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Smart Agriculture Monitoring System

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***Abstract*— Agriculture significantly contributes to the country's economic growth and development. In the advent of the future, traditional methods are becoming tedious for the farmers to monitor the farm. The plants are affected by diseases and pests like late blight, Bacterial spot, Early Blight etc,. which affect the efficiency of crop yield. So, the early detection of diseases is a vital step for enhanced productivity and also the farm is to be monitored in terms of temperature and soil moisture for the welfare of plants [1]. In this paper, a Convolutional Neural Network (CNN) model for identifying and categorising insect infestations and plant leaf diseases is presented. Pre-existing architectures such as VGG-16, Inception, ResNet-50, and AlexNet are used in the model's construction[2]. The various limitations of the specified predefined models such as design complexity, large size and less accuracy has been reduced in the developed model. The dataset was collected from Kaggle, an opensource platform, that comprises more than 5000 images for various plants.[3] In addition, this research detects soil moisture, temperature and humidity using sensors that are controlled by a microprocessor (i.e. Raspberry pi). The closeness of the training and validation accuracies of various ratios of training, testing and validation datasets, demonstrates the robustness of the model with different training and testing sets. About 98% accuracy is attained by this model. In image-based classification tasks, Convolutional Neural Networks (CNNs) have demonstrated better performance than other deep learning models and conventional machine learning techniques, especially for plant disease diagnosis. CNNs automatically learn spatial feature hierarchies from images, which improves accuracy and robustness over traditional methods like Decision Trees or Support Vector Machines (SVMs), which rely on manually derived features. In contrast to architectures such as VGG-16, Inception, ResNet-50, and AlexNet, CNNs offer the best possible compromise between computational efficiency and accuracy[5]. VGG-16, though effective in feature extraction, suffers from high computational complexity and large model size, making it inefficient for real-time applications. Inception networks, while reducing computational load through parallel convolutions, introduce design complexity, requiring careful hyperparameter tuning. ResNet-50, with its residual learning framework, improves gradient flow but has a higher inference time, making it less suitable for edge computing devices like Raspberry Pi. AlexNet, one of the earliest CNN architectures, lacks the depth required for capturing complex plant disease patterns, resulting in lower classification accuracy. In contrast, the proposed CNN model is designed with optimized layers, dropout regularization, and dense connections, ensuring higher accuracy (98%) while reducing overfitting. The CNN model effectively extracts edge details, color variations, and texture patterns associated with different plant diseases, making it far more reliable than conventional methods. Additionally, CNN's ability to process large-scale datasets ensures that it generalizes well across different plant species and disease conditions. Given its scalability, robustness, and real-time detection capability, CNN remains the most efficient and accurate model for smart agricultural monitoring systems, providing automated disease classification with minimal human intervention [6]. Additionally, an increased dense layer is applied to enhance overall accuracy further, establishing the model's consistency across diverse test sets. This ensemble approach enhances overall accuracy, establishing the model's consistency across diverse test sets.**

***Keywords*— CNN, Plant disease classification, VGG-16, Inception, Resnet-50, AlexNet, Kaggle, Raspberry pi, Enhanced Accuracy**

I. INTRODUCTION

A rapid rise in the demand for agricultural products at the international level, increases the requirement for more accurate and effective farming techniques that will help in increasing production and improving sustainability. It is highly possible that the conventional farming practices could be constraints and challenges for climatic changes or controlling pest outbreaks as well as ease in the scarcity of resources. To this end, it becomes essential to apply innovative ideas and advanced technologies. Automation in agriculture can enhance crop productivity and management with increased efficiency.[7]

The Smart Agriculture Monitoring System (SAMS) employs an integrated methodology that combines IoT-based environmental sensing, machine learning-driven disease detection, and real-time farmer communication. The methodology follows a structured approach that includes data acquisition, preprocessing, model training, deployment, and alert generation to optimize crop management and productivity.Real-time data gathering using IoT-enabled

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sensors, such as the DHT11 for temperature and humidity measurements and a resistive soil moisture sensor for soil condition monitoring, is the first step in the process. These sensors continuously gather environmental data, which is then processed by a Raspberry Pi 4B microcontroller, acting as the central computing unit. The Raspberry Pi interfaces with the sensors through Python-based scripts utilizing GPIO and Pigpio libraries, ensuring efficient data acquisition and storage.

For disease and pest detection, the system employs Convolutional Neural Networks (CNNs) to analyze leaf images [8]. The dataset, sourced from Kaggle, contains over 5000 labeled images depicting various crops suffering from different diseases. To improve detection accuracy, the data is preprocessed using techniques including noise reduction, scaling, normalisation, and segmentation before being fed into the model. Data augmentation techniques, such as flipping, rotation, contrast modifications, and zooming, are used to increase robustness and make sure the model generalises well under a variety of environmental situations.

The CNN model is trained using transfer learning techniques with pretrained architectures like AlexNet, ResNet-50, Inception, and VGG16. However, due to the complexity and computational demands of these models, an optimized CNN architecture is proposed, incorporating dropout layers to prevent overfitting and the Adam optimizer for faster convergence. The model is trained on different train-validation-test splits (8:1:1, 7:2:1, 6:2:2), and experimental results indicate that the 8:1:1 ratio yields the highest accuracy of 96% [9].

Once trained, the model is deployed on the Raspberry Pi, which processes incoming images from a connected camera module. The Twilio API is integrated into the system to enable real-time SMS notifications to farmers when critical factors like insufficient soil moisture, excessive humidity, or signs of disease are detected. These alerts contain actionable insights, allowing farmers to take immediate corrective measures [10].

The proposed methodology effectively bridges the gap between traditional farming methods and modern AI-driven precision agriculture, reducing crop losses, optimizing resource utilization, and empowering farmers with real-time, data-driven decision-making capabilities. Also, Early disease detection is crucial for ensuring efficient crop yield. Many plant diseases, primarily identified through leaf symptoms, significantly impact crop growth and quality. Moreover, such issues escalate production costs and lead to substantial financial losses for farmers. For infections to be effectively managed and prevented, early detection is essential.

The Smart Agriculture Monitoring System (SAMS) in this research utilizes automation through IoT, machine learning, and real-time communication to enhance crop productivity and farm efficiency. By integrating DHT11 sensors for temperature and humidity, and resistive soil moisture sensors, the system facilitates real-time monitoring of environmental conditions without the need for manual intervention.

The Raspberry Pi 4B acts as the central processing unit, collecting and analyzing data to ensure optimal irrigation control, reducing water wastage, and maintaining ideal soil conditions [11]. Additionally, CNN-based disease detection models, including Inception, ResNet-50, and VGG16, analyze plant leaf images to detect early-stage diseases and pest infestations with 98% accuracy. This automated early detection system helps farmers take immediate preventive measures, minimizing yield losses while reducing the excessive use of pesticides. Beyond real-time monitoring and disease detection, automation enhances decision-making and predictive analytics. The Twilio API is integrated to provide automated SMS alerts to farmers when critical conditions such as insufficient soil moisture, extreme temperature, or disease presence are detected.

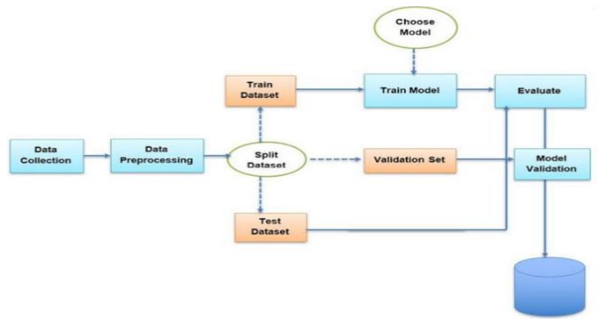

Fig.1 Flowchart

This real-time alert system reduces response time, allowing immediate corrective actions, thereby optimizing farm productivity and reducing labor dependency. Furthermore, historical sensor data is stored and analyzed to identify long-term trends in soil conditions, weather patterns, and disease outbreaks, enabling AI-driven predictive analytics. This data-driven approach allows farmers to plan irrigation schedules, pesticide applications, and crop rotations more efficiently, ensuring sustainable farming practices, improved yield quality, and reduced operational costs. This research aims to enhance crop production through early disease detection, environmental monitoring, and automation using machine learning and IoT technologies.

The aim of the Smart Agricultural Monitoring System research is to develop an automated system that tracks the ambient environment conditions all the time through an embedded machine learning model built into an Internet of Things device driven by a Raspberry Pi, the system detects agricultural illnesses and pest infestations using sensors such as humidity and soil moisture sensors.and a communication protocol, so as to send instant reports to farmers. This system seeks to enhance crop condition, enhance utilization of resources, and raise agricultural outputs all in the reduction of physical surveillance on crops and reducing spoilage of crops due to viruses and insects.

The goal of this research is to develop and deploy a real-time monitoring system that uses sensors to assess environmental factors like temperature, humidity, and soil moisture while also employing image processing techniques to detect pests and leaf diseases. The proposed system also creates a user-friendly interface that allows farmers to access real-time data and historical trends for better crop management via SMS or mobile application.

Structure of the paper: In order to synthesize current knowledge and place the project within the larger scientific context, Section 2 conducts a survey of the literature specifying the limitations of existing and current techniques. The suggested methodology is described in Section 3 which also describes the overview of the method used in Smart Agriculture Monitoring System. The Section 4 of this paper emphasize on interpreting the results of the project's goals and discusses the main findings, outlines the implications and recommends the direction for further study. The Final section is the reference section that guarantees the studies and sources cited throughout it are properly credited.

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II. LITERATURE SURVEY

In [7] By measuring temperature, humidity, and soil moisture levels and sending the gathered data to an IoT platform, the authors' smart agricultural robotic system is based on the Internet of Things. The system incorporates two microcontrollers: Arduino Nano for control operations and ESP32 for sensor data management. The ESP32's built-in Wi-Fi capability enables real-time transmission of sensor data to the ThingSpeak IoT platform, where historical records are maintained. Additionally, a customized application allows farmers to control the robotic car's movements and receive sensor data. The data, including temperature, humidity, and soil moisture, is wirelessly transmitted to the Arduino Nano via Bluetooth, enabling real-time system control and monitoring.

In [12] By conducting a web-based agricultural survey to assess crop temperature, moisture conditions, soil moisture levels, and water quality, the authors explored the application of Precision Agriculture with the Internet of Things (IoT). Their strategy is to increase precision and offer useful farming solutions to deal with issues facing the sector. A microprocessor board (LPC 2148) and a number of sensors, including temperature, water level, and soil moisture sensors, were connected with IoT technology to enable precision agriculture.To validate security algorithms, they tested a Wireless Sensor Network (WSN) system architecture. Additionally, they examined the ARM7 processor and its role in the research, highlighting its capability to manage components within the development package. The LPC 2148 processor was configured with an OFF engine linked to the horticultural control water pump, setting specific sensing limits. The estimated heat levels were updated to the server or framework via IoT at one-minute intervals from the integrated development package. This paper proposes a modern, user-friendly farming approach that simplifies agricultural operations.

In [13] The authors focused on fine-tuning hyperparameters in well-known transfer learning architectures such as DenseNet-121, ResNet-50, VGG-16, and Inception V4 and used convolutional neural network (CNN)-based pre-trained models for effective plant disease identification. The well-known PlantVillage dataset, which includes 54,305 picture samples depicting different plant diseases in 38 classifications, was used in their research. Each network uses varying filter sizes to extract unique features from feature maps, where filters are crucial to feature extraction. The pre-trained models were chosen based on how well they classified plant diseases. Classification accuracy, sensitivity, specificity, and the F1 score were used to assess the model's performance. In order to improve recognition and classification accuracy while reducing time complexity, the study also compared several transfer learning models with deep CNNs. According to experimental data, DenseNet-121 outperformed state-of-the-art models with an exceptional classification accuracy of 99.81%.

In [14] For fine-tuning through transfer learning, the authors created a model using pre-trained architectures like VGG19. This allowed them to extract pertinent features from a dataset that included roughly 55,000 well-labeled photos of both healthy and diseased leaves from a variety of fruits and vegetables, such as apples, blueberries, cherries, grapes, peaches, peppers, oranges, tomatoes, and potatoes. VGG19 is used in a CNN-based feature extraction framework in the suggested method. Multiple machine learning algorithms, such as Support Vector Machines (SVM), Neural Networks, K-Nearest Neighbours (KNN), and Logistic Regression, are then used to classify the retrieved features. On the test dataset, Logistic Regression outperformed the other classifiers by achieving the greatest classification accuracy of 97.8%.

In [15] Emma Harte assessed a pretrained ResNet34 model's ability to detect crop diseases. The created model can distinguish between healthy leaf tissue and seven plant illnesses when it is implemented as a web application. For training and validation, the study used 8,685 leaf photos taken in a controlled setting from the Rice Disease Image Dataset on Kaggle. 20% of the dataset was used for validation, while the remaining 80% was used for training. A CNN-based architecture with several image sizes was used for the classification process. According to validation data, the suggested method obtained an F1 score of more than 96.5% and an accuracy of 97.2%. The experiments indicated that increasing image size enhances feature extraction but also increases computational time. The trials revealed that an image size of 224×224 yielded the highest accuracy and F1 score. This study highlights the technical feasibility of CNNs in plant disease classification and paves the way for AI-driven solutions tailored to smallholder farmers.

In [16] In order to create a framework for identifying fluffy caterpillars in crop photos, the authors carried out study. In order to improve feature extraction, this work uses Wavelet Transformation in conjunction with Orientated FAST and Rotated BRIEF (ORB) to propose an automated pest identification method. By concentrating on edge detection and key point extraction, the main goal is to increase detection efficiency. The success of the suggested approach, which consists of five essential stages—database collection, normalisation, feature extraction, training, testing, and validation—is confirmed by experimental results. The dataset was collected in the winter months from fava bean and mustard crop farms in Jhalawar, Rajasthan, India. MATLAB 2019a was used to implement the pest detection algorithm for leaf pictures, which produced an accuracy of 91.89%. In order to create a real-time pest monitoring system, the authors also suggested combining this strategy with the Internet of Things (IoT) and wireless sensor networks (WSN).

In [17] The authors proposed a novel image-based orchard automation method for insect classification and identification, aiming to develop a robust technique capable of handling varying conditions in crop images. They introduced Three models were used to classify insects: a hybrid model, a local feature model, and a global feature model. The hybrid model performed better than the other two. The study, which focused on eight insect species, showed that global features are especially susceptible to changes in lighting, rotation, and occlusion. Although local features aid in getting around these

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restrictions, estimating them is difficult. Using field-collected images for experiments, the hybrid model's integration with pest image classification produced an 86.6% classification training rate. The results highlight how well the hybrid model works to increase the accuracy of insect classification for use in agriculture. The study also comes to the conclusion that Integrated insect Management (IPM) is essential for integrating characterisation algorithms with image-based automated insect detection, which improves agricultural pest monitoring and management methods.

In [18] For accurate plant disease classification, a CNN-based deep learning model was created and trained using a dataset of 87,000 RGB photos that were made publically available. CNNs were used for preprocessing, segmentation, and classification. Despite achieving 93.5% identification accuracy, the model encountered issues including class misclassification and performance deterioration as a result of the restricted amount of available data. Their method used a median filter to maintain standard dimensions and preserved raw image information during preprocessing in order to increase recognition accuracy. CNN and a fusion Support Vector Machine (SVM) were used in the model. A phase 1 SVM distinguished between healthy and diseased banana leaves, while a multiclass SVM determined the kind of infection. The model's remarkable 99% classification accuracy was attained by using CNN outputs as input for SVM. While prior CNN models demonstrated superior accuracy compared to traditional methods, this approach still lacked diversity in classification.

In [19] The authors used an object detection model in conjunction with an improved classifier to present a method for identifying and detecting pests in crops. An IoT platform is integrated into the system, where data is gathered by agricultural sensors and input photographs are processed using an optimised YOLOv3 model for pest detection. Hidden neurones are optimised using the Adaptive Energy-based Harris Hawks Optimisation (AE-HHO) method to increase performance. ResNet50 and VGG16 are used for deep feature extraction, and a Weight Optimised Deep Neural Network (WO-DNN) is used for classification. AE-HHO is also used to optimise weight factors. The final classification output is predicted using the AE-HHO algorithm, ensuring improved accuracy. The model's accuracy and F1-score reached 96% and 84%, respectively, demonstrating superior performance compared to existing pest detection techniques. The findings validate that the suggested approach is a useful tool for precision agriculture since it greatly increases the effectiveness of pest identification and classification.

In [20] For automated plant disease identification, the scientists created a hybrid model that combines a Convolutional Autoencoder (CAE) with a Convolutional Neural Network (CNN). The model can be modified for different plant diseases, even though it was tested particularly on Bacterial Spot disease in peach plants. In contrast to traditional deep learning models, this method greatly reduces the amount of training parameters while optimising processing performance by utilising CAE for dimensionality reduction. The PlantVillage dataset, which includes pictures of peach leaves, was used to assess the model's performance. With just 9,914 training parameters, the experimental results showed a training accuracy of 99.35% and a testing accuracy of 98.38%, demonstrating a significant improvement over existing methods in terms of efficiency and accuracy.

LIMITATIONS

Parameters: The external parameters analysed such as soil moisture, temperature and humidity are measured with various traditional techniques such as Feel and appearance method, Field observation, Weather observation, Visual inception, etc. These traditional techniques are time consuming, tedious and are less accurate. In contrast to conventional methods, the suggested system proposes an Internet of Things device that employs a variety of digital sensors, including DHT11 sensors and resistive soil moisture sensors, to measure the parameters more precisely.

Leaf disease and pest detection: The leaf disease and pest detection have been done by various traditional techniques such as visual inception and indication of plants. As the technologies emerged predictive machine learning models have been created for creation. The various pre defined architectures that are analysed in this research are VGG-16, Inception, Resnet-50, Alexnet. VGG-16 has 3 fully connected layers with more than 5000 neurons it has a large model size which requires significant computational resources and time for training and also it shows less accuracy compared to other models which makes it unsuitable for training and validating the model. Inception model uses multiple filters connected in parallel, increases the design complexity and cost of design which is a major drawback of this architecture. The reliance on these dense layers makes the model less efficient and prone to overfitting compared to newer architectures that emphasize convolutional layers. The Resnet model and Alexnet have limitations such as reduced inference speed, less accuracy and overfitting.

III. PROPOSED METHODOLOGY.

The Smart Agriculture Monitoring System, which uses IoT-enabled sensors to measure and analyse critical environmental data like temperature, humidity, soil moisture, and crop health, was developed using the techniques described in this section. The Smart Agriculture Monitoring System employs an integrated methodology combining IoT, machine learning, and communication technologies to address modern farming challenges. This multi-faceted approach involves real-time data acquisition, advanced image processing, predictive modeling, and robust communication systems to deliver actionable insights, making it an indispensable tool for precision agriculture.

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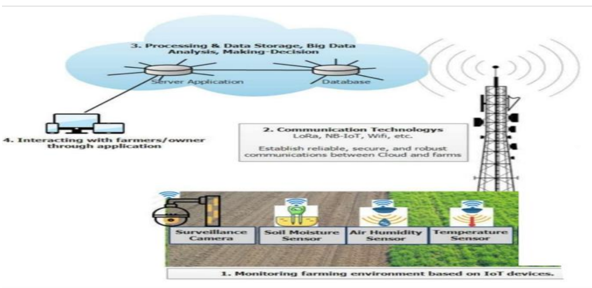

Fig 2. Block Diagram

In order to continuously monitor important environmental parameters, such as soil moisture, temperature, and humidity, the process begins with the placement of IoT-enabled sensors. The accuracy with which the DHT11 sensor measures temperature and humidity makes it useful for providing real-time atmospheric data that has a direct impact on crop health. Similarly, to determine the water content of the soil and ensure ideal irrigation while avoiding drought stress and overwatering, a resistive soil moisture sensor is employed. By integrating these sensors into the system, real-time monitoring is enabled, allowing farmers to make data-driven decisions that enhance crop management and overall resource efficiency. This sensor detects changes in soil conductivity, classifying the soil as “Wet” or “Dry.” The continuous monitoring of these parameters ensures that optimal conditions are maintained for plant growth, minimizing risks such as overwatering or dehydration.

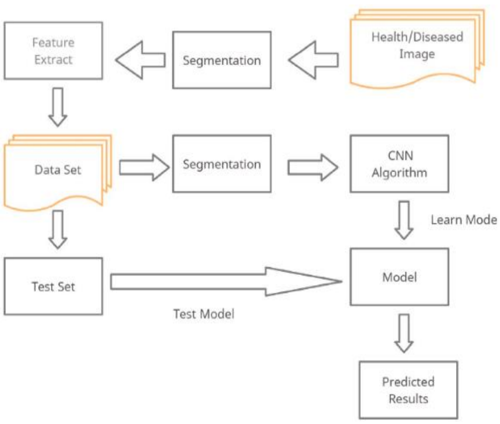

Fig.3 Flowchart of proposed model

The Raspberry Pi 4B, a powerful microcontroller that serves as the system's central processing unit, is at its heart. It converts unprocessed measurements into insightful information by processing sensor data. Furthermore, the Raspberry Pi makes it possible to integrate communication protocols and machine learning models, guaranteeing seamless and effective system functioning. Python scripts are utilized to interface with the hardware, leveraging libraries like GPIO and Pigpio to handle data acquisition and control. The simplicity and cost-effectiveness of the Raspberry Pi make it an ideal choice for scalable and adaptable agricultural systems. The incorporation of machine learning for the identification of pests and plant leaf diseases is a substantial advancement in approach. Utilising its capacity to extract spatial characteristics from images, a Convolutional Neural Network (CNN) serves as the central component of the image processing module. CNNs are therefore quite good at spotting trends linked to insect infestations and plant illnesses. The training dataset for the CNN model was sourced from open-access repositories like **Kaggle**, which offer a diverse collection of labeled images. These datasets include examples of healthy, diseased, and pest-infested leaves, providing a comprehensive foundation for the model to learn and generalize effectively.

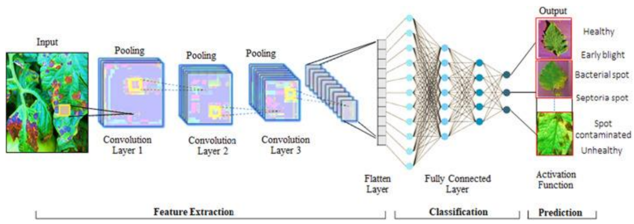

Fig 4. CNN Algorithm

A. Data Acquisition

All Tomato imagery is derived from “Tomato leaf Disease detection dataset” an open access repository from Kaggle that contains 11000 images [31]. A variety of classes were selected, with further details provided in Table I. Additionally, images of other plants, such as rice, were sourced from the 'Rice Image Dataset,' an open-access repository available on Kaggle. This dataset, comprising 75,000 images [32], was utilized to comprehend the execution process.

TABLE I: DATASET USED

Species	Class	No. of Images
Tomato	Bacterial Spot	1000
Tomato	Early Blight	1000
Tomato	Late Blight	1000
Tomato	Leaf mould	1000
Tomato	Septorial leaves	1000
Tomato	Spider Mites	1000
Tomato	Target Spots	1000
Tomato	Yellow Leaf Curl Virus	1000
Tomato	Mosaic Virus	1000
Tomato	Healthy	1000

B. Data Pre- Processing

For training, testing, and validation, the dataset is divided into different sections. It was decided to use three different distribution ratios: (i) 70% for training, 20% for testing, and 10% for validation; (ii) 70% for training, 20% for testing, and 10% for validation; and (iii) 60% for training, 20% for

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testing, and 20% for validation. Augmentation settings were first applied to the training data, with each operation assigned a weighted probability of occurrence during each epoch. These settings included horizontal and vertical flips, rotations, zoom adjustments, and contrast modifications. Finally, the augmented images were resized and normalized.

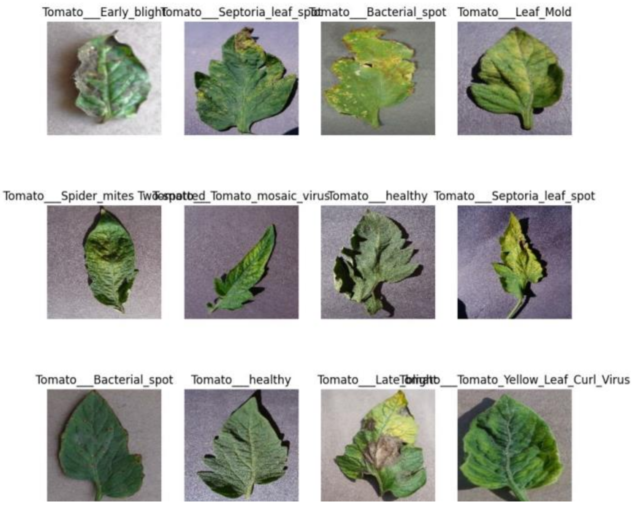

Fig 5. Pre-Processed Images

C. Feature extraction

A specific kind of artificial neural network called a convolutional neural network (CNN) is made to analyse structured input, especially images. These networks perform exceptionally well in tasks including segmentation, recognition, and image detection. The convolutional layer (CONV), pooling layer (POOL), and fully connected layer (FC) are the three main parts of a CNN[20]. Model optimization was approached from two perspectives. Before optimizers got involved, the models were examined closely, providing insight into unadulterated potential. The next stage was to include Adam optimizers and perform a comparative analysis. This investigation produced a remarkable discovery, that using optimizers cautiously can significantly improve the loss function.

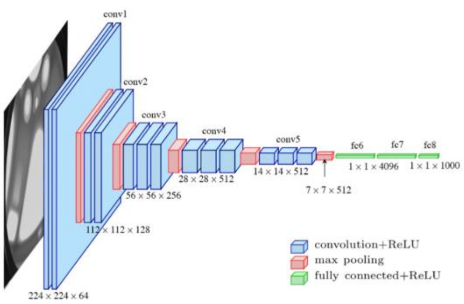

Fig 6. Feature Extraction Layer

According to this study, Convolutional Neural Networks (CNNs) are essential for identifying plant pests and diseases, allowing for the early detection and categorisation of crop-related problems. CNNs automatically learn and extract spatial characteristics, such as leaf textures, shape variations, and colour changes, in contrast to standard machine learning methods that rely on manual feature extraction. This capability makes them exceptionally efficient for disease detection and classification. A dataset of more than 5,000 plant photos from Kaggle is used to train the suggested CNN model, which was constructed using pretrained architectures like VGG-16, ResNet-50, Inception, and AlexNet. The model identifies and classifies plant diseases with an impressive 98% accuracy rate by using pooling layers for dimensionality reduction and convolutional layers for feature extraction.

To perform multiclass classification of plant diseases, the CNN model employs a softmax function in the final layer. The softmax function calculates the probability distribution over NNN classes and is defined as:

$$P(y_i) = \frac{e^{z_i}}{\Sigma_{j=1}^{N} e^{z_j}}$$

Where Z_i is the input to the softmax layer and NNN is the number of output classes. This ensures that the sum of predicted probabilities equals 1, allowing the model to assign the most likely class to each input image.

By supporting automated decision-making and enhancing real-time disease detection, CNN's integration with the Smart Agriculture Monitoring System (SAMS) raises agricultural productivity overall. The trained model processes leaf images captured by a camera module, runs image classification on the Raspberry Pi 4B, and instantly identifies the plant's health status, determining whether it is healthy or afflicted by a disease. This eliminates the need for manual crop inspections, saving farmers time and effort while ensuring early intervention before the disease spreads. Additionally, the CNN model is optimized using data augmentation techniques such as rotations, flipping, and contrast adjustments to enhance its generalization across various plant species and environmental conditions. This AI-driven approach not only improves crop yield and productivity but also minimizes excessive pesticide usage, making precision agriculture more efficient and sustainable. Beyond CNN, this research explores multiple pretrained deep learning architectures, including VGG-16, ResNet-50, Inception, and AlexNet, for plant disease detection and classification. Each architecture is evaluated based on key performance metrics such as accuracy, computational efficiency, and suitability for real-time implementation within the Smart Agriculture Monitoring System (SAMS). VGG-16, with its deep convolutional layers, extracts high-level features effectively but requires significant computational power and storage, making it less efficient for deployment on Raspberry Pi 4B. ResNet-50, on the other hand, introduces residual learning, allowing for deeper networks without suffering from vanishing gradient issues. Although it provides higher

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accuracy, it has longer inference times, which may impact real-time processing in resource-constrained environments. Inception improves feature extraction by applying multiple convolutional filter sizes in parallel, making it more computationally efficient than VGG-16 and ResNet-50. However, its complex architecture increases design difficulty and processing time. AlexNet, one of the earlier CNN architectures, is lightweight and computationally less expensive, but it does not perform as well as modern deep learning models due to its limited depth and lower feature extraction capability. The research compares these models and optimizes the CNN-based approach to achieve a balance between high accuracy (98%) and real-time performance, ensuring faster disease detection, reduced resource consumption, and improved farm productivity.

Preprocessing is a crucial step in the methodology to prepare the dataset for analysis. The raw images undergo transformations such as noise reduction, resizing, segmentation, and normalization. These preprocessing techniques promote consistency throughout the dataset, enabling the model to concentrate on crucial features. For example, edge detection methods emphasize the boundaries of infected regions, allowing the model to pinpoint disease-affected areas with higher precision. By lowering noise, enhancing feature extraction, and guaranteeing better generalisation across a range of environmental conditions, this preprocessing phase not only improves the quality of the input data but also dramatically increases the CNN model's overall accuracy and performance.[15]

Data augmentation is another key component of the methodology, addressing the challenge of limited datasets. Augmentation techniques such as rotations, flips, zooms, and contrast adjustments artificially expand the dataset, increasing its size and diversity. This process mimics real-world variations in image orientation, scale, and lighting conditions, enabling the model to perform robustly under different scenarios. By reducing overfitting and improving generalization, data augmentation ensures that the CNN model delivers consistent results across diverse test sets.

Complexity and processing efficiency are carefully balanced in the CNN model architecture. It includes fully connected layers for classification, pooling layers for dimensionality reduction, and convolutional layers for feature extraction. By using batch normalisation to stabilise training, dropout layers to prevent overfitting, and activation functions like ReLU to incorporate non-linearity, the architecture guarantees optimal learning and eventually improves the model's accuracy and robustness.

The Rectified Linear Unit (ReLU) activation function is mathematically defined as

$$f(x) = \max(0,x)$$

This function eliminates negative values and introduces non-linearity into the model while maintaining computational efficiency.

The model is further optimized using dropout layers to prevent overfitting and the **Adam optimization algorithm** to accelerate convergence[26]. The final design is a dependable tool for identifying plant diseases and pests, outperforming conventional techniques and achieving an amazing 96% accuracy on test datasets. By enabling proactive disease management and lowering reliance on chemical treatments, this high accuracy highlights the value of deep learning in precision agriculture.

Communication is a critical aspect of the methodology, enabling real-time dissemination of insights to farmers. The Twilio API is integrated into the system to send automated SMS notifications whenever critical thresholds are crossed. For example, low soil moisture levels or high humidity conditions trigger an alert, prompting immediate action. Similarly, the detection of a disease or pest infestation generates a notification detailing the type of issue and the affected crop. These alerts are concise and actionable, ensuring that farmers can respond promptly to mitigate risks and optimize resource usage.

IV. RESULTS AND DISCUSSIONS

A. Experimental Setup

Connect the GND pin to any GND pin on the Raspberry Pi and the VCC pin to either the 3.3V or 5V pin, depending on the sensor's voltage requirements. The Digital Output pin (D0) of the DHT11 sensor should be connected to a general-purpose input-output (GPIO) pin on the Raspberry Pi, such as GPIO 27 in this setup, ensuring accurate temperature and humidity readings. Similarly, the digital pin of the soil moisture sensor is connected to GPIO pin 4 on the Raspberry Pi to monitor soil conditions in real time. Proper wiring and secure connections are essential to prevent signal interference and ensure reliable data transmission. Additionally, using appropriate pull-up resistors, if required, can improve sensor stability and enhance overall system performance.

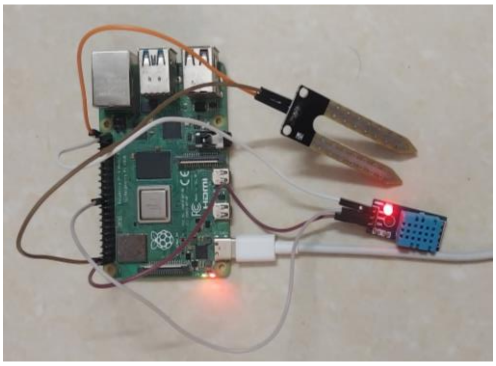

Fig.7 Experimental Setup

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The output monitored in the Pi desktop is shown below.

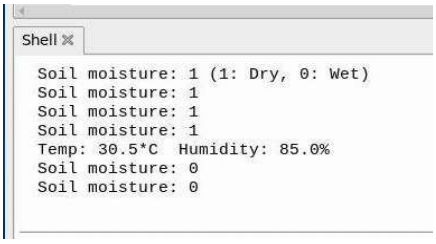


Fig 8. Console Output

B. Inference from existing machine learning model.

Model	Training accuracy (%)	Training Loss (%)	Test accuracy (%)	Test Loss (%)
VGG16	84.27	0.52	82.75	0.64
Inception	100	0	99.98	0.5
ResNet-50	99.82	6.12	98.73	0.027
AlexNet	92.07	0.2449	90.68	0.086
Proposed model	97	0.069	96.2	0.0425

TABLE II Inference

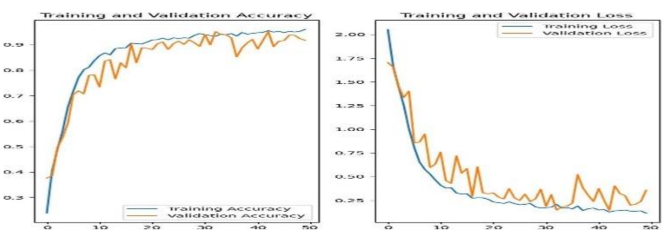
C. Proposed machine learning model.

Leaf Disease Detection — The preprocessed and augmented images of the training set were used to train the CNN model based proposed architecture. During training, the model attained a validation accuracy of 94.17% and a validation loss of 0.3130, when trained with the ratio (8:1:1). The model is trained with different ratios of training and validation set for 4 different plants. The ratio used for training is Train: Validation: Test = 8:1:1; Train: Validation: Test = 7:2:1; Train: Validation: Test = 6:2:2; The various plants whose leaf images were trained are Tomato, Mango, Corn and Tea. The accuracy based on different models is mentioned in the below table.

Ratios/ plants	Tomato	Mango	Corn	Tea	Pest
8:1:1	0.96	0.97	0.96	0.96	0.95
7:2:1	0.99	0.99	0.76	0.85	0.94
6:2:2	0.91	0.98	0.92	0.93	0.91

TABLE III Accuracy of various ratios

From the table the other two ratios are either less accurate or overfitting and hence the ratio 8:1:1 is chosen for the proposed model. The accuracy plot, loss plot and confusion matrix are shown below for tomato plant.



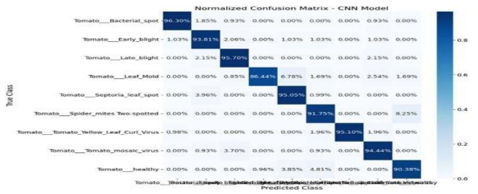


Fig 9. Accuracy, loss plot and Confusion matrix

Pest Detection — The preprocessed and augmented images of the training set were used to train the CNN model based proposed architecture. During the training, the model achieved a validation accuracy of 94.17% and a validation loss of 0.3130. The model is trained with different ratios of training and validation set for pest dataset. The ratio used for training is Train: Validation: Test = 8:1:1; Train: Validation: Test = 7:2:1; Train: Validation: Test = 6:2:2

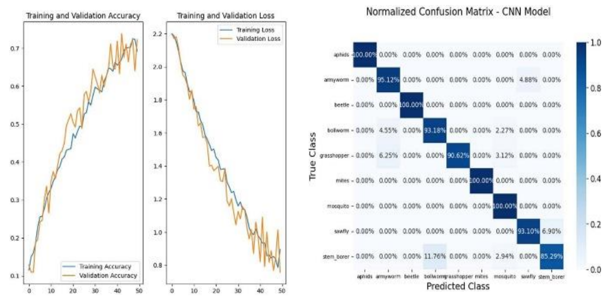


Fig 10. Accuracy, loss plot and confusion matrix

D. Output received.

Communication is a critical aspect of the methodology, enabling real-time dissemination of insights to farmers. The Twilio API is integrated into the system to send automated SMS notifications whenever critical thresholds are crossed. For example, low soil moisture levels or high humidity conditions trigger an alert, prompting immediate action. Similarly, the detection of a disease or pest infestation generates a notification detailing the type of issue and the affected crop. These alerts are concise and actionable, ensuring that farmers can respond promptly to mitigate risks and optimize resource usage.
The message is received from the twilio account which is shown in the figure.

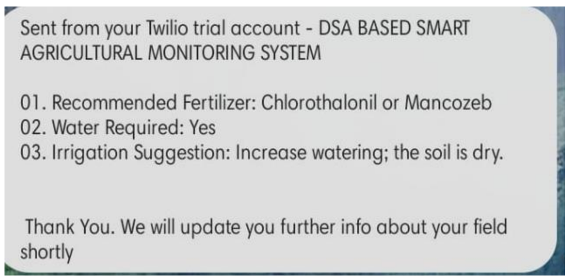


Fig 11. Received Output

E. Conclusions

In the culmination of this research, the significance of this approach within the domain of Internet of Things is underscored by a culmination of dedicated efforts and innovative methodologies. By leveraging advanced technologies such as ML, IoT, cloud computing, this system can empower farmers with real-time, actionable insights, helping to increase crop yields, reduce resource usage, and promote sustainable practices.

The paramount contribution to this discipline is the conception and application of integrating the soil moisture and DHT sensors with Raspberry Pi. In addition to utilizing sensors, a Convolutional Neural Network (CNN) model is specifically designed and optimized for plant leaf and pest detection.The training of the proposed model involved the meticulous curation of a predefined open-source dataset sources from Kaggle.

To evaluate the robustness of the proposed model, the dataset was divided and trained using different ratios (8:1:1, 7:2:1, 6:2:2). The model demonstrated reliability across diverse training and testing scenarios, as indicated by the consistent alignment observed between training and validation accuracies. The methodology implemented in this project comprises meticulous descriptions of libraries, datasets, input images, data augmentation techniques, and the proposed architecture of the CNN model. The accuracy arrived in this model is 96%.

Additionally, the integration of an adam classifier has proven instrumental in elevating overall accuracy and ensuring uniformity across diverse test sets. This ensemble technique fortifies the model's efficacy and dependability in the nuanced task of fingerprint categorization. The methodology implemented in this project comprises meticulous descriptions of libraries, datasets, input images, data augmentation techniques, and the proposed architecture of the CNN model.

In short, this project demonstrates how cutting-edge technology, strict methodology, and a deep understanding of leaf datasets can all work together to successfully advance the field of agriculture.

F. Future Scope

Future systems might even predict outbreaks based on weather patterns and past data, helping farmers take proactive measures. Future systems could integrate with autonomous machinery (like drones or robots) for automated crop care, applying water, nutrients, or pesticides precisely where needed based on sensor data, reducing resource usage and environmental impact. The future work of this project aims to expand the existing model by including a camera which can capture the real time images from the particular area in the fields automatically and detect the pests and diseases in it.

These systems can play a role in monitoring sustainable practices, reducing pesticide/fertilizer overuse, and tracking soil health for long-term environmental conservation. The system could be used in collaboration with governmental agencies for large-scale agricultural health monitoring, contributing to policy development, subsidies allocation, and national food security programs.

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