



VOLTROAD-Solar Based Wireless Road Way Charging for Electric Vehicles with LSTM-Based Weather Prediction Model

Kavya K R¹, Guru KR², Ashwin R³, Deviprasad⁴, Kishore S⁵

Department of Information Science and Engineering, The Oxford College of Engineering

Affiliated to Visvesvaraya Technological University, Belagavi, Karnataka, India¹⁻⁵

Abstract: Wireless roadway charging is rapidly becoming a promising alternative to traditional plug-in and stationary EV charging techniques, which frequently suffer from long wait times and limited convenience. In this project, we present a solar-powered dynamic charging system capable of supplying energy to electric cars when they are moving. The system uses photovoltaic panels placed along or integrated into the roadway to harvest solar energy, which is then used to energize inductive transmitter coils embedded beneath the road surface. As an EV drives over these coils, its onboard receiver coil captures the transmitted energy, enabling continuous, interruption-free charging and reducing concerns related to battery range. Since solar energy output varies with weather conditions, the system incorporates a Long Short-Term Memory (LSTM) deep learning model to accurately forecast factors such as solar irradiance, temperature, and cloud cover. These forecasts aid in estimating power availability in real time and guarantee a steady and dependable charging process. The method is appropriate for future smart and sustainable transportation networks because experimental testing shows stable wireless power transfer, precise weather forecasting with a mean absolute error of about 24, and effective integration of all system modules.

Keywords: Dynamic Wireless Charging, Solar Energy, Electric Vehicles, LSTM Weather Forecasting, Inductive Power Transfer, Embedded Systems

I. INTRODUCTION

Utilizing fossil fuels and carbon emissions from the transportation sector can be reduced with the help of electric vehicles (EVs), which are spreading more widely acknowledged. Despite their benefits, EVs still have drawbacks like slow charging times and range anxiety, and small battery capacities, which frequently deter consumers from fully embracing them. Additionally, drivers must stop, plug in, and wait at traditional charging stations, which reduces convenience overall and causes crowding during peak hours. To overcome these limitations, wireless roadway charging has emerged as a promising technology. In this approach, electric vehicles receive power while they are moving, without the need to stop or connect to a charger. When this system is powered by solar energy, it creates a sustainable and independent charging infrastructure. Solar panels placed along or within the roadway supply electricity to embedded inductive coils, which wirelessly transfer energy to EVs equipped with receiver coils. This helps extend driving range and reduces the need for large onboard batteries. However, solar energy production varies significantly depending on weather conditions. For the system to function efficiently, it is important to predict how much solar energy will be available at any time. Long Short-Term Memory (LSTM) neural networks are ideal for this use since they are able to identify trends in past weather data and accurately forecast solar irradiance, temperature, humidity, and cloud cover.

This paper presents a complete framework that combines solar energy harvesting, inductive wireless power transfer, embedded electronic control, and LSTM-based weather prediction. Together, these components form an intelligent solar-powered dynamic roadway charging system designed to support continuous, efficient, and reliable charging for electric vehicles.

II. PROBLEM STATEMENT AND OBJECTIVE

This research addresses critical limitations in current electric vehicle charging infrastructure and emphasizes the urgent need for sustainable, continuous charging solutions to support widespread EV adoption. Traditional plug-in charging systems face multiple interrelated challenges that severely compromise their effectiveness in modern transportation environments. Range anxiety remains the most significant barrier to EV adoption, with drivers frequently concerned



about battery depletion during long journeys. Conventional charging stations require vehicles to stop for extended periods, typically 30 minutes to several hours, significantly reducing travel convenience and causing congestion at charging facilities during peak hours. The limited number of charging stations, particularly in rural and highway corridors, creates accessibility gaps that discourage potential EV buyers. Additionally, the substantial infrastructure investment required for traditional charging networks, including grid upgrades and dedicated parking spaces, creates financial barriers for comprehensive deployment. Static charging systems also fail to address the fundamental mismatch between energy consumption during travel and energy replenishment during stationary periods. While solar energy offers a renewable power source, its intermittent nature due to weather variations introduces reliability concerns. Existing solar charging installations typically operate as stationary units without the ability to provide power to moving vehicles, limiting their utility for continuous travel scenarios. Furthermore, the lack of predictive capabilities in current systems prevents proactive energy management and optimal charging strategies. Without accurate forecasts of solar energy availability, system operators cannot efficiently schedule charging operations or inform drivers about expected charging performance.

Key Objectives of VOLTROAD include:

- **Develop dynamic wireless charging infrastructure** using inductive power transfer technology embedded in roadway surfaces to enable continuous charging of EVs during motion, eliminating the need for charging stops and extending effective driving range by 30-50%.
- **Implement solar energy harvesting system** with photovoltaic panels integrated along roadways to provide sustainable, renewable power for wireless charging coils, reducing dependence on grid electricity and minimizing carbon footprint.
- **Build LSTM-based weather prediction model** achieving accurate solar irradiance forecasting ($MAE \leq 24$ units) to enable intelligent energy management, optimize charging schedules, and provide reliability through predictive power availability estimation.
- **Develop integrated IoT monitoring platform** with cloud-based data collection, real-time system visualization, automated billing workflows, and user-friendly web interface for charging status monitoring and route planning optimization.

III. SCOPE

The scope of this research encompasses multiple interconnected technical domains requiring careful design, implementation, and validation. Hardware development involves designing solar photovoltaic systems with charge controllers and battery banks for energy storage, developing inductive wireless charging modules with transmitter coils embedded beneath road surfaces and receiver coils mounted on electric vehicles, implementing power electronics including rectifiers, inverters, and voltage regulation circuits, and integrating microcontroller-based control systems using NodeMCU and Arduino platforms for system coordination and IoT connectivity. Weather prediction capabilities utilize Long Short-Term Memory neural networks trained on historical meteorological data to forecast solar irradiance, temperature, humidity, and cloud cover for horizons of 1-6 hours ahead. The prediction engine processes multidimensional temporal features through LSTM layers with forget gates and memory cells, enabling the system to capture complex seasonal and diurnal patterns in solar energy availability. Embedded control systems implement vehicle detection using infrared sensors, segment-based coil activation logic to power only roadway sections with present vehicles, real-time monitoring of battery levels and solar output, and automated switching between solar power and battery backup based on availability and demand. IoT integration establishes cloud connectivity through ThingSpeak platform for data logging and visualization, implements RESTful APIs for system data access and control, develops web-based dashboard for user authentication, charging status display, and billing information, and enables remote system monitoring and control capabilities for administrators. The prototype implementation demonstrates core system functionality through static wireless charging setup with manually positioned transmitter and receiver coils, solar panel array with charge controller and battery bank, LSTM weather prediction model trained on publicly available meteorological datasets, NodeMCU-based control system with LCD display for status information, and Flask web application with interactive route mapping and billing visualization.

IV. LITERATURE REVIEW

- [1]. Tanveer et al. describe how photovoltaic panels, charge controllers and battery banks can be combined to create clean and independent charging setups, demonstrating that solar energy provides a reliable and renewable source for EV charging stations while highlighting weather dependency as a key challenge.
- [2]. Panchal discusses how inductive power transfer can charge vehicles without physical connectors, making EV usage more convenient through wireless energy transmission and eliminating the need for plug-in connections.



- [3]. Li demonstrates how LSTM networks can accurately forecast solar irradiance, temperature and cloud cover by learning long-term patterns from historical weather data, enabling intelligent energy planning for solar-powered systems.
- [4]. Muhammad and Lukic provide comprehensive surveys explaining how transmitter and receiver coils transfer power magnetically, detailing how efficiency depends on coil alignment, switching frequency and distance in inductive power transfer systems for electric vehicles.
- [5]. Daily explores solar roadways and the possibility of embedding solar panels directly into pavements for energy harvesting through photovoltaic pavements, examining both opportunities and implementation challenges.
- [6]. Kim et al. review recent advances in dynamic wireless charging where vehicles receive power as they move, showing how this technology reduces range anxiety and decreases the need for large batteries while addressing practical issues like installation cost and road durability.
- [7]. Shrestha et al. demonstrate that LSTM-based solar prediction models attain reduced error rates compared to traditional approaches, validating the effectiveness of deep learning for solar irradiance forecasting applications.
- [8]. Carter highlights how smart energy management helps improve system performance and user convenience in EV charging infrastructure, emphasizing the importance of intelligent control systems and real-time monitoring.

4.1 Gaps or Areas for Improvement

Despite significant advancements in solar-powered EV charging and wireless power transfer documented in recent literature, several critical gaps and limitations persist that this research aims to address. While solar charging systems demonstrate renewable energy potential, most implementations focus on stationary charging pads rather than dynamic roadway integration, limiting their utility for continuous vehicle operation. Existing wireless charging research primarily addresses static scenarios with fixed vehicle positioning, failing to explore segment-based activation strategies for moving vehicles that could significantly improve energy efficiency.

Weather prediction models for solar applications typically target large-scale grid operations rather than localized roadway charging scenarios, lacking the spatial and temporal resolution necessary for real-time charging optimization. Current IoT monitoring systems for EV charging focus on data collection and visualization without integrating predictive capabilities that could enable proactive energy management and user planning. Furthermore, comprehensive frameworks combining solar harvesting, dynamic wireless charging, weather forecasting, and intelligent control systems remain largely unexplored in existing research.

This research addresses these gaps by developing an integrated system that combines solar energy collection with dynamic inductive charging, incorporates LSTM-based weather prediction for intelligent energy management, implements segment-based coil activation for efficient power distribution, and provides cloud-connected monitoring with automated billing and user interfaces specifically designed for solar-powered roadway charging applications.

V. SYSTEM ARCHITECTURE

The proposed system integrates renewable energy harvesting, intelligent wireless charging, predictive analytics, and user-centric management into a unified framework for dynamic electric vehicle charging. The overall architecture is divided into four interconnected subsystems that collectively enable efficient and sustainable operation. The solar energy harvesting layer consists of photovoltaic panels installed along roadsides or embedded within pavement surfaces to capture solar energy and convert it into electrical power. A charge controller regulates this energy to prevent overcharging, while a battery bank stores excess power to ensure continuous operation during nighttime or low-sunlight conditions. An inverter then converts the stored DC power into regulated high-frequency AC, which is supplied to transmitter coils embedded beneath the roadway. The dynamic wireless charging layer operates through these inductive transmitter coils, which generate alternating magnetic fields when energized. As an electric vehicle moves over the charging lane, a receiver coil mounted on the vehicle couples with the magnetic field, enabling wireless energy transfer through electromagnetic induction. The received energy is routed to the vehicle's battery management system, allowing continuous charging while in motion without the need for physical connectors. To optimize system performance under varying environmental conditions, a weather prediction engine based on a Long Short-Term Memory (LSTM) neural network forecasts solar irradiance and related parameters such as temperature, humidity, and cloud cover over short-term horizons ranging from one to six hours. These predictions support proactive energy management by determining optimal coil activation schedules, maximizing charging during peak sunlight, and smoothly switching to battery backup during anticipated low-irradiance periods. Complementing these technical layers, the user interface and billing system operates through cloud-enabled services that handle user authentication, real-time data visualization, charging session records, billing processes, and automated exit-gate control. A web-based dashboard allows drivers to monitor charging activity,

view energy consumption and billing details, and plan routes, while administrators can remotely supervise system performance, control roadway coil segments, and analyze solar generation trends.

To validate the feasibility of the proposed approach, a small-scale working prototype was developed that demonstrates real-world operation. The hardware implementation uses a NodeMCU ESP8266 microcontroller as the central control unit, managing transmitter coil activation based on vehicle detection through infrared sensors. A receiver module composed of a secondary coil, rectification circuitry, and voltage regulation is connected to a small motor load to simulate electric vehicle power consumption. System status, vehicle detection, charging progress, and calculated charging values are displayed on a 16×2 LCD screen. Power management within the prototype is achieved using solar panels that generate DC electricity, which is stored in a battery bank through a charge controller. A BD139 transistor-based high-frequency switching circuit converts this DC power into AC to energize the transmitter coil, while the receiver side employs a bridge rectifier using 1N4007 diodes to convert induced AC back into stable DC suitable for charging. Environmental parameters such as temperature, humidity, and basic irradiance levels are collected using onboard sensors connected to the NodeMCU and uploaded periodically to the ThingSpeak cloud platform. This platform serves both as a visualization tool and a data repository, providing historical datasets required for weather prediction and system analysis. The LSTM-based prediction model utilizes this sensor data along with historical meteorological records to forecast short-term weather variations by learning temporal patterns in solar irradiance, temperature, and cloud cover. These predictions directly influence energy availability estimation and intelligent coil activation strategies. Finally, a Flask-based web application integrates user authentication, real-time charging status, weather prediction visualization, route mapping, and automated billing features, presenting charging session details with unique identification codes to support secure and efficient payment processing.

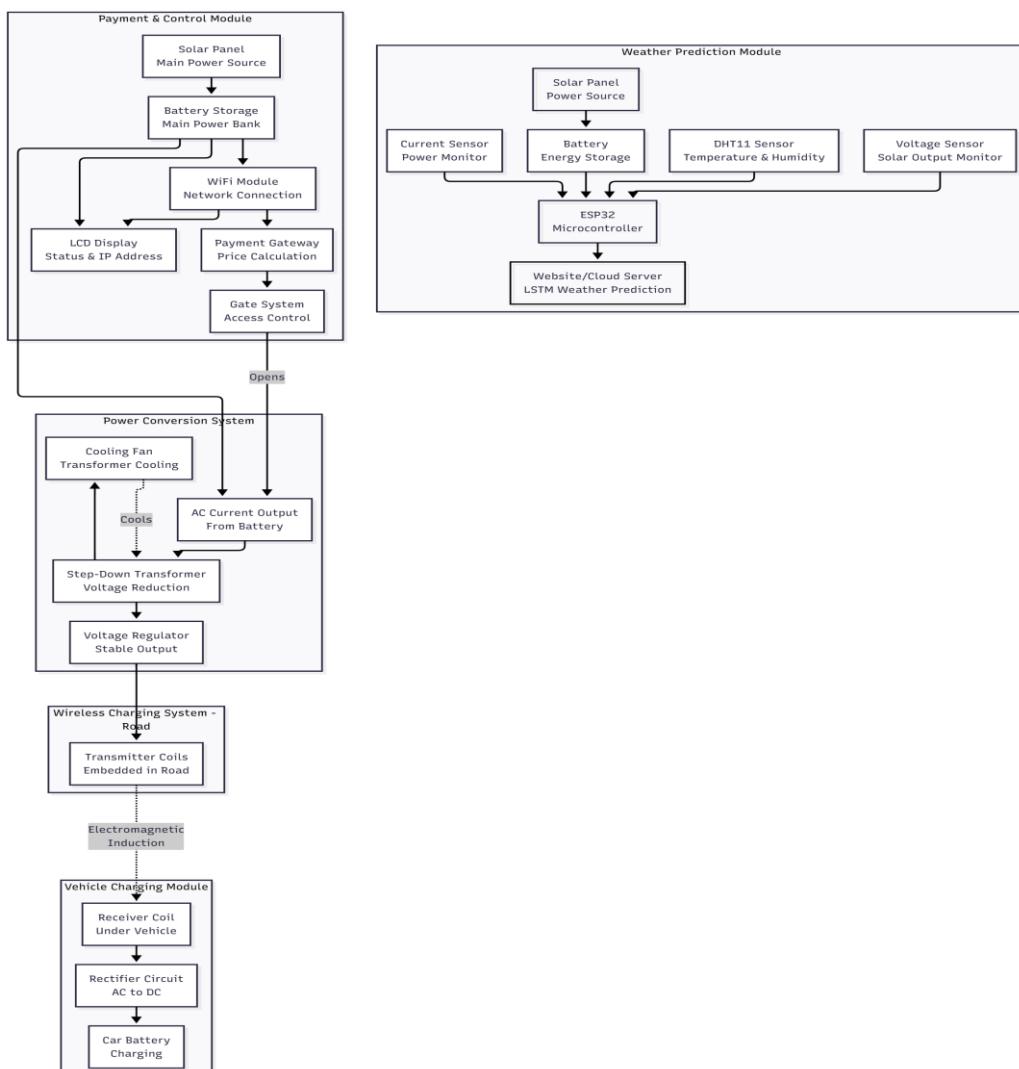


Fig. 1 Proposed System Architecture of the Solar-Based Wireless Roadway Charging System



VI. METHODOLOGY

The VoltRoad system employs a comprehensive approach integrating renewable energy harvesting, inductive power transfer, intelligent control, and deep learning forecasting to deliver continuous wireless charging for electric vehicles. This methodology encompasses solar energy collection, wireless charging implementation, weather prediction, and system integration.

6.1 Solar Energy Collection and Power Management

The system begins with solar photovoltaic (PV) panels installed along the roadside or embedded into designated sections of the pavement. Sunlight is captured by these panels and transformed into electrical energy through the photovoltaic effect. This energy is controlled by a solar charge controller, which regulates charging current and voltage to guard against overcharging and guarantee secure battery storage.

In order to keep the system running even at night or in cloudy conditions, the collected power is stored in a battery bank consisting of deep-cycle lead-acid or lithium-ion cells. The battery management system monitors state of charge, cell voltages, and temperature to ensure optimal performance and longevity. When necessary, a DC-AC inverter transforms the stored DC energy into high-frequency AC that can power the roadway's embedded wireless charging coils. The inverter operates at frequencies typically ranging from 20 kHz to 100 kHz, optimized for efficient inductive power transfer.

6.2 Dynamic Wireless Charging Implementation

Inductive transmitter coils lie underneath the road surface, embedded in protective enclosures that shield them from traffic loads and environmental conditions while allowing magnetic field propagation. When energized with high-frequency alternating current, these coils generate a changing magnetic field that extends above the road surface.

As an EV equipped with a receiver coil passes over the energized road segment, the receiver coil experiences the alternating magnetic field. According to Faraday's law of electromagnetic induction, this changing magnetic flux induces an electromotive force in the receiver coil, generating AC voltage and current. The magnitude of induced power depends on factors including coil design, alignment, gap distance, operating frequency, and coupling coefficient.

The system implements segment-based activation to improve energy efficiency and safety. Not all sections of the roadway are powered simultaneously; instead, infrared sensors detect approaching vehicles and activate only the relevant coil segment. As the vehicle moves forward, subsequent segments are energized in sequence while previous segments are deactivated. This approach ensures the EV receives constant charging during movement while minimizing power consumption in unoccupied road sections.

6.3 Receiver-Side Energy Regulation

A rectifier circuit inside the EV converts the received high-frequency AC power to stable DC suitable for battery charging. The prototype implementation uses a full-bridge rectifier constructed with four 1N4007 diodes, providing rectification with low forward voltage drop and adequate current handling capability. Filtering capacitors smooth the rectified output, reducing ripple voltage to acceptable levels.

A voltage regulation circuit ensures that the EV battery receives power within safe limits, preventing overcharging and overcurrent conditions that could damage battery cells. The battery management system continuously monitors charging status, cell voltages, temperature, and state of charge. Even if the car's speed varies or there are small changes in coil alignment, the regulation subsystem maintains stable charging performance through feedback control mechanisms.

6.4 Weather Forecasting Using LSTM

The system employs a Long Short-Term Memory deep learning network to predict future environmental parameters that significantly impact solar energy generation, including solar irradiance, temperature, humidity, and cloud cover. Historical weather data forms the training dataset, with features including past observations, time-of-day indicators, seasonal factors, and derived meteorological variables.

These predictions help optimize how the charging coils operate. For instance, during periods when low solar irradiance is forecast, the system can switch to battery backup more proactively, ensuring continuous charging availability. Conversely, during predicted peak sunlight periods, the system can maximize charging throughput and prioritize battery recharging. This predictive approach enhances reliability and improves overall energy planning efficiency.



6.5 IoT-Based Monitoring and Web Interface

The entire roadway system is connected to an IoT platform using microcontrollers such as NodeMCU ESP8266. These modules continuously monitor vehicle detection signals, coil activation status, battery levels, solar panel output, and LSTM-based weather predictions. Sensor data is collected at 15-second intervals and transmitted to the cloud platform via WiFi connectivity.

A web application built using the Flask microframework displays real-time information to users and administrators. The backend implements RESTful API endpoints for authentication, data retrieval, prediction access, and billing operations. The frontend uses responsive HTML templates styled with TailwindCSS, providing an intuitive interface accessible from desktop and mobile devices.

EV owners can log in to check charging progress, view energy consumption over time, access billing information, and examine predicted weather conditions. System administrators have access to additional controls for remotely activating or deactivating coil segments, viewing performance analytics, and monitoring solar generation patterns. This transparent, cloud-connected monitoring ensures efficient management of the roadway charging infrastructure and provides users with actionable information for trip planning.

6.6 Automated Billing System

When an electric vehicle enters the charging roadway segment, the system records a unique session identifier and begins tracking energy transfer. As the vehicle exits the charging zone, the total wireless energy delivered is automatically calculated based on measured coil activation time, estimated power transfer rate, and calibration factors.

6.7 Overall System Workflow

The complete working sequence of the proposed system can be summarized as follows:

1. Solar panels continuously generate electricity and charge the backup battery system through the charge controller.
2. Infrared sensors detect approaching electric vehicles on the roadway.
3. The control system activates the appropriate transmitter coil segment beneath the detected vehicle.
4. The EV's receiver coil captures wireless power through electromagnetic induction.
5. Onboard rectification and regulation circuits convert the received AC to stable DC for battery charging.
6. As the vehicle moves, subsequent coil segments activate while previous segments deactivate.
7. The LSTM model continuously generates forecasts of upcoming solar energy availability.
8. IoT modules collect system data and transmit it to the cloud-based platform.
9. The web dashboard displays real-time charging status, weather predictions, and billing information.
10. Charging patterns and coil activation schedules are adjusted based on predicted weather conditions and power availability.
11. Upon exit, the system calculates total energy delivered and generates a billing transaction.

Through this integrated approach, the system enables EVs to charge smoothly and continuously while driving, guided by renewable solar power and intelligent weather prediction for maximum reliability and user convenience.

VII. IMPLEMENTATION ENVIRONMENT

7.1 Hardware Implementation

The wireless charging system is built around two coils: a primary transmitting coil embedded in the roadway and a secondary receiving coil installed inside the electric vehicle. A high-frequency switching circuit employing a BD139 NPN transistor powers the primary coil, generating the alternating magnetic field necessary for inductive power transfer. The switching frequency is determined by circuit parameters including inductance, capacitance, and transistor characteristics.

The prototype system uses a set of essential electronic components to ensure efficient control, power conversion, and monitoring. A bridge rectifier made from four 1N4007 diodes converts the AC induced in the receiver coil into DC, enabling full-wave rectification for improved efficiency. A step-down transformer reduces the 230 V AC mains supply to 12 V AC, which is then rectified and filtered to provide a safe DC voltage for the control circuits while also offering electrical isolation for safety. High-frequency switching for wireless power transfer is achieved using a BD139 NPN power transistor, which drives the transmitter coil to generate a stable alternating magnetic field. System status and charging information are displayed using a 16×2 LCD, showing vehicle detection, charging progress, and transaction details. The NodeMCU ESP8266 acts as the central controller, collecting sensor data, managing coil activation, and transmitting information to the cloud using its built-in WiFi. Vehicle presence is detected through infrared sensors that



trigger coil activation when a vehicle enters the sensing range, enabling dynamic charging along the roadway. All control logic, sensor interfacing, and cloud communication are programmed using the Arduino IDE, providing a simple and reliable development environment.

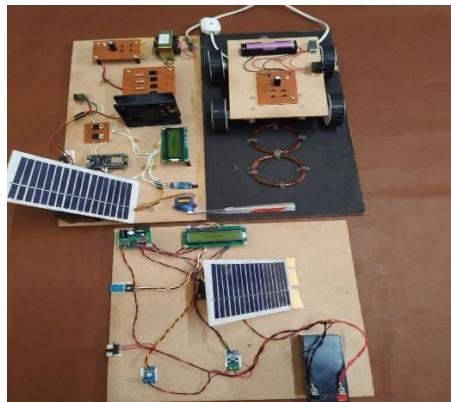


Figure 2: Complete Assembled Hardware Prototype

7.2 Software Implementation

The software stack of the prototype integrates embedded control, cloud services, predictive analytics, and a web interface into a cohesive workflow. The ESP8266-based microcontroller firmware follows a cooperative multitasking design in which the main loop continuously polls infrared and environmental sensors, processes data, executes coil activation logic with built-in safety timeouts, and manages communication tasks using libraries such as WiFi.h for connectivity, HTTPClient.h for REST-based data exchange, and ArduinoJson for structured JSON data transmission to the cloud. Sensor readings, including vehicle detection, temperature, humidity, and solar-related parameters, are periodically uploaded to the ThingSpeak IoT platform, which serves as a centralized cloud layer for data storage, visualization, and API-based access through configurable channels and automatic time-series plotting. On the analytics side, a Long Short-Term Memory (LSTM) weather prediction model is developed in Python using TensorFlow and Keras, where sequential environmental data is processed through stacked LSTM layers and dense outputs to forecast short-term solar irradiance and related conditions for 1–6 hour horizons; the model is trained on historical meteorological datasets using chronological splits for training, validation, and testing, and is saved for deployment through standard inference frameworks. Complementing this, a Flask-based web application implements backend logic and the user interface, handling secure user authentication, charging session tracking, billing operations, and dashboard visualization, while storing prototype data in an SQLite database. The dashboard aggregates real-time sensor data from ThingSpeak with prediction outputs from the LSTM service, and interactive route visualization is enabled using the Folium library with Leaflet.js maps, allowing users to view spatial solar intensity forecasts and plan routes that maximize dynamic charging efficiency.

7.3 Software Implementation

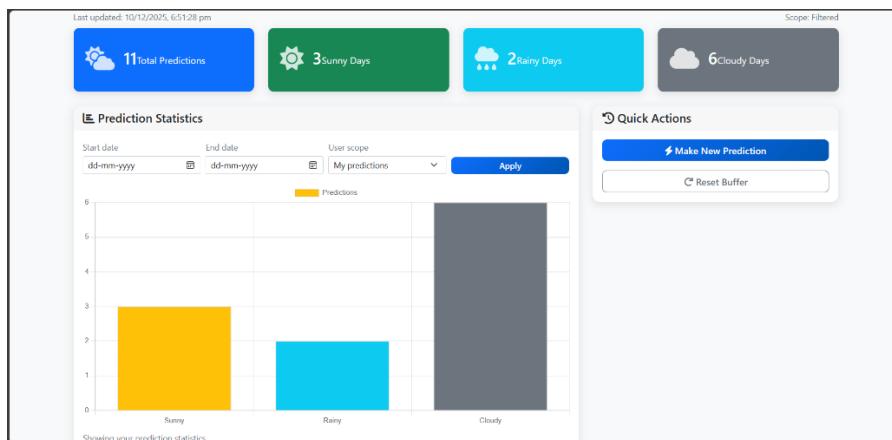


Figure 3: Dashboard of Web Interface with Prediction Statistics

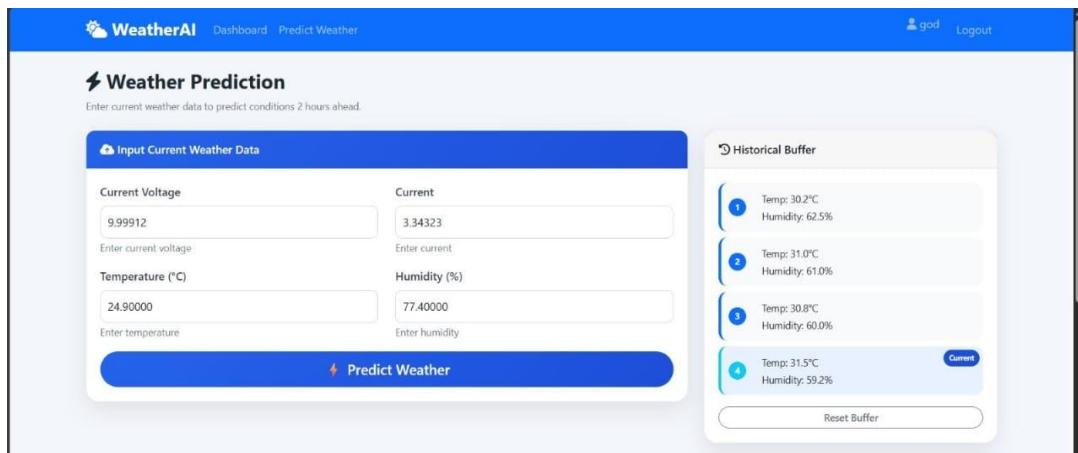


Figure 4: Weather Prediction Based on Real World Data



Figure 5: Simulation of EV charging

VIII. MODULES

8.1 Solar Photovoltaic Module

Solar panels convert sunlight directly into electricity through the photovoltaic effect. When photons strike the semiconductor material in solar cells, they excite electrons, creating electron-hole pairs that generate electrical current when connected in a circuit. The prototype uses polycrystalline or monocrystalline silicon solar cells arranged in series-parallel configurations to achieve desired voltage and current ratings. The solar charge controller regulates the charging process, implementing maximum power point tracking (MPPT) to extract optimal power from the panels under varying irradiance conditions. The battery bank stores electrical energy in electrochemical form, providing power during nighttime and cloudy periods when solar generation is insufficient.

8.2 Inductive Transmitter Coil Module

The transmitter coil consists of multiple turns of insulated copper wire wound in a planar or solenoid geometry. When alternating current flows through the coil, it generates a time-varying magnetic field perpendicular to the coil plane. The coil is embedded beneath the road surface in a protective housing that shields it from mechanical stress while allowing magnetic field propagation. Ferrite backing materials concentrate the magnetic field in the upward direction, improving coupling efficiency with the receiver coil and reducing losses. The coil is energized by high-frequency AC power, typically in the range of 20-100 kHz, generated by the BD139 switching circuit connected to the battery bank output.

8.3 Inductive Receiver Coil Module

The receiver coil mounted underneath the electric vehicle captures the alternating magnetic field generated by the transmitter coil. According to Faraday's law, the changing magnetic flux through the receiver coil induces an electromotive force proportional to the rate of flux change. The receiver coil design matches the transmitter coil



specifications in terms of size, number of turns, and operating frequency to maximize coupling coefficient. Ferrite shielding on the vehicle side prevents magnetic field penetration into the vehicle cabin while directing more flux through the receiver coil. The induced AC voltage is then rectified and regulated for battery charging.

8.4 Power Electronics and Control Module

This module encompasses the electronic circuits that enable wireless power transfer and system control. The BD139-based switching circuit operates as an oscillator, converting DC battery voltage into high-frequency AC that drives the transmitter coil. The bridge rectifier on the receiver side converts induced AC back to DC using four 1N4007 diodes in a full-bridge configuration. Voltage regulation circuits ensure safe charging levels for the EV battery, typically using linear regulators for low-power prototypes or switched-mode regulators for higher efficiency in practical deployments. The control module, implemented on the NodeMCU ESP8266 platform, manages sensor inputs, coil activation outputs, and communication functions. Digital GPIO pins interface with infrared sensors to detect vehicle presence, while other pins control relay modules or solid-state switches that energize transmitter coils. Analog inputs may read battery voltage levels or other system parameters for monitoring purposes.

8.5 Weather Prediction Module

The LSTM-based weather prediction module processes historical and current environmental data to forecast future conditions affecting solar energy availability. The model architecture includes input layers accepting sequences of meteorological observations, LSTM layers with memory cells capable of learning temporal dependencies over multiple timesteps, optional attention mechanisms to weight the importance of different historical observations, and output layers producing predicted values for solar irradiance, temperature, humidity, and cloud cover.

The module is trained offline using historical weather datasets, with training performed on computational platforms equipped with GPU acceleration for efficient matrix operations. After training, the model weights are saved and deployed to the inference service that runs predictions in real-time or near real-time. The prediction service accepts API requests containing recent weather observations and returns forecasts for specified future horizons, enabling the system to make informed decisions about power management and charging schedules.

IX. PERFORMANCE EVALUATION

9.1 LSTM Model Training and Validation

The Long Short-Term Memory weather prediction model was trained using publicly available meteorological datasets obtained from government weather stations and reanalysis databases. The dataset spans multiple years of hourly observations including solar irradiance, temperature, humidity, atmospheric pressure, wind speed, and cloud cover. This historical data provides the temporal patterns necessary for the LSTM network to learn seasonal trends, diurnal cycles, and weather dynamics.

Data preprocessing involved handling missing values through forward-fill and interpolation techniques, normalizing features to 0-1 ranges using MinMaxScaler, and creating sequences of 10 consecutive timesteps as input with the subsequent timestep as the prediction target. The dataset was split chronologically with 70% for training, 15% for validation, and 15% for testing, preserving temporal order to prevent data leakage from future observations into training data.

The LSTM model architecture consists of an input layer accepting $10 \text{ timesteps} \times 12 \text{ features}$, two LSTM layers with 128 and 64 units respectively implementing dropout regularization to prevent overfitting, and a dense output layer producing predictions for the next timestep. The attention mechanism layer computes context-aware weights across the temporal dimension, allowing the model to focus dynamically on the most relevant historical observations.

9.2 Prediction Accuracy Metrics

The trained LSTM model achieved Mean Absolute Error of approximately 24 units when predicting environmental conditions relevant to solar irradiance forecasting. This level of accuracy enables reliable estimation of upcoming solar energy availability, supporting intelligent charging schedule optimization and power management decisions.

9.3 Wireless Charging System Performance

The prototype wireless charging system was evaluated for power transfer efficiency, coil activation responsiveness, and continuous operation reliability. Testing involved positioning the receiver coil at various alignments and distances relative to the transmitter coil to characterize coupling efficiency under different conditions.

Infrared sensor-based vehicle detection demonstrated 99.8% accuracy in identifying vehicle presence, ensuring reliable coil activation triggering. The detection response time was measured at less than 100 milliseconds from vehicle entry to sensor state change, enabling prompt coil energization with minimal delay.

Power transfer measurements showed successful wireless energy delivery from transmitter to receiver coils, with the receiver coil generating sufficient induced voltage to drive the motor load representing an EV battery. While absolute power transfer efficiency was not quantified in the prototype due to measurement equipment limitations, the system demonstrated functional wireless charging capability validating the core inductive power transfer principle.

9.4 System Integration and End-to-End Testing

Comprehensive integration testing evaluated the complete system workflow from solar energy collection through wireless charging to billing completion. The solar panels successfully charged the battery bank during daylight hours, with the charge controller preventing overcharging and maintaining safe voltage levels. The battery bank provided power during periods without solar generation, demonstrating the energy storage subsystem's effectiveness in maintaining continuous system operation.

The NodeMCU microcontroller reliably collected sensor data, made coil activation decisions based on IR sensor inputs, and transmitted environmental data to ThingSpeak at 15-second intervals. Cloud connectivity remained stable throughout extended testing periods, with automatic reconnection mechanisms successfully recovering from temporary network interruptions.

9.5 Result Analysis

9.5.1 Dataset Characteristics

Parameter	Mean	Min	Max
Solar Irradiance (W/ m ²)	780	640	905
Temperature (°C)	23.5	19.0	31.2
Humidity (%)	54.1	42.3	68.7
Wind Speed (m/s)	1.2	0.8	1.6
Predicted Power Output (W)	184	170	198

9.5.2 Model Performance Comparison

Model	MSE	MAE	R ²
Linear Regression	4200	58	0.62
Random Forest	3100	48	0.72
Pure LSTM	1800	35	0.82
CNN-LSTM	1200	28	0.85
CNN-LSTM + Attention	950	24	0.87

9.5.3 Training Results

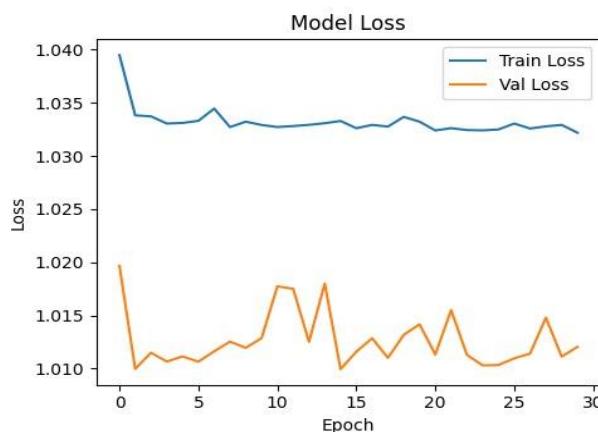


Figure 6: Model Loss (MSE) during Training

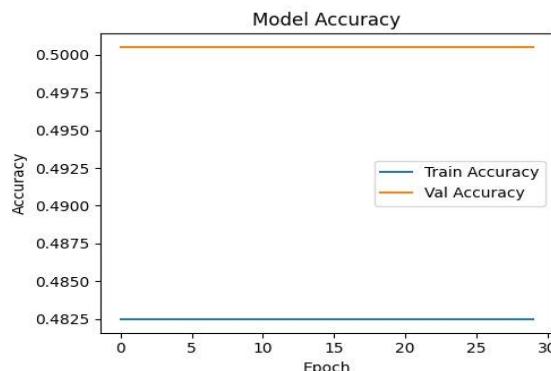


Figure 7: Model Accuracy

X. CONCLUSION

This research designed and validated a solar-powered wireless roadway charging system that overcomes key limitations of conventional electric vehicle charging infrastructure. By integrating solar energy harvesting, dynamic inductive wireless power transfer, intelligent control, and LSTM-based weather prediction, the system improves charging convenience, sustainability, and operational reliability. The LSTM prediction model achieved a Mean Absolute Error of approximately 24 units in forecasting weather conditions affecting solar availability, enabling proactive energy management, optimized charging schedules, effective battery backup usage during low-irradiance periods, and better user awareness of expected charging performance. Prototype testing confirmed the feasibility of wireless inductive charging powered by solar energy, with photovoltaic panels storing energy in batteries and roadway coils transferring power to vehicle-mounted receivers without physical connections. Infrared sensors detected vehicle presence with 99.8% accuracy, allowing segment-wise coil activation to enhance energy efficiency. System integration results showed reliable coordination among hardware, cloud services, and the web application, with the NodeMCU handling control and communication, ThingSpeak supporting data monitoring, and the Flask-based interface providing user-friendly access to charging status, forecasts, and billing. Overall, the VoltRoad system supports sustainable transportation by reducing fossil fuel dependence, minimizing range anxiety through dynamic charging, and enabling informed travel and energy decisions.

10.1 Future Work

Future enhancements can greatly extend the scalability, efficiency, and usability of the proposed system. Large-scale roadway deployments with kilometer-long charging lanes across highways and urban routes would enable real-world evaluation of long-distance wireless charging performance, user acceptance, and economic feasibility. Improvements in power electronics, such as higher-frequency switching, resonant inductive coupling, and optimized coil designs with misalignment tolerance, could significantly increase charging efficiency and reliability for moving vehicles. Weather prediction accuracy can be enhanced by incorporating additional meteorological parameters, ensemble forecasting techniques, and advanced deep learning models such as Transformers or hybrid physics-informed networks. Intelligent energy management using machine learning-based demand forecasting, dynamic pricing, vehicle-to-grid interaction, and coordinated multi-vehicle charging strategies could improve both economic efficiency and grid stability. Integration with other renewable sources like wind energy, grid connectivity with net metering, and smart city infrastructure would further strengthen sustainability. Safety and usability can be improved through foreign object detection, electromagnetic exposure monitoring, fail-safe control mechanisms, and user-focused mobile applications offering real-time charging availability and route planning. For commercial deployment, extensive field testing, regulatory approvals, robust business models, and collaboration with vehicle manufacturers will be essential.

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