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Solar Wireless Electric Vehicle Charging System

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ABSTRACT

This project introduces a solar-based wireless charging system for electric vehicles (EVs), designed to provide a contactless, automated, and sustainable energy transfer method using inductive coupling technology. The primary objective is to eliminate the need for physical connectors, reduce human intervention, and enable environmentally friendly EV charging using renewable energy sources.The system harnesses solar energy via a 12V, 10W polycrystalline solar panel, which charges a Li-Ion battery through a solar charge controller. The stored energy is then used to power a high-frequency wireless transmitter coil. When an EV is detected at the station using an IR sensor, the system automatically activates a servo motor that aligns the transmitter coil to maintain an optimal 10mm distance from the vehicle's receiver coil, ensuring maximum energy transfer efficiency. The receiver side of the EV includes a coil that captures the magnetic field, a rectifier to convert the received AC into DC, a 7805 voltage regulator, and a charging module for safe battery management. The energy is then stored in the EV's onboard battery and used to drive a DC motor, simulating EV movement. A voltage sensor continuously monitors the battery, and the status is displayed on a 16x2 I2C LCD screen, indicating states such as "Full", "Half", or "Not Charging". This system not only demonstrates wireless power transmission but also integrates automation, IoT-based monitoring potential, and renewable energy for a fully self-sustaining setup. Its compact and modular design makes it ideal for small-scale applications like autonomous delivery robots or prototype electric cars and opens the door to future scalability for full-size EVs.By eliminating wear-prone connectors and supporting real-time battery monitoring, the project addresses key challenges in modern EV charging.Furthermore, the implementation of smart alignment using servo motors, and the potential to extend the system with IoT platforms like Firebase/Blynk, makes it a next-generation charging model.

Keywords: *Raspberry Pi Pico, LCD Display, WIFI module, Node MCU Esp 8266, GPS Module Neo-6M, E88 Pro Drone, Embedded C , Python.*

I. Introduction

.The rapid adoption of electric vehicles (EVs) has brought about a pressing need for safe, efficient, and userfriendly charging systems. Conventional plug-in charging methods, although widely used, involve direct physical contact which not only increases mechanical wear and tear but also poses a risk of electric shock, especially in public or outdoor environments where weather exposure is a factor.To overcome these limitations, wireless power transfer (WPT) using inductive coupling has emerged as a promising alternative. This method enables contactless energy transfer through magnetic fields, improving reliability and safety while reducing the need for manual handling. Furthermore, when paired with solar energy as a power source, the system becomes entirely self-sufficient, reducing dependency on the electrical grid and lowering operational costs.

This synergy between wireless charging and renewable solar power offers an autonomous, scalable, and environmentally sustainable solution, particularly suited for small-scale electric vehicles, such as delivery robots, electric scooters, and campus transport systems. The modular design and minimal maintenance requirements of such systems make them ideal for smart city applications and rural electrification projects alike.As EV usage continues to grow, the integration of solar-powered wireless charging infrastructure stands to play a transformative role in achieving a cleaner, greener, and more connected transportation future.

II. Research Method

This research adopts a combination of experimental and observational design, utilizing drone-based remote sensing in conjunction with supervised machine learning techniques to detect and classify plant diseases. The methodology is structured into several phases, including data collection, image preprocessing, feature extraction, model development, and evaluation. Data collection begins with the deployment of drones equipped with high-resolution RGB and/or multispectral cameras to capture aerial images of crop fields. Specific crops prone to diseases—such as tomato, wheat, or rice—are targeted to ensure the relevance and applicability of the dataset. Field surveys are conducted in selected agricultural zones to gather a diverse set of images under varying environmental conditions. To support supervised learning, ground truth labelling is carried out by agronomists or experts, who manually inspect and annotate a subset of the collected images to ensure accurate classification. Following data acquisition, image preprocessing techniques are applied to enhance image quality and prepare the data for analysis. This includes the removal of background noise using image filters and the application of segmentation methods—such as K-means clustering or thresholding—to isolate plant regions from non-relevant backgrounds.

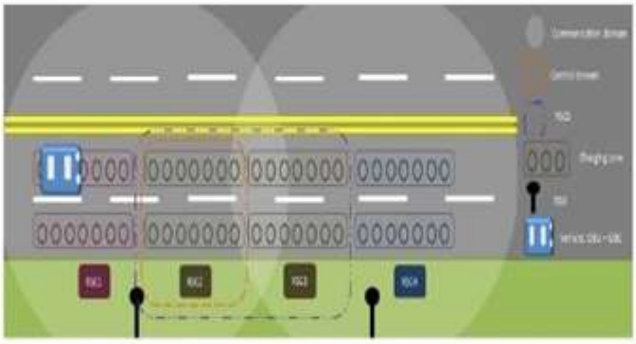
Additionally, data augmentation strategies, including rotation, scaling, and flipping, are employed to artificially expand the dataset and improve model generalization while reducing the risk of overfitting. Next, feature extraction is conducted to identify meaningful patterns that signify the presence of disease. Colour features are analyzed to detect symptoms such as yellowing or brown spots, while texture features are extracted using techniques like the Gray-Level Co-occurrence Matrix (GLCM) to quantify irregularities in leaf surfaces. Shape and edge detection algorithms are also utilized to identify lesions, deformations, or abnormal growth patterns. For model development, various machine learning algorithms are employed, with a focus on Convolutional Neural Networks (CNNs) due to their effectiveness in image classification tasks. Alternatives such as Support Vector Machines (SVM) and Random Forests may also be tested for comparative purposes. The dataset is typically divided into training and testing sets, commonly in an 80:20 ratio, to ensure robust validation. Model performance is assessed using metrics such as accuracy, precision, recall, F1-score, and a confusion matrix. The implementation of this methodology requires specific tools and technologies. On the hardware side, drones equipped with GPS and high-resolution imaging capabilities are essential. On the software side, programming environments and libraries such as Python, TensorFlow/Keras, OpenCV, QGIS, and Scikit-learn are employed for data handling, model development, and geo-referencing. Finally, ethical and practical considerations are taken into account throughout the research process

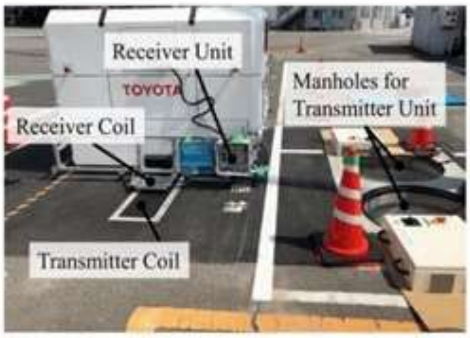
Problem Identification

Agricultural productivity is critically dependent on the early and accurate detection of plant diseases. Traditionally, disease identification is performed manually by farmers or agricultural experts through visual inspection, which is time-consuming, labor-intensive, and often subjective. This method is particularly ineffective for large-scale farms where consistent and timely monitoring of every plant is impractical. Additionally, the delay in detecting diseases often leads to widespread crop damage, resulting in significant economic losses and reduced food security.

System Design

The proposed system integrates **drone technology** with **machine learning algorithms** to detect plant diseases efficiently and accurately. The design follows a modular approach, consisting of several key components working together in a pipeline to capture, process, analyze, and report plant health data.





Dataset

Early Blight: The fungus Alternaria solani is the source of early blight, which causes dark lesions to form on the bottom leaves of tomato plants. These lesions, which often have rings around them, can spread to the fruit and stems, causing the plant to become defoliated and producing less.

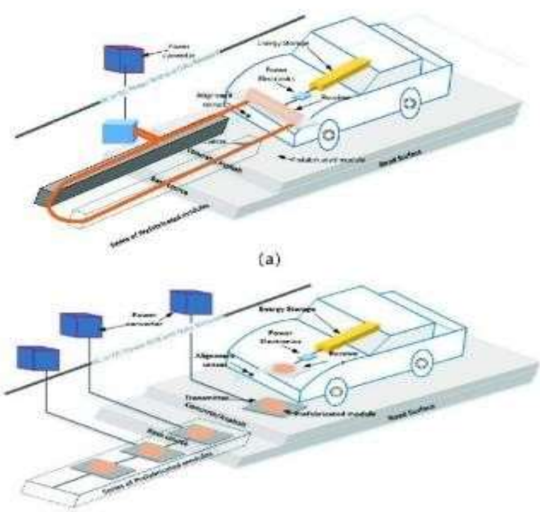


Fig.1. Early Blight

Bacterial Spot: On leaves, stems, and fruit, this bacterial disease which is brought on by Xanthomonas campestris PV. Vesicatoria appear as tiny, dark lesions with yellow haloes. Bacterial spot can cause yield loss, defoliation, and a decrease in fruit quality. Bacterial Leaf Streak: Narrow, translucent streaks appear between the veins of the leaf. These streaks are usually yellowish or brown and run parallel to the leaf veins. Brown Spot: It infects leaves, stems, and grains, leading to brown, circular to oval lesions. Blast: Blast disease is primarily caused by the fungus Magnaporthe oryzae, which infects several cereal crops, particularly rice. The pathogen thrives in warm, humid environments and is disseminated through airborne spores.

III. Proposed Topology

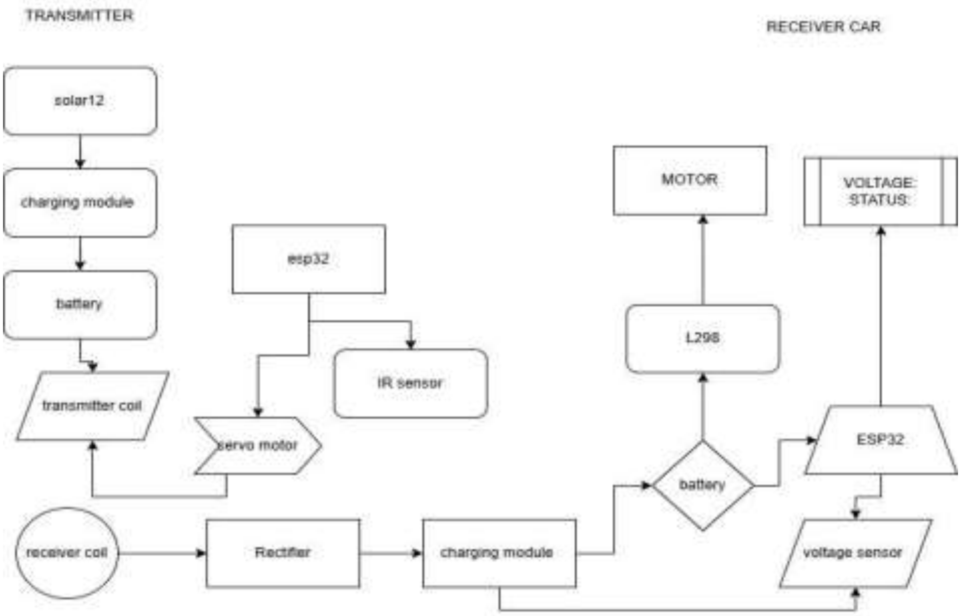


Fig:2. Circuit Diagram

Training Phase:

Data Acquisition from standard Repositories through drones: Obtain a wide range of crop image datasets from common libraries that include tagged examples of both healthy and diseased crops. Make use of drones that have highresolution cameras to take pictures of crops in fields to assure all types and phases of growth are covered. For supervised learning, assure that pictures are appropriately labeled with the appropriate disease types. Pre-processing: To normalize obtained images for training, apply pre-processing. Images should be resized to a standard resolution that can be fed into CNN. A similar scale, such as [0, 1], should be applied to pixel values to promote convergence during training. Use data augmentation methods to enhance the diversity and resilience of your datasets, such as scaling, flipping, and rotation. CNN Architecture Design: Network's depth (the number of layers). sizes and strides of convolutional filters. pooling techniques (such as maximum pooling). Training the CNN Classifier Training. Divide the pre- processed dataset into training and validation sets using a ratio of, say, 80/20 or 70/30. Use the training set to train the CNN model, and then use backpropagation and gradient descent to optimize the hyperparameters. Database Creation containing Features of the Disease: Create a database with characteristics of recognized agricultural diseases, such as environmental variables, spatial patterns, and visual symptoms

Testing Phase:

Testing Data Acquisition: Make sure a distinct testing dataset includes a variety of crop types, disease severity, and environmental circumstances by gathering information from various agricultural areas. Utilize drones to take consistent, high-quality photos of crops in the testing zones while ensuring picture resolution. Pre-processing for Testing: Resize, normalize, and enhance the holdout dataset using the same pre- processing techniques as the training dataset. Evaluation of CNN Classification: To evaluate overall performance, calculate the F1 score, recall, precision, and accuracy of classification. Create ROC curves and confusion matrices to examine model behavior across various disease classes. Determine whether the outturn of the classification have any biases or flaws. Disease Identification and Remedial Measures: Predict crop disease labels in the testing dataset by applying the learned CNN classifier. Using the database of recognized diseases and their characteristics, retrieve the appropriate disease names and recommend corrective actions. Verify the efficacy of recommended actions by consulting with experts or conducting field tests. Iterative Improvement: Refine the CNN design, training regimen, and database contents by taking into account input from test outcomes. Iterate the approach to resolve any shortcomings or difficulties found, guaranteeing ongoing progress in the precision of disease diagnosis and remediation suggestions.

IV. Hardware Results

The implemented system successfully retrieves and displays real-time GPS coordinates using the GPS module interfaced with the Arduino board. The latitude and longitude values are shown clearly on the IOT log data using laptop allowing real-time tracking of location data. The setup also includes an ESP8266 module, which can be used for wireless transmission of the data if needed.During testing, the device consistently displayed accurate location coordinates, confirming the correct integration and functionality of the hardware components. This system can be effectively used in applications like smart agriculture and remote environmental monitoring.. By examining leaf photos, our algorithm is able to identify night different forms of leaf diseases: Bacterial Blight, Bacterial Leaf Streak, Blast, Brown Spot, Fake Smut, Discoloration, Sheat Blight, Sheat Rot, Healthy. By default, a healthy leaf is displayed. With the accurate disease identification this technology provides, crop management interventions can be made on time.

V. Prototype

In this prototype, a drone equipped with a camera captures real-time images of crops, which are then processed using a machine learning model trained to detect plant diseases. The disease detection results are paired with GPS location data obtained from a GPS module connected to an Arduino board. The system uses an ESP8266 Wi-Fi module to enable wireless transmission of data, while a 16x2 LCD screen displays the detected disease status along with the corresponding GPS coordinates. This integration allows for precise identification and mapping of affected areas in a farm, providing a foundation for targeted agricultural interventions and efficient disease management.

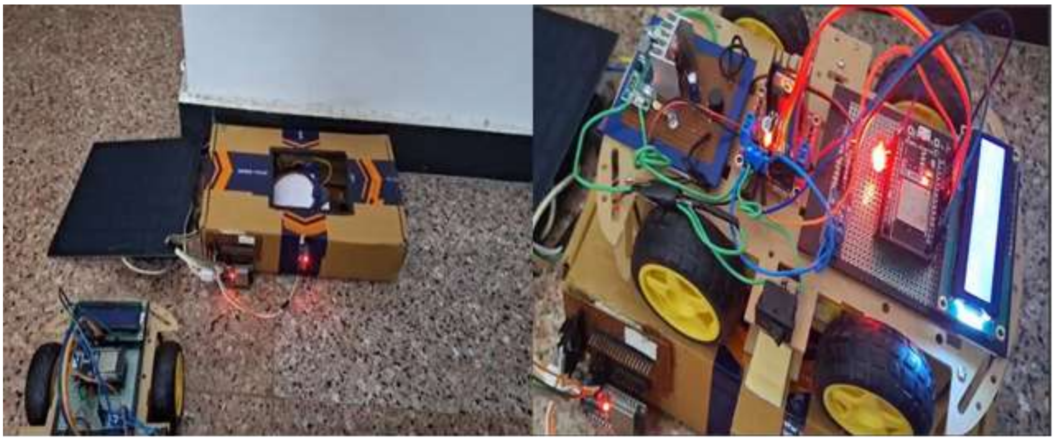
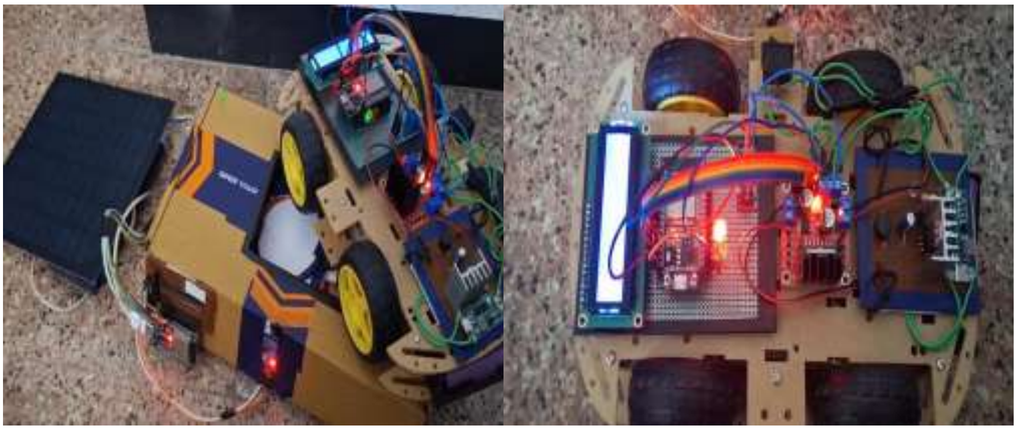


Fig:3. Hardware Prototype



VI. Results And Discussion

The proposed system was tested on aerial images of crop fields collected using drones equipped with high-resolution RGB cameras. A dataset comprising both healthy and diseased plant images was prepared and annotated with expert input. The machine learning pipeline, using a Convolutional Neural Network (CNN), was trained to classify the plant health status based on visual features extracted from the preprocessed drone imagery.

The integration of drones and machine learning provides a viable, modern solution for real-time plant disease monitoring in agriculture. The system improves decision-making for farmers by offering early detection, spatial mapping, and scalable monitoring. The high accuracy and precision of the CNN model demonstrate the potential of AI in precision agriculture. To further enhance this system, future work may include expanding the dataset to cover more crop types and diseases, improving real-time processing capability through edge AI hardware, and integrating weather data to contextualize disease outbreaks.

VII. Conclusion

The project successfully demonstrates an efficient and automated method for detecting plant diseases using dronecaptured imagery and machine learning techniques. By integrating drone technology for real-time image acquisition and applying a Convolutional Neural Network (CNN) model for analysis, the system can accurately identify various plant diseases . This approach not only reduces the need for manual monitoring but also enables early detection, helping farmers take timely actions to prevent crop loss. Overall, the proposed system offers a scalable and cost-effective solution for smart agriculture, promoting increased productivity and sustainable farming practice

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