTP requests. Each device connected to charging station is uniquely identified by its MAC address which allowing the backend to track multiple charging stations simultaneously and provide real time availability monitoring.

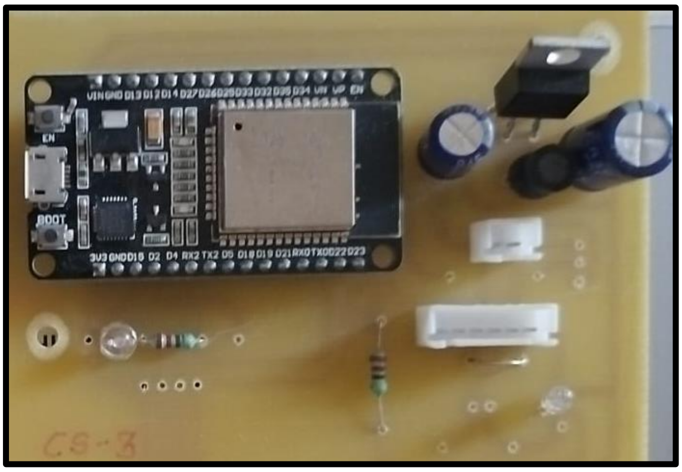

Figure 4 IoT enabled charging station Prototype

2.2. Machine Learning Framework

The hybrid machine learning model is designed to predict the remaining travel distance of an EV by combining a physics-based baseline model with residual correction learned through

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machine learning.

The model calculates the expected energy consumption using interpretable parameters such as battery capacity, road condition and battery temperature. This produces an initial range estimate physical relationships. For example, higher temperatures or uphill driving increase energy consumption, while downhill driving reduces it. The baseline vehicle range under ideal conditions is expressed as:

$$\text{R ideal} = \frac{C\ batt\ .\ 1000\ .\eta}{E\ base}$$

Where,

C batt is the battery capacity (kWh),

η is the drivetrain efficiency, and

E base is the baseline energy consumption (Wh/km).

Accordingly, the predicted driving range at a given SOC is:

$$\text{R(SOC)} = \frac{C\ b(\text{C batt}\ \cdot\ 1000\ \cdot\ \eta\ \cdot\ (\text{SOC}/100))\ att\ .\ 1000\ .\eta}{E}$$

While the physics-based model captures interpretable trends, it cannot fully represent unmodeled dynamics such as motor inefficiencies under specific loads, or the impact of weather conditions. To address this, a machine learning residual correction is introduced.

The residual is defined as the difference between actual observed consumption and the physics-based prediction:

R = E actual – E physics

A feature vector is constructed as:

X = [SOC, (T b −T opt), 1uphill, 1downhill, v]

The final hybrid energy consumption is then obtained as:

E hybrid = E physics + r, with E hybrid ≥ 10

leads to the hybrid-predicted range:

Volume 38 No. 11s 2025,
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$$\text{R hybrid (SOC)} = \frac{(\text{C batt} \cdot 1000 \cdot \eta \cdot (\text{SOC}/100))}{E\ hybrid}$$

This hybrid approach combines the interpretability and reliability of physics based models with the adaptability of machine learning. Since the residual model is updated online and it adapts continuously to new data without requiring full retraining. Over time it learns to correct systematic biases in the physics model making the system self-improve and suitable for long term deployment in EV range prediction.

3 Experimental Setup

The prototype of IoT based EV monitoring unit was tested on a prototype vehicle chassis as shown in as shown in Figure 5 A four 10 RPM DC motor parallelly connected and mounted on the chassis to emulate the driving function of an electric vehicle. During testing scenarios, the system successfully monitored temperature, humidity, road gradient, battery voltage, state of charge, and distance traveled based on motor RPM. The collected data was displayed on an OLED module for local visualization and simultaneously transmitted to a cloud server via Wi Fi for remote access.

Figure 5 Experimental Setup of EV

The experimental observations for different road types under full battery charge, where distance traveled varied. The travelled distance measured on flat surface is 1200 m, uphill it 1000 m. These results clearly demonstrate how road gradient directly influences battery consumption and range prediction.

The collected data was transmitted via Wi-Fi to a cloud server and dynamically mapped using a Leaflet [24] map as shown in figure 6. The visualization framework assigned distinct colors to different road profiles (flat, uphill, downhill) and plotted them along the GPS trajectory of the test route. This allowed a clear spatial representation of road condition variations throughout the journey.

Figure 6 shows the trip visualization interface where the system successfully identified road segments in this you need to select location from to on selected coordinates it will show

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road conditions.

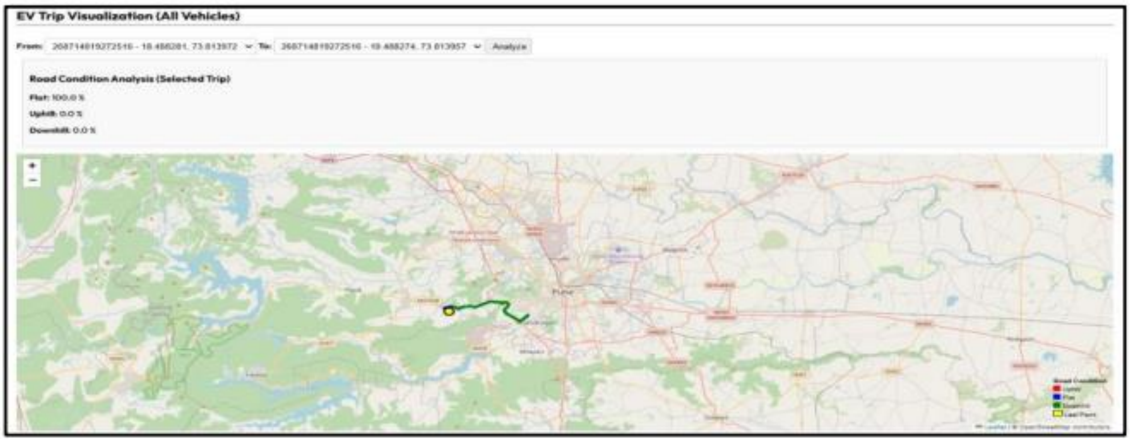

Figure 6 Road condition based on selected latitude and longitude on leaflet map [24].

4 Result

The proposed Smart IoT based EV monitoring unit was evaluated through multiple experimental scenarios to validate its effectiveness in predicting travel range and analyzing road conditions with recommending charging stations. As illustrated in the figure 6 above the user begins by selecting the latitude and longitude of the intended travel route. This terrain aware analysis forms the basis for predicting the expected travel distance from the current battery status as shown in figure 7.

In addition to range estimation as shown in figure 7, the system integrates real time charging infrastructure data. Each station is displayed with its availability status as shown in figure 8 type the charging station is public or private and whether fast charging is supported and there availability.

To further improve reliability of charging station the platform allows user provide his input and verify the classification of stations i.e. public or private through crowdsourcing as shown in figure 9.

During testing the system also demonstrated its capability to support emergency situations.

Figure 7 Based on available battery charge travel distance prediction.

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If the vehicle is running low on charge during travel the system highlights the nearest available charging station and provides the option to instantly book a slot as shown in figure 9. Once a station is booked its status is updated in real time and the charging station is marked unavailable offline red color as shown in figure 8 for other users to avoid conflicts. This feature reduces uncertainty in charging access and enhances user confidence during long or unplanned trips.

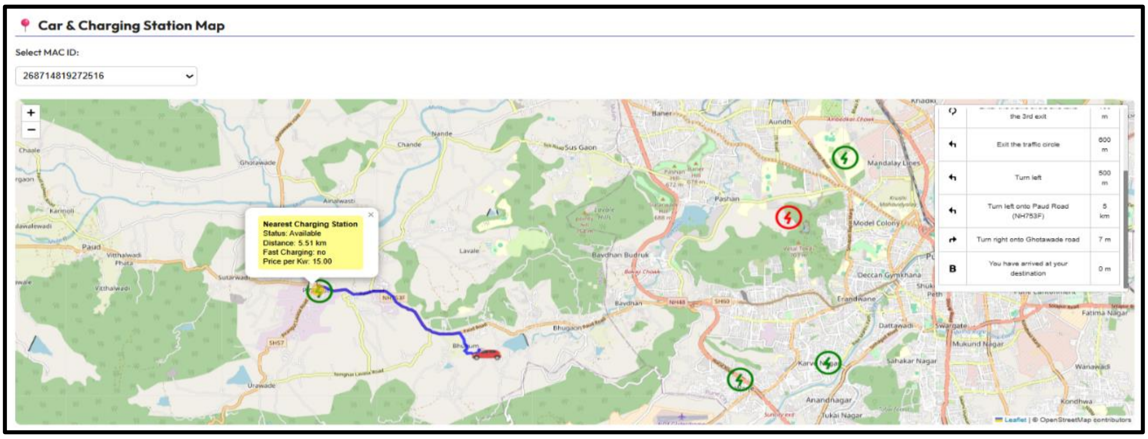

Figure 8 Available Charging stations; Nearest charging station recommendation on leaflet map [24].

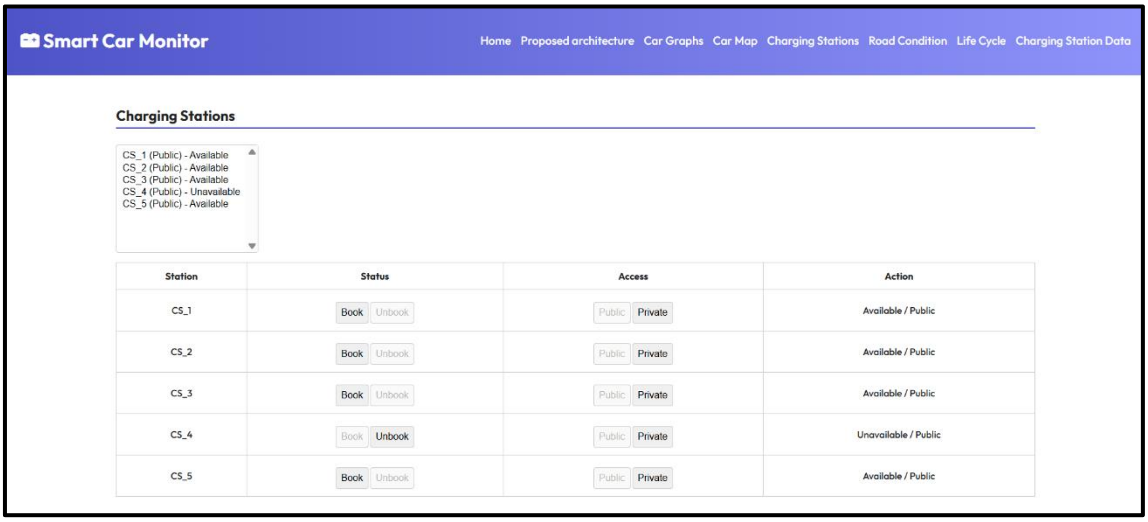

Figure 9 Charging station booking and Crowdsourcing information

Overall, the system results shows that the integrating hardware with software machine learning framework successfully combines road condition sensing and predictive analytics and crowdsourced charging station helps in travel range estimation in EV along with efficient

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trip planning and reliable charging accessibility thereby minimizing the risk of stranding and improving the overall EV driving experience for future and this system continuously updating based on travel history from one or more EVs.

5 Conclusion

The proposed collaborative hardware and machine learning driven framework provides EV range prediction and charging accessibility by integrating road condition sensing with crowdsourced station verification. The incorporation of road conditions captured through onboard sensors and shared via V2V or cloud platforms supports others for their efficient route planning. In parallel the crowdsourced charging station data improves the reliability of infrastructure data thereby reducing range anxiety with knowing upcoming charging stations which strengthening user confidence.

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