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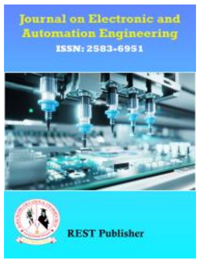

Smart Robot for Plant Disease Detection

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Abstract: *The designed Project introduces an innovative autonomous robot for plant disease detection, harnessing the power of a Raspberry Pi, advanced imaging technology, and real time SMS alerts to revolutionize agricultural practices. Designed to navigate fields independently, this robot captures detailed images of plant leaves and employs sophisticated image processing algorithms to identify early signs of diseases, including fungal infections, bacterial blight, and nutrient deficiencies. When a potential disease is detected, the system sends instant SMS notifications to farmers, enabling immediate action to mitigate crop loss. Central to the design is the Raspberry Pi microcontroller, which orchestrates the robot's operations and runs the detection algorithms. The high-resolution camera module plays a crucial role in ensuring accurate diagnosis, while the integrated GSM module facilitates seamless communication. Utilizing cutting-edge machine learning techniques, this system achieves high accuracy in disease recognition, even in diverse agricultural settings. Field tests have showcased its effectiveness, delivering rapid alerts and enhancing decision-making for farmers. By empowering growers with timely insights and proactive disease management, this robot not only promotes sustainable farming practices but also paves the way for smarter, technology driven agriculture.*

Keywords: *Plant disease detection, Raspberry Pi, image processing, SMS alerts, precision agriculture, camera module, agricultural robotics, sustainable farming.*

1. INTRODUCTION

The rise of automation and technology in agriculture has led to the development of innovative solutions aimed at enhancing crop health and maximizing agricultural productivity. One such solution is the integration of smart robots for plant disease detection, which plays a vital role in safeguarding crops against harmful pathogens and pests. Traditional methods of detecting plant diseases are often labor-intensive, time-consuming, and prone to human error. They usually rely on visual inspection by experts or agricultural extension workers, which can lead to delayed diagnoses and the unnecessary use of pesticides. In contrast, the advent of smart robotics combined with Raspberry Pi and GSM modules provides an intelligent and efficient alternative. In this system, the Raspberry Pi, a small yet powerful single-board computer, serves as the central processing unit. It works with a camera and image processing algorithms to capture and analyze images of plant leaves to detect signs of diseases such as blights, rusts, and fungal infections. The system can be configured with machine learning models or classical image processing techniques to identify and classify diseases based on visual symptoms. Once a disease is detected, the system uses a GSM module to send an SMS alert to the farmer's mobile phone, notifying them of the specific issue. This immediate feedback allows farmers to take swift action, such as applying the appropriate treatment or adjusting environmental conditions, even if they are not physically present in the field. The use of a GSM module is particularly beneficial in remote or rural areas where internet connectivity might be unavailable, providing a low-cost and reliable communication method. The integration of automation, image recognition, and wireless communication ensures that plant disease detection becomes faster, more accurate, and accessible. This system is expected to reduce the use of pesticides, promote sustainable farming practices, and minimize crop loss, ultimately contributing to more efficient and environmentally friendly agricultural practices. Additionally, the accessibility and affordability of the Raspberry Pi platform make this solution scalable for small-scale farmers, helping them enhance crop health management without requiring large investments.

2. PROBLEM STATEMENT

Plant diseases are a major concern in agriculture, contributing to substantial crop losses worldwide and threatening food security. These diseases, which can be caused by fungi, bacteria, viruses, and pests, can spread rapidly across fields, significantly affecting both yield and quality of crops. Early detection and management of plant diseases are crucial in preventing widespread damage. However, traditional methods of disease detection, such as visual inspection by farmers or agricultural experts, have several limitations. These methods are time-consuming, subjective, and prone to human error. As a result, diseases are often not identified until they have already caused considerable damage, leading to a delay in taking corrective action. In many cases, delayed disease detection leads to the overuse of pesticides, as farmers apply chemicals preventively or in response to symptoms they fail to recognize early. This overuse of pesticides not only increases the financial burden on farmers but also harms the environment, contributing to soil degradation, water pollution, and reduced biodiversity. Furthermore, the reliance on chemicals can lead to the development of pesticide-resistant strains of pathogens, making future disease management even more challenging. The situation is particularly problematic for small-scale farmers in rural or remote areas, where access to expert knowledge, advanced diagnostic tools, and modern technologies is limited. These farmers often rely on outdated methods and lack the resources to adopt more efficient disease management strategies. Many remote agricultural regions also face issues with poor or no internet connectivity, which further hampers the ability to use modern, internet-based tools for disease detection and management. This gap in technological adoption not only limits the farmers' ability to detect diseases early but also leaves them vulnerable to crop failure and financial instability. Given these challenges, there is a growing need for an automated, affordable, and reliable solution to detect plant diseases at an early stage. Such a system should be capable of analyzing plant images to identify signs of disease, alerting farmers in real time, and providing recommendations for corrective action. Moreover, it should be accessible to small-scale farmers, particularly in rural areas, where advanced agricultural technologies are often out of reach. By leveraging affordable technologies such as Raspberry Pi and GSM modules, it is possible to create an intelligent system that can autonomously monitor crops, detect diseases, and communicate alerts via SMS, even in areas with limited or no internet connectivity. Such a solution would empower farmers to take timely actions, reduce their dependency on harmful pesticides, improve crop yields, and contribute to more sustainable farming practices, ultimately benefiting both farmers and the environment.

3. LITERATURE REVIEW

D.A. Shaikh et al. – Intelligent Autonomous Farming Robot with Plant Disease Detection Using Image Processing (2016): The paper introduces introduced an innovative robotic system aimed at automating the detection of plant diseases in agricultural fields. The project was designed to address the inefficiencies and delays associated with traditional, manual inspection methods used by farmers to identify crop health issues. The robot developed in this study is equipped with a camera module, a microcontroller, and image processing capabilities to analyze the captured images of plant leaves. It uses a predefined algorithm to detect visual symptoms of diseases such as leaf spots, blights, and mildew based on changes in color, texture, and shape of the leaves. The system features autonomous navigation, allowing the robot to move through the field without manual control, ensuring complete and consistent scanning of crops. L.R. Priya et al. – Crop Disease Detection and Monitoring System (2019): The paper presents a comprehensive system aimed at detecting and monitoring crop diseases through the integration of image processing and IoT technologies. The study addresses the challenges faced by farmers in early disease detection and effective crop management, especially in regions with limited access to agricultural experts. The system developed in this project utilizes a high-resolution camera for capturing images of plant leaves and employs image processing algorithms to identify early symptoms of diseases like Alter aria Alternate, Anthracnose, Bacterial Blight, and Cercospora Leaf Spot. Alongside visual analysis, environmental sensors are integrated into the system to monitor key parameters such as temperature, humidity, and soil moisture, which are critical for understanding the conditions that foster disease growth Monica K. M. et al. – A Plant Disease Detection Robot (2023): The paper introduces a robotic solution specifically designed for automating the detection of plant diseases in agricultural fields. The project aims to address the inefficiencies and delays associated with traditional, manual inspection methods used by farmers to identify crop health issues, which can be time-consuming and prone to human error. The robot developed in this study is equipped with a camera system and a robotic arm. The camera captures high-resolution images of plant leaves, which are then processed using image processing algorithms. These algorithms analyze the images to detect visual symptoms of diseases such as leaf spots, lesions, and discoloration, which are indicative of various plant diseases. Machine learning techniques are employed to classify the diseases based on these visual features. N.M. Ramalingeswararao et al. – Smart Farming Robot for Detecting Plant Diseases Using Machine Learning (2024): The paper explores the integration of machine learning techniques in smart farming robotics for plant disease detection. The primary objective of the project is to enhance disease identification accuracy by utilizing convolutional neural networks (CNNs), which analyze plant leaf images and classify diseases with high precision. The robot captures high-resolution images of plant leaves and processes them through CNN models, trained to detect visual symptoms of various plant diseases. These models, trained on large datasets of labeled images, enable the system to identify and classify diseases based on visual features. Upon detection, real-time alerts are sent to farmers via GSM modules, facilitating timely intervention to prevent further spread of the disease. Sharada P. Mohanty et al: In 2016 has proposed deep learning techniques to detect plant diseases through image analysis. This approach utilizes advanced algorithms to analyze visual data and identify signs of plant illnesses accurately. By harnessing deep learning, it enables efficient and automated detection of crop diseases, aiding in timely interventions for agricultural management have achieved 99% accuracy. M. Arun et al: In 2018 has designed a robotic system for smart agriculture applications. This technology aims to automate various tasks in farming operations, contributing to increased efficiency and productivity. The smart agriculture robot integrates advanced sensing and control mechanisms to optimize crop management processes. Yan Guo et al: In 2020 has proposed utilizing deep learning techniques to address plant diseases within the framework of smart agriculture. This approach integrates advanced algorithms to enhance disease detection and management strategies in agricultural settings. By leveraging deep learning capabilities, it aims to improve crop health monitoring and mitigate potential losses in smart farming systems that have achieved 83.57% accuracy. Prachi Chauhan et al: In 2021 has proposed utilizing deep learning techniques to address plant diseases within the framework of smart agriculture. This approach integrates advanced algorithms to enhance disease detection and management strategies in agricultural settings. By leveraging deep learning capabilities, it aims to improve crop health monitoring and mitigate potential losses in smart farming systems that have achieved 99% accuracy. Tiago Domingues et al: In 2022 has proposed a thorough survey on the application of machine learning for detecting and predicting crop diseases and pests. This survey delves into various methods and approaches employed within the agricultural domain to enhance disease and pest management strategies. It aims to provide a detailed overview of the role of machine learning in tackling agricultural challenges related to crop health.Vibhor Kumar Vishnoi et al : In 2022 has proposed detecting diseases in apple plants by analyzing leaf images through Convolutional Neural Networks. Identifying diseases in apple plants involves analyzing leaf images using Convolutional Neural Networks, which enable automated and accurate detection with high efficiency and have achieved 98% accuracy. Jyoti Dinkar Bhosale et al: In 2023 has proposed an Algorithms Based on Machine Learning for Detecting Leaf Diseases in Agricultural Crops. Implementing ML-based approaches to identify diseases affecting leaves in farming. Applying machine learning algorithms to detect diseases in crop foliage within agricultural settings have achieved 95% accuracy. Minah Jung et al: In 2023 has developed a disease detection model in plants based on deep learning techniques. The process involves constructing a model utilizing deep learning methods to detect diseases present in plants. By leveraging deep learning techniques, the model can effectively learn and adapt to different types of plant diseases, enhancing its ability to provide accurate detections have achieved 97% accuracy.

4. EXISTING SYSTEM

The existing system for plant disease detection have primarily relied on traditional, manual, and semi-automated methods, which often face challenges in terms of efficiency, scalability, and real-time responsiveness. A common approach involves manual inspection, where farmers or agricultural experts visually examine plants for signs of diseases such as spots, discoloration, and wilting. This method is labor-intensive, time-consuming, and prone to human error, especially when dealing with large areas or subtle disease symptoms. Another existing method uses image processing and computer vision to detect plant diseases, where cameras capture high-resolution images of plant leaves, and algorithms analyze these images to identify symptoms. While these systems offer some level of automation, they are often limited by the need for fixed equipment, meaning they are stationary and unable to move autonomously across large fields. Furthermore, these systems may not have the capability to send real-time alerts to farmers, which means that diseases can spread undetected for extended periods. Drones, which are sometimes used for aerial surveillance, can capture images over large areas, but their high cost, limited battery life, and the need for human intervention in flight operations and data analysis restrict their widespread use. In some cases, environmental sensors are employed to monitor conditions like humidity, temperature, and soil moisture, which may signal favorable conditions for disease development. However, these sensors do not directly detect diseases and only provide indirect clues about potential disease risks. Other systems rely on smart phone applications, where farmers take pictures of diseased plants and upload them to a cloud database for analysis, but these apps can suffer from inaccurate diagnoses and require a stable internet connection, which is not always available in rural or remote farming areas. The GSM module, commonly used in communication systems, is also sometimes integrated with sensors and devices to send alerts about environmental conditions, but it may not be used in conjunction with autonomous systems for real-time disease detection. Therefore, while these existing systems have their merits, they are limited by their reliance on manual inspection, fixed setups, or expensive technologies, and often lack real-time disease detection and alerts.

5. PROPOSED SYSTEM

The proposed system is an intelligent, autonomous robotic platform specifically designed for early detection of plant diseases in agricultural fields. It integrates hardware components such as a Raspberry Pi 4 Model B, USB webcam, GSM module, L298N motor driver, DC motors, and a battery powered mobility system. The core idea behind this system is to combine real-time image processing with artificial intelligence to monitor plant health efficiently and minimize the time between disease onset and farmer awareness. The robot navigates autonomously across the crop field using a preprogrammed path or sensor-guided input, allowing it to move between plant rows without human intervention. A USB camera mounted on the robot captures high-resolution images of plant leaves during its movement. These images are processed on the Raspberry Pi, which acts as the brain of the system. Image capture can be triggered either at regular intervals or manually through a GUI, ensuring flexible control over when and where data is collected. Once images are captured, they undergo a preprocessing stage to improve quality and enhance key features needed for disease detection. This involves resizing the images for consistency, converting them to grayscale, and applying various filters to enhance brightness, contrast, and texture. Such preprocessing ensures that the data passed to the machine learning model is clean and uniform, thereby improving the accuracy of subsequent classifications. After preprocessing, the system performs feature extraction to identify key characteristics of the leaf. Features such as color (e.g., yellowing or browning), texture (e.g., roughness, spots), and shape (e.g., holes, curling, or edge distortion) are analyzed to distinguish between healthy and diseased plants. These extracted features are then fed into a trained Convolutional Neural Network (CNN) model, which has been trained on a diverse dataset of labeled leaf images. The CNN processes these inputs and classifies the leaf as either healthy or affected by a specific disease, such as Tomato Septoria Leaf Spot, Early Blight, or Potato Late Blight, among others. Upon detecting a disease, the Raspberry Pi immediately activates the GSM module to send an SMS notification to the farmer or agricultural officer. The message includes the type of crop, the detected disease name, and the time of detection. This real-time alerting system allows farmers to respond quickly, potentially applying targeted treatment or isolating infected plants before the disease spreads further. Such timely action can help prevent significant crop loss and reduce the use of broad-spectrum pesticides. In addition to alerting the farmer, the system logs the image, the classification result, and the timestamp locally on the Raspberry Pi. This data logging feature allows for long-term monitori ng, future reference, or expert review. In extended versions of the system, this data can be integrated into a decision support module that offers treatment recommendations based on the type of disease identified, helping farmers take informed, data-driven decisions. The robot continues its journey through the field after analyzing each plant, enabling continuous and real-time monitoring of the entire crop area. The autonomous operation ensures scalability across large fields without the need for continuous human supervision. Overall, this system provides a smart, affordable, and efficient solution for precision agriculture, promoting sustainable farming practices and enhancing productivity by enabling early disease detection and management.

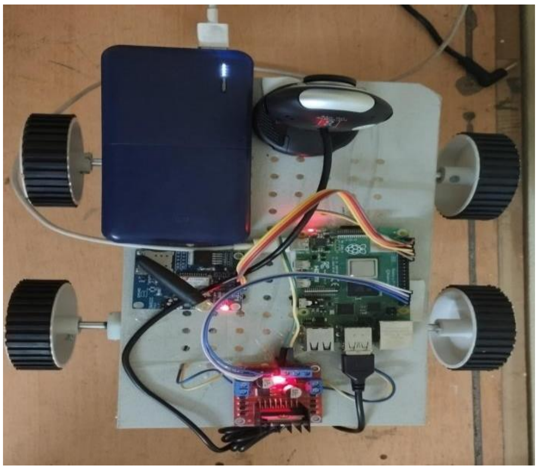

FIGURE 1. Plant Disease Detection Robot

BLOCK DIAGRAM

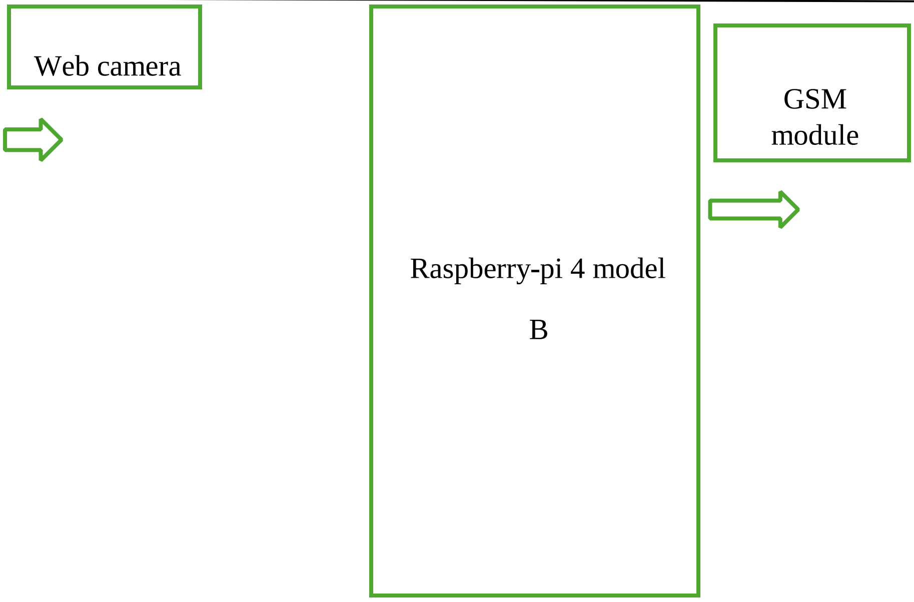

FIGURE 2. Block Diagram of Smart Robot for Plant Disease Detection

Raspberry Pi 4 Model B: The Raspberry Pi 4 Model B serves as the brain of the entire system, acting as both the controller and processor. It is a compact yet powerful single-board computer equipped with multiple GPIO (General Purpose Input/Output) pins, USB ports, and HDMI output. In this project, it plays a central role by controlling motor movements via GPIO pins, interfacing with the USB webcam to capture images, running deep learning models for plant disease classification, and communicating with the GSM module to send SMS alerts. It receives power from the battery and regulates the functioning of all the peripheral components. Its Linux-based environment and Python support make it ideal for running image processing libraries (like OpenCV), deep learning frameworks (like TensorFlow/Keras), and communication protocols. L298N Motor Driver: The L298N motor driver module is a crucial component that allows the Raspberry Pi to control high-power DC motors that require more current and voltage than the Pi can directly provide. It functions as a dual H-bridge driver capable of controlling the direction and operation of two motors independently. The GPIO pins from the Raspberry Pi are connected to the input pins (IN1 to IN4) of the L298N driver, allowing the robot to move forward, backward, and turn left or right. The motor driver receives power from the battery and transfers that power to the motors based on control signals. Without this module, the Raspberry Pi would not be able to drive motors directly, making it an essential intermediary in the robot’s motion system. DC Motors: Two DC motors are used to enable mobility in the robot, allowing it to move through the crop field or greenhouse autonomously. These motors are controlled via the L298N motor driver based on the commands from the Raspberry Pi. Each motor responds to a pair of input signals to determine its rotational direction, enabling the robot to move in all four directions—forward, backward, left, and right. The motors receive their operating voltage from the external battery through the motor driver. The smooth and directional control of the DC motors enables the robot to navigate and position itself accurately for plant leaf image capture. USB Web Camera: The USB camera plays a critical role in the detection part of the system. It is responsible for capturing real-time images of plant leaves, which are then processed to identify signs of disease. Connected directly to the USB port of the Raspberry Pi, the camera continuously streams video or still images that are later analyzed using image processing libraries such as OpenCV and Pillow. These images are pre-processed and passed to a pre-trained deep learning model (e.g., MobileNetV2 or VGG16) which classifies the images into healthy or diseased categories. This component is central to the core function of the robot—plant disease detection through image analysis. GSM Module: The GSM module, typically a SIM800C or similar, is used to send SMS alerts to farmers or users when a plant disease is detected. It is connected to the Raspberry Pi via the UART interface, using TX and RX pins for serial communication. The Raspberry Pi sends AT commands to the GSM module to configure it for text messaging. Once a disease is detected in the captured image, a pre-defined message including the disease name is transmitted to the user’s mobile number. This feature is especially useful in remote areas where internet connectivity may be unreliable, allowing real-time alerts and actions without depending on cloud services. Battery: The battery serves as the power source for the entire system. It supplies voltage to the Raspberry Pi, motor driver, GSM module, and other peripherals. The type of battery used depends on the current and voltage requirements of the components—commonly a 7.4V or 12V rechargeable lithium-ion battery is used for such projects. The battery ensures the system can operate independently in outdoor or field conditions without being tethered to a wall socket. Efficient power management ensures stable operation of the motors and accurate data processing by the Raspberry Pi.

SCHEMATIC DIAGRAM

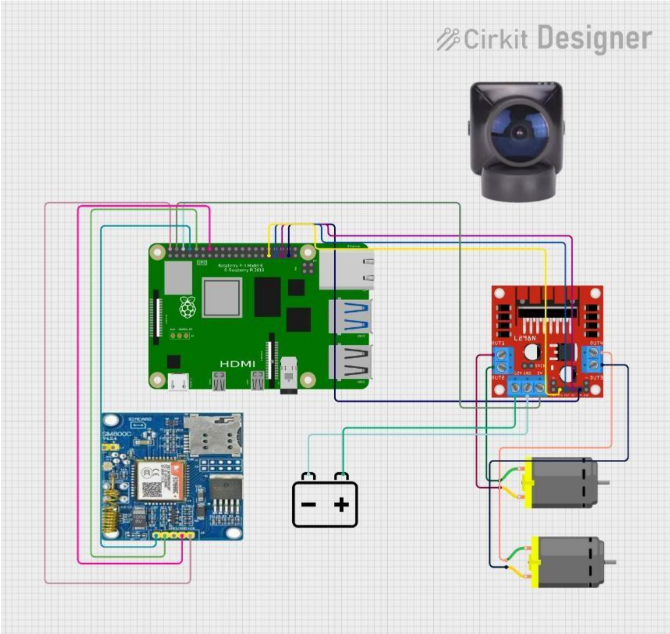

FIGURE 3. Schematic Diagram of Smart Robot for Plant Disease Detection

Raspberry Pi 4 Model B Pin Assignments

	FUNCTION	PIN	PIN	FUNCTION	
3V3	3V3	1	2	5V	5V
GPIO2	SPI3 MOSI/SDA3	3	4	5V	5V
GPIO3	SPI3 SCLK/SCL3	5	6	GND	GND
GPIO4	SPI4 CE0 N/SDA 3	7	8	TXD1/SPI5 MOSI	GPIO14
GND	GND	9	10	RXD1/SPI5 SCLK	GPIO15
GPIO17		11	12	SPI6 CEO N	GPIO18
GPIO27	SPI6 CE1 N	13	14	GND	GND
GPIO22	SDA6	15	16	SCL6	GPIO23
3V3	3V3	17	18	SPI3 CE1 N	GPIO24
GPIO10	SDA5	19	20	GND	GND
GPIO9	RXD4/SCL4	21	22	SPI4 CE1 N	GPIO25
GPIO11	SCL5	23	24	SDA4/TXD4	GPIO8
GND	GND	25	26	SCL4/SPI4 SCLK	GPIO7
GPIO0	SPI3 CE0 N/TXD2/SDA6	27	28	SPI3 MISO/SCL6/RXD2	GPIO1
GPIO5	SPI4 MISO/RXD3/SCL3	29	30	GND	GND
GPIO6	SPI4 MOSI/SDA4	31	32	SDA5/SPI5 CEO N/TXD5	GPIO12
GPIO13	SPI5 MISO/RXD5/SCL5	33	34	GND	GND
GPIO19	SPI6 MISO	35	36	SPI1 CE2 N	GPIO16
GPIO26	SPI5 CE1 N	37	38	SPI6 MOSI	GPIO20
GND	GND	39	40	SPI6 SCLK	GPIO21
	I2C			Ground	
	UART			5V Power	
	SPI			3V3 Power	

FIGURE 4. Raspberry pi 4 model B Pin Description

The Raspberry Pi 4 Model B is the central processing unit (CPU) of your project. It communicates with all the connected peripherals, including the motor driver, GSM module, and USB camera. GPIO6 → Motor Driver (IN1): Sends a signal to the motor driver to move the robot forward. GPIO13 → Motor Driver (IN2): Sends a signal to move backward. GPIO19 → Motor Driver (IN3): Controls the left movement of the motor. GPIO26 → Motor Driver (IN4): Controls the right movement of the motor. 5V (Pin 2, 4) → Power for Motor Driver: Supplies power to the motor driver to drive the motors. GND (Pin 6, 9, etc.) → Ground Connection: Connects all components to a common ground reference, ensuring stable operation. The GPIO (General Purpose Input/Output) pins of Raspberry Pi act as a control interface for the motor driver, sending HIGH or LOW signals to operate the motors. The 5V and GND pins provide power to the motor driver circuit.

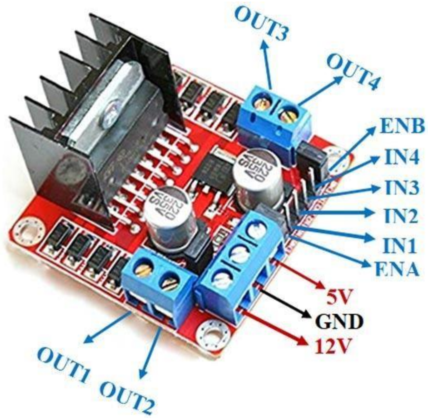

FIGURE 5. Motor Driver Pin Description

The L298N motor driver is a dual H-Bridge motor driver that allows the Raspberry Pi to control DC motors with higher voltage and current than the Raspberry Pi can handle directly. IN1 (Input 1) → GPIO6: Controls the direction of Motor A (Forward). IN2 (Input 2) → GPIO13: Controls the direction of Motor A (Backward). IN3 (Input 3) → GPIO19: Controls the direction of Motor B (Left Turn). IN4 (Input 4) → GPIO26: Controls the direction of Motor B (Right Turn). VCC → 5V Power Supply: Provides power to the logic circuit of the motor driver. GND → Ground: Connects the motor driver to the Raspberry Pi's ground. 12V (if required) → External Battery: Some motors require a 12V power supply, which is connected to the L298N driver to run high-power motors. The L298N driver acts as an intermediary between the Raspberry Pi and the motors, allowing the Raspberry Pi to control the motors efficiently. The motor speed can be controlled using PWM (Pulse Width Modulation) signals, but in your case, you are using GPIO pins for simple ON/OFF control.

USB Camera Connection: The USB camera is used to capture images of plant leaves for disease detection. It is connected directly to the USB port of the Raspberry Pi. The camera takes images, which are processed using image processing and machine learning algorithms (such as VGG16 or MobileNetV2). The Raspberry Pi analyzes the images and detects whether the plant is affected by a disease. Once the disease is detected, the result is displayed on the GUI and sent via the GSM module as an SMS notification. The USB camera plays a crucial role in real-time plant disease detection by capturing images that are processed through deep learning models to classify plant diseases.

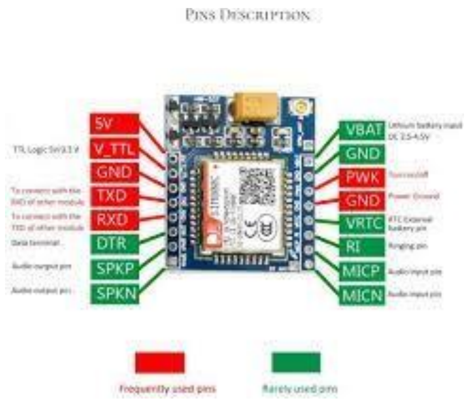

FIGURE 6. GSM Module Pin Description

The GSM module (SIM800C) is used to send SMS notifications to the user about the plant disease detection results. VCC → 5V (Can use 3.7V if required): Powers the GSM module. GND → Ground: Connects to the Raspberry Pi's ground for stable operation. TXD → GPIO15 (RXD of Raspberry Pi): The TX (Transmit) pin of the GSM module sends data to the Raspberry Pi's RX pin. RXD → GPIO14 (TXD of Raspberry Pi): The RX (Receive) pin of the GSM module receives data from the Raspberry Pi's TX pin. RST (Reset) → GPIO27 (Optional): Used to reset the GSM module if needed. The GSM module is responsible for communication and ensures that disease detection results are sent to the farmer's phone via SMS. The Raspberry Pi uses AT commands to interact with the GSM module and send messages.

6. HARDWARE DESCRIPTION

RASPBERRY PI 4 MODEL B (2GB)

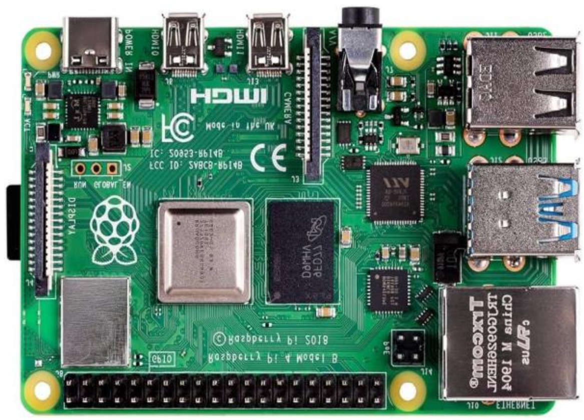

FIGURE 7. Raspberry pi 4 model B

The Raspberry Pi 4 Model B is a powerful, compact single-board computer designed for a wide range of applications, from DIY projects to industrial automation. It features a 64-bit quad-core Broadcom BCM2711 Cortex-A72 processor running at 1.8GHz and is available in configurations with 1GB to 8GB of LPDDR4-3200 SDRAM. With support for dual 4K displays via two micro HDMI ports, hardware decoding for H.265 and H.264 video, and advanced graphics through OpenGL ES 3.1 and Vulkan 1.0, it delivers desktop-like performance in a palm-sized form. The device supports high-speed connectivity, including dual-band 802.11ac Wi-Fi, Bluetooth 5.0, Gigabit Ethernet, USB 3.0, and Power over Ethernet (via a PoE HAT). It runs on Linux-based operating systems and supports languages like Python, C++, and Java, making it ideal for projects involving robotics, machine learning, home automation, and sensor integration. The standard 40-pin GPIO header allows hardware interfacing, while ports for display (MIPI DSI), camera (MIPI CSI), and audio/video expand its capabilities. Although limited by RAM and prone to heating under load, the Raspberry Pi 4's performance and versatility make it a preferred platform for embedded systems, education, and prototyping. It requires a stable 5V power supply via USB-C, with a minimum of 3A for full functionality.

USB WEB CAMERA

FIGURE 8. USB Camera

A USB web camera is a digital video camera that connects to a computer or embedded system via a Universal Serial Bus (USB) interface. These cameras are widely used for applications such as video conferencing, security surveillance, machine vision, and image processing tasks. They are plug-and-play devices, meaning they do not require complex installation procedures and can be easily integrated with various systems, including laptops, desktops, Raspberry Pi, and embedded AI projects. USB web cameras capture video and still images using an image sensor, typically a CMOS (Complementary Metal-Oxide-Semiconductor) sensor. The sensor converts light into electrical signals, which are then processed and transmitted to the connected device via the USB interface. The video stream can be processed in real-time using software applications such as OpenCV for further analysis, filtering, or storage. Specifications: Resolution: Varies from 640×480 (VGA) to Full HD (1080p) and beyond, Frame Rate: Typically ranges from 30 FPS to 60 FPS, Interface:

USB 2.0 / USB 3.0, Lens: Fixed or adjustable focus, Image Sensor: CMOS or CCD sensor, Compatibility: Supports major operating systems like Windows, Linux, and macOS.

GSM MODULE SIM800C

FIGURE 9. GSM module

Global System for Mobile Communications (GSM) modems are specialized types of modems that operate over subscription based wireless networks, similar to a mobile phone. A GSM modem accepts a Subscriber Identity Module (SIM) card, and basically acts like a mobile phone for a computer. Such a modem can even be a dedicated mobile phone that the computer uses for GSM network capabilities. Traditional modems are attached to computers to allow dial-up connections to other computer systems. A GSM modem operates in a similar fashion, except that it sends and receive data through radio waves rather than a telephone line. This type of modem may be an external device connected via a Universal Serial Bus (USB) cable or a serial cable. More commonly, however, it is a small device that plugs directly into the USB port or card slot on a computer or laptop. It is widely used mobile communication system in the world. GSM is an open and digital cellular technology used for transmitting mobile voice and data services operates at the 850MHz, 900MHz, 1800MHz and 1900MHz frequency bands. Features: Improved spectrum efficiency, International roaming, Compatibility with integrated services digital network (ISDN), Support for new services, SIM phonebook management, fixed dialing number (FDN), Real time clock with alarm management.

L298N 2A DUAL MOTOR DRIVER

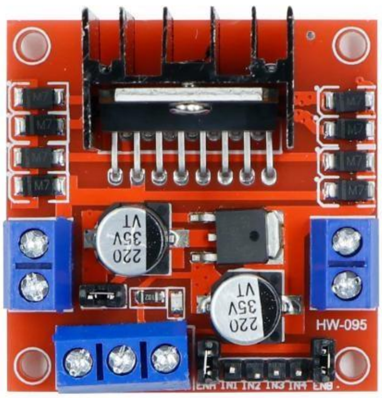

FIGURE 10. L298N Motor Driver

The L298N motor driver is a dual H-Bridge module that enables bidirectional control of two DC motors or a single stepper motor. It operates on an input voltage range of 5V to 35V, with each channel supporting up to 2A of current, making it ideal for robotic and automation applications. The module includes PWM (Pulse Width Modulation) support, allowing speed regulation, and a built-in 5V voltage regulator, which can power logic circuits if the motor voltage exceeds 7V. It also features a heat sink for overheat protection, ensuring stable performance during prolonged operation. The working principle of the L298N motor driver is based on an H-Bridge circuit, which controls the polarity of voltage applied to the motors to change their direction. Using GPIO pins from a microcontroller like a Raspberry Pi or Arduino, users can send HIGH or LOW signals to the input pins (IN1, IN2, IN3, IN4) to rotate the motors forward, backward, or stop them. The enable pins (ENA, ENB) allow for PWM-based speed control. This motor driver is widely used in applications such as robotic vehicles, smart farming robots, conveyor belt systems, and industrial automation, making it an essential component in various motion control projects. Features of L298N Motor Driver: Dual H-Bridge Design: Supports bidirectional control of two DC motors or one stepper motor. Wide Voltage Range: Operates within 5V to 35V and can handle currents up to 2A per channel. PWM Speed Control: Allows motor speed control using Pulse Width Modulation (PWM) signals. Built-in Overheat Protection: Prevents damage due to excessive heat during operation. 5V Regulator: Provides a regulated 5V output, which can power other components. Enable Pins: Control motor activation for precise operation.

DC MOTOR

A DC (Direct Current) motor is an electromechanical device that converts electrical energy into mechanical motion. It operates on the fundamental principle of electromagnetic induction, where a current-carrying conductor placed within a magnetic field experiences a force that causes motion. This simple yet powerful concept has made DC motors essential in a wide range of applications, including robotics, electric vehicles, industrial automation, and household appliances.

FIGURE 11. DC Motor

A DC motor is a vital electromechanical component that converts electrical energy into mechanical motion through the principle of electromagnetic induction, where a current-carrying conductor within a magnetic field experiences a force that results in motion. Widely used in robotics, electric vehicles, industrial automation, and household appliances, DC motors play a key role in providing the torque and speed necessary for movement. In the context of a smart robot designed for plant disease detection, a reliable power supply is crucial for field operations. This is typically achieved using a 12V battery, which powers high-current components like the motor driver (L298N) and DC motors, and a power bank, which supports lower-voltage electronics such as microcontrollers or communication modules. To ensure component safety and efficiency, a voltage regulator or buck converter is employed to step down the 12V supply to 5V, protecting sensitive devices like the Raspberry Pi. This power architecture enables the robot to operate autonomously and reliably across varying agricultural conditions.

FIGURE 12. 12V Battery

On the other hand, the power bank is used to supply clean and regulated 5V power to the Raspberry Pi 4 Model B, which is the central processing unit of the entire system. The Raspberry Pi handles tasks such as image processing, disease classification using deep learning models, and sending alerts via the GSM module. Since the Raspberry Pi is sensitive to voltage fluctuations, a reliable power source is crucial. A high-capacity power bank, generally rated at 5V and 2.4A or higher, ensures the Raspberry Pi runs smoothly without sudden reboots or performance issues. The power bank also powers the USB camera, which captures leaf images for disease analysis. One of the major advantages of using a power bank is its portability—it allows the robot to operate independently of external power sources, making it ideal for agricultural field conditions. Additionally, most modern power banks support pass-through charging, meaning they can charge themselves while simultaneously powering the system, which is beneficial during long hours of operation.

FIGURE 13. Power Bank

Together, the 12V battery and the power bank create a hybrid power setup that distributes the load efficiently. The high-power components such as motors and drivers rely on the 12V battery, while the control and processing units rely on the more delicate and regulated 5V power bank. This separation ensures that any fluctuations in motor current do not affect the stability of the processing system, ultimately contributing to a more reliable and field-ready robot for plant health monitoring.

7. SOFTWARE DESCRIPTION

Raspberry Pi Setup and Initial Configuration: Powering Up the Raspberry Pi: Connect the Raspberry Pi to a power source using the appropriate adapter. Wait for the Raspberry Pi to boot up completely. Enabling VNC for Remote Access: Open the terminal and type the following command: sudo raspi-config Navigate to 5. Interfacing Options and press Enter. Navigate to P3 VNC and press Enter. Select Yes to enable VNC. Select OK, then choose Finish to exit the configuration.

FIGURE 14. Raspberry Configuration VNC Enable Screen

Install VNC Viewer on Your Computer: Download VNC Viewer from RealVNC. Launch VNC Viewer and enter the IP address of your Raspberry Pi or use raspberry pi.local if it’s available on the network o Log in with the default username (pi) and password (raspberry). Now, the screen to remotely access the Raspberry Pi's desktop using VNC Viewer is success.

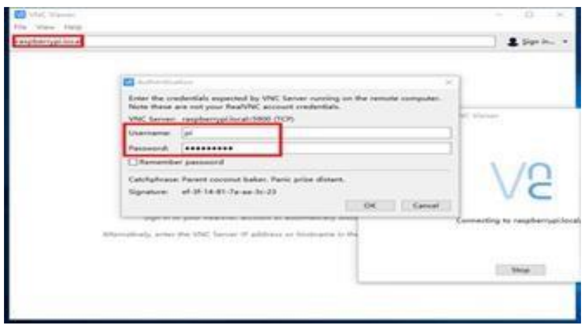

FIGURE 15. VNC Viewer with Raspberry Pi IP entered

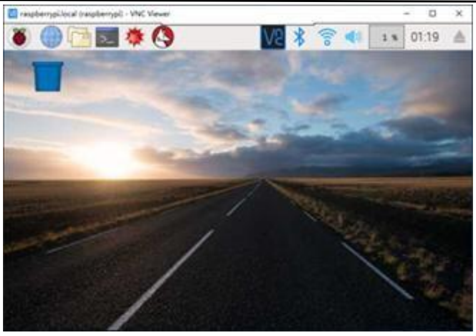

FIGURE 16. Successful VNC Connection Screen

Installing Required Software for Development: Install Python and Dependencies: Ensure Python 3 is installed on your Raspberry Pi. If not, install it using the following command: sudo apt-get install python3 python3-pip Install. OpenCV for Image Processing: OpenCV will be used to process images from the camera and analyze them for plant diseases. Install OpenCV with: o sudo apt-get install python3-opencv. Install TensorFlow for Machine Learning (CNNs): TensorFlow is required for the deep learning model that will classify plant diseases. Install TensorFlow with: pip3 install tensorflow. Install Other Required Libraries: Install essential libraries like NumPy and Matplotlib: pip3 install numpy matplotlib

8. RESULTS

The developed system successfully integrates a mobile robot with a mounted camera, machine learning model, GUI-based interface, and GSM communication module to detect plant leaf diseases and alert users via SMS. The project combines both hardware and software components effectively to automate the monitoring and disease diagnosis process in agricultural fields. The smart robot was deployed in a test environment to validate its functionality. Once powered on, the Raspberry Pi 4 Model B loads the custom GUI application, allowing the user to control the robot's movement through directional buttons (Forward, Backward, Left, Right, Stop). The mounted webcam captures images of the plant leaves as the robot navigates the area. As seen below, the robot is equipped with a webcam, Raspberry Pi, GSM module, and motor driver circuit, all mounted on a chassis with four wheels for movement. This configuration ensures both mobility and image capturing capabilities.

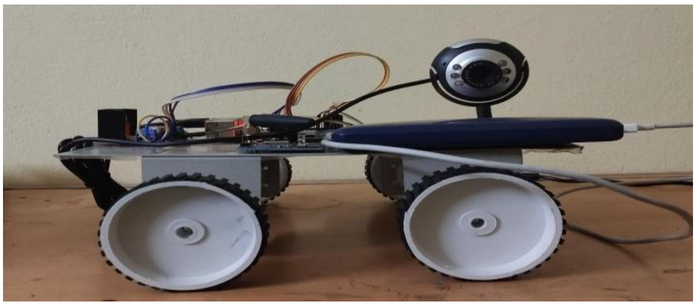

FIGURE 17. Robot Hardware Setup

The GUI developed using Tkinter provides real-time control and interaction with the robot. A live camera feed is displayed, and users can click the “Capture” button to take a picture of a plant leaf. Movement buttons help guide the robot near plants.

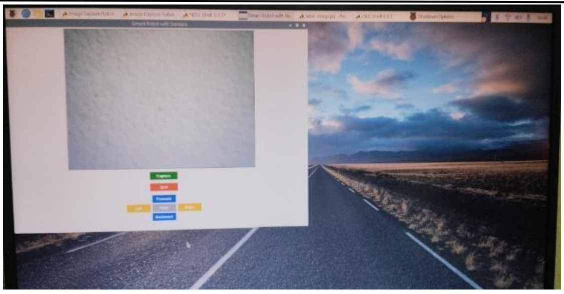

FIGURE 18. GUI Interface

After capturing the image, the system processes the photo using a trained CNN (MobileNetV2/VGG16). The predicted result is displayed along with the captured leaf image. The GUI allows users to select the crop type and view results instantly.

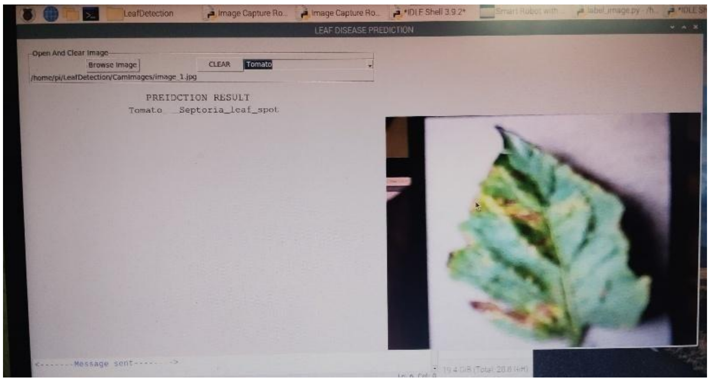

FIGURE 19. Disease Detection Result

Once a disease is detected, the result is automatically sent to the registered farmer's mobile number via the GSM module. The image below shows real-time SMS alerts received for different leaf disease types like Tomato septoria leaf spot and potato late blight.

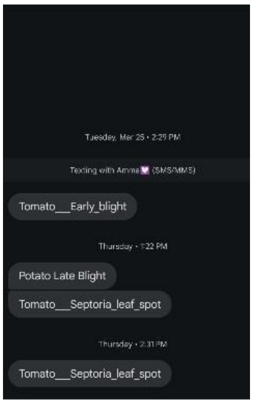

FIGURE 20. SMS Notification Result

9. APPLICATIONS, ADVANTAGES & DISADVANTAGES

Applications: Smart Agriculture Monitoring: The robot can be deployed in farms and greenhouses to autonomously monitor crops and detect diseases in real-time, reducing dependency on manual inspections. Early Disease Prevention: By identifying symptoms at an early stage, the system helps prevent the spread of infections across large crop areas, leading to healthier and more productive farms. Precision Farming: Integrating AI with image processing, this robot enables precision farming by identifying affected plants and targeting them for treatment, saving time, chemicals, and cost. Remote Crop Health Alerts: With GSM module integration, farmers receive SMS alerts instantly when any disease is detected, allowing them to take immediate action—even from remote locations. Low-Cost Solution for Small Farmers: Compared to commercial drones or expensive crop health systems, this Raspberry Pi-based robot offers a budget-friendly alternative for small and marginal farmers. Government and NGO Use: It can be used by government agricultural departments or NGOs for large-scale disease surveillance in rural areas with minimal infrastructure. Integration with IoT Systems: The robot can be linked with IoT dashboards and cloud platforms for centralized monitoring of multiple fields from a single interface. Pesticide Optimization: By detecting only diseased plants, targeted spraying can be implemented, reducing excessive use of pesticides and promoting eco-friendly farming.

Advantages: Early Disease Detection and Prevention: The system identifies plant diseases at an early stage, allowing farmers to take timely action to prevent further crop damage. Reduces crop losses and increases agricultural productivity. Automation and Reduced Manual Labor: The robot automates the monitoring process, eliminating the need for constant manual inspection by farmers. Saves time, effort, and labor costs, especially in large farmlands. Real-Time Alerts via GSM Module: Instant SMS alerts notify farmers about detected diseases, ensuring quick response and treatment. Works even in rural areas where internet connectivity may be limited. AI-Powered High Accuracy Disease Classification: Uses Machine Learning (CNNs and Transfer Learning) to detect diseases with high precision. The model can be trained with more data to further improve accuracy. Cost-Effective and Scalable: Affordable compared to manual disease detection or hiring agricultural experts. It can be expanded to monitor different crops, diseases, and environmental conditions. 24/7 Continuous Monitoring: The robotic system can operate continuously, ensuring real-time monitoring of the farm. Eliminates human errors and oversight in detecting early-stage plant diseases. IoT and Cloud Integration Possibilities: Can be enhanced with cloud-based AI analytics for long-term disease trend analysis. IoT integration can help monitor environmental conditions (humidity, temperature, soil moisture) for predictive analysis.

Disadvantages: Limited Disease Recognition Capability: The system is only capable of identifying diseases it has been explicitly trained on. It cannot recognize new, rare, or evolving plant diseases without retraining the model with updated datasets, limiting its adaptability in dynamic agricultural environments. Dependency on High-Quality Image Input: Accurate detection relies heavily on clear and well-lit images. Poor lighting conditions, overlapping leaves, or obstructions like dirt and shadows can significantly reduce prediction accuracy, leading to false positives or missed diagnoses. Reliance on GSM Network for Alerts: The system depends on stable mobile network coverage to send SMS alerts. In remote or rural farming areas where GSM signals are weak or inconsistent, crucial alerts may be delayed or fail to deliver, compromising timely intervention.

10. CONCLUSION AND FUTURE SCOPE

The development of the smart robot for plant disease detection demonstrates the successful integration of embedded systems, computer vision, and machine learning to address real-world agricultural challenges. Using the Raspberry Pi 4 Model B as the central control unit, along with a camera module, motor driver, and GSM communication, the system performs autonomous navigation and realtime disease detection with high efficiency. The deployment of deep learning models such as MobileNetV2 or VGG16 has enabled accurate classification of plant leaf diseases, while image preprocessing and feature extraction steps have enhanced reliability under varying field conditions. The system not only automates the process of disease identification but also assists farmers by sending timely SMS alerts and storing data for future analysis. This minimizes crop loss, reduces the need for manual inspection, and supports precision agriculture. Furthermore, the user-friendly GUI developed using Python and Tkinter provides a visual interface for monitoring and result visualization. In essence, the project contributes a significant step toward digital transformation in agriculture, offering an affordable and scalable solution for modern-day farming challenges. Future Scope: The Smart Robot for Plant Disease Detection has immense potential for future advancements and scalability. Some key areas of development include: Enhanced AI Models: Improving the accuracy and efficiency of disease detection by training the system with larger and more diverse datasets. Multi-Disease Detection: Expanding the system to identify a wider range of plant diseases and nutritional deficiencies. IoT Integration: Connecting the robot to cloud-based platforms for real-time monitoring and data analysis. Drone-Based System: Upgrading to drone-based disease detection for large-scale farms and difficult terrains. Automated Treatment Mechanism: Integrating pesticide spraying mechanisms for automated disease control upon detection.

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