A Hybrid Edge-Cloud IoT Framework for Real-Time Plant Disease Detection using Multimodal Data Fusion

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Abstract— **The rising rate of plant diseases poses a significant risk to global agriculture, leading to reduced yield and financial loss. The current approaches of disease detection are through manual visual inspection, or processing using cloud images, with all methods struggling with latency, scalability and power consumption limitations; especially in remote rural areas. This work presents a new, light-weight, and effective IoT-based system called SmartSense+, which is aimed for real-time detection of plant diseases using hybrid edge-cloud infrastructure and multimodal data fusion. The system incorporates NodeMCU and ESP32-CAM modules for image acquisition at the edge level and for monitoring environmental parameters such as temperature, humidity, and soil moisture. By using adaptive thresholding and light-weight feature extraction processes on the edge device, only the necessary data is sent through MQTT protocol to a cloud server. The cloud layer uses a Decision Tree classifier with decision-level data fusion augmented features, which are combined with sensor data to enhance the prediction capability. Experimental results validate that the devised system provides a detection accuracy of 92.3% with considerably smaller data transmission size and latency in comparison with traditional cloud-only and TinyML techniques. In addition, the system facilitates real-time alerts and includes an easy-to-use mobile and web dashboard for farm surveillance. The contribution of this paper is a scalable, energy-efficient, and cost-effective solution optimized for small and medium-scale farms. The suggested hybrid IoT platform is highly promising for solving actual agricultural problems by facilitating early and precise detection of plant diseases to protect plant health and develop more sustainable agriculture.**

Keywords— Plant Disease Detection, Edge Computing, cloud computing, NodeMCU, Internet-of-Things

I. INTRODUCTION

In most economies, especially in rural and developing parts of the world, agriculture is still the major contributor to economic stability and food security. Regardless of the improvements that technology has made in agriculture, plant diseases continue to be the most significant risk to production, yield quality, and profit. Based on the Food and Agriculture Organization (FAO) estimates, plant programs worldwide account for 20–40% of annual world crop loss, and ultimately affect the livelihoods of millions of farmers globally, as well as the price of food[1]. Timely and accurate diagnosis of plant diseases therefore is absolutely essential in preventing massive crop losses before they occur and ensuring sustainable agricultural practices. In the past, farmers utilized manual field surveys or specialist advice in detecting plant diseases, but the approaches are time-consuming, labor-intensive, subjective, and ineffective in large or inaccessible farmlands.

With the rise of IoT and Artificial Intelligence (AI), the agricultural industry is going digital. IoT-enabled monitoring systems with environmental sensors can provide the data for real-time temperature, humidity, and soil moisture monitoring, while AI-based image processing software can evaluate leaf photos for visible diseases. However, most existing plant disease detection systems are cloud-based, requiring constant internet connectivity to analyze high-resolution images and environmental data. The technique has the drawback of being latency-prone, bandwidth-limited, increased operating costs, and dependent upon a robust network connection, which is not always present in remote rural farm locations[2].

To tackle these issues, this paper proposes an innovative, cost-effective, and efficient IoT-based system for plant disease identification in real-time that is developed as a hybrid edge-cloud architecture by fusing multi-modal data sources. The proposed system utilizes the abilities of NodeMCU microcontrollers, ESP32-CAMs, and environmental sensors all working seamlessly together to produce leaf images and acquire contextual environmental information. The collected data is preprocessed partially on the edge using lightweight preprocessing techniques for extracting meaningful features, which are then transmitted over the effective MQTT protocol to a cloud server. At the cloud level, a machine learning classifier aided by decision-level data fusion employs both image-derived features and environmental factors to develop more precise and reliable diagnoses of plant diseases[3].

The prototype system's performance is evaluated with metrics utilizing accuracy of disease detection, data transmission latency, energy consumption, and scalability. The comparison is made against three other approaches including, traditional cloud based image analysis system, sensor-only IoT type framework, and new TinyML[4] based edge computing devices. The prototype system should demonstrate better disease detection accuracy, lower latency, and lower cost in recent agricultural areas that have limited or no network coverage. The objectives of the study are as follows

- To develop a lightweight and scalable hybrid edge-cloud IoT type framework for real-time plant disease detection using leaf image analysis and environmental sensors using both NodeMCU and ESP32-CAM hardware.
- To employ a multimodal data fusion approach, image derived features and environmental parameters to improve overall accuracy of disease classification and expedite decision making.

- To assess the performance based on accuracy, latency, transmission efficiency, and scalability against existing systems which used cloud based approach, sensor-only systems, and TinyML based systems.

II. RELATED WORKS

The growth and progress of deep learning (DL), machine learning (ML), and Internet of Things (IoT) technologies have improved the accuracy and time for scanning and detecting plant diseases. In particular, recent findings demonstrate that models including YOLOv5, BiCMT, and CNN-based models for real-time image-based diagnosis in the agricultural context are remarkably efficient even when consuming from edge-cloud-based infrastructures. More importantly, the advances covered in this review paper advance opportunities to mitigate data collection, multi-object detection, and cross-device processing challenges present in agricultural settings. The innovations, including transfer learning, attention mechanisms, and hybrid deep networks developments present in the innovation category, help to push the processing and detection accuracy and signal data processing scalability. This review article identified some of the state-of-the-art detecting methods, model architectures, and applications improving the future of intelligent agriculture.

Mohammed *et al.*, (2024) demonstrates how to use deep neural networks with transfer learning to detect plant diseases using edge-cloud remote sensing data. The goal is to resolve the previously listed problems, including collecting data from a variety of sources, detecting diseases, and processing information more accurately and quickly across various devices. Based on combinatorial optimisation issues, we propose commutative fuzzy deep CNN (FCDCNN) strategies for transfer learning[5]. Tanveer et al., (2024) provides a sophisticated method for real-time plant disease identification and classification utilising the YOLOv5 (You Only Look Once) model, a cutting-edge object detection algorithm. The YOLOv5 model is perfect for agricultural applications since it provides great accuracy and efficiency, especially for jobs that require the simultaneous detection of many objects[6].

Feng et al., (2022) suggested end-to-end illness identification model consists of a disease classifier (YOLOv5s + BiCMT) and a disease-spot region detector. In particular, the disease-spot regions were identified using the YOLOv5s network, which offered a regional attention mechanism to help the classifier with the disease identification task[7]. Sajitha et al., (2024) provide a review article that highlights image-based plant disease classification and detection systems and discusses ML and DL success stories. The study looks at a number of these systems' features, such as the origins of plant datasets, the kinds of algorithms, and the methods employed in ML and DL[8].

Prasad et al., (2024) examines how to use IoT, ML and DL approaches to identify disease symptoms at different stages so that prompt actions can be taken to stop large crop losses and disease spread inside agricultural plots[9]. Khalid et al., (2024) examines the revolutionary potential of DL models, with a primary focus on the early and accurate identification of plant diseases utilizing CNNs and MobileNet architectures [10]. An image-based deep CNN called the Multi-head Attention Mechanism Depthwise Separable Convolution Inception Reduction Network (MDSCIRNet) architecture is suggested for the classification of potato leaf diseases[11].

Wang et al., (2025) outlines the latest developments in using DL algorithms for the identification of plant diseases and pests. The limitations of conventional approaches in this field are first described, and then the most recent advancements in the application of different DL techniques such as image classification, object detection, semantic segmentation, and change detection to the identification of plant diseases and pests are systematically discussed.

DL, ML, and IoT have completely shifted the model for detecting plant disease and allowed farmers to take early action to mitigate crop losses. Transfer learning, attention-based CNNs, and lightweight mobile models appear very promising for leveraging scalable, real-time use in agriculture. Despite the substantial progress in this area, issues remain with dataset diversity, model generalization, and implementation of a model on variable field conditions. Continuing research on hybrid models, optimization strategies and appropriate metrics will be important. In summary, the move to leveraged automation will continue to foster advancements towards smarter and more resilient precision agricultural processes.

III. METHODOLOGY

This Study outlines a new, lightweight, real-time plant disease detection system using a combination edge-cloud IoT model that incorporates NodeMCU microcontroller boards. The proposed system also includes multimodal data fusion by using leaflet image features and environmental sensor data to increase prediction accuracy for the plant disease. The proposed plant disease detection system is built as a three-layer design framework, which engages the Edge Layer, Communication Layer, and Cloud Processing Layer. The layered edge-cloud system is aimed to reduce data acquisition, transmitting sensing, processing, and analysis to real-time monitoring and detection of plant disease with low latency and less consumed resources[13]. The overall flow diagram is depicted in figure 1.

Edge Layer (NodeMCU & ESP32-CAM): The edge layer is the first play to acquire the data and allows for primary processing of the data. It consists of IoT devices with microcontroller-based capabilities like the NodeMCU and the ESP32-CAM module. The ESP32-CAM allows us to capture high-resolution images of the plant leaves while the NodeMCU is wired to multiple environmental sensors to measure parameters, such as temperature, humidity, and soil moisture. This layer is expected to perform lightweight preprocessing and feature extraction on the downloaded data to minimize the amount of data sent to the cloud (e.g. in the place of sending full raw images, the edge devices extract certain features or compression of images to mitigate excessive bandwidth). The edge layer will also make local auto decision-making when performing some basic checks or if anomaly detection is determined which will enhance response time on the cloud connected system. The NodeMCU and ESP32-CAM are an excellent choice for cost, size, and integrated Wi-Fi capabilities to be strategically placed in limited resources of an agricultural environment. This edge device, by keeping the data in close proximity to sensory data, will generate the fastest and most reliable plant disease detection

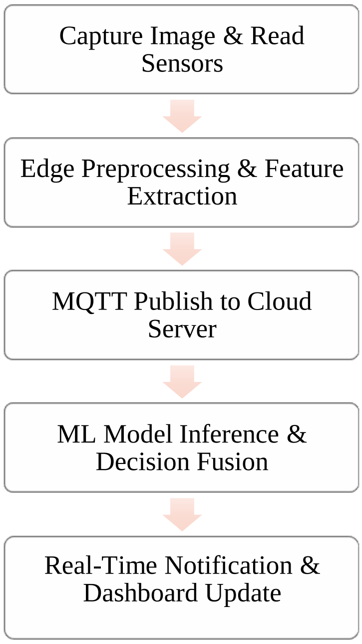

Figure 1. Proposed Workflow diagram

Communication Layer (MQTT Protocol): The communication layer is the data channel between edge devices and the cloud structure. The communication layer that we selected is the MQTT protocol (Message Queuing Telemetry Transport). MQTT is a lightweight, publish-subscribe messaging protocol intended for constrained devices and low-bandwidth, high latency networks. Given these characteristics, MQTT is a good protocol to use for IoT applications, because it provides reliable delivery of messages with a reduced overhead to the network and lower power requirements. The edge devices will publish their preprocessed sensor data and image features as messages to specific topics identified by the provided MQTT broker in the cloud. The cloud has subscribed to the specific topic so it can receive the real time data streams for further processing. The MQTT publish-subscribe model has decoupled the data producers (the edge devices) from the data consumers (the cloud services) allowing an increased scale and elasticity of the architecture. Additionally, the levels of Quality of Service (QoS) that MQTT supports will permit the right balance of delivery reliability for data transmissions, and subsequent communication overhead, which is of utmost importance when working in an agricultural context with intermittent connectivity[14].

Cloud Processing Layer (Firebase or AWS IoT with ML Model): The cloud processing layer acts as the main control station for all advanced data analytics, machine learning inference, data storage, and user interface services. Cloud platforms, like Firebase or AWS IoT, provide elastic infrastructure to collect, store, and process the data messages received via MQTT. The cloud processes a trained machine-learning model, like Decision Tree, or Random Forest or lightweight neural network that performs decision-level fusion, synthesizing the multimodal data input streams (image features + environmental sensor information) to identify and classify plant diseases. By performing decision-level fusion, it takes advantage of the complementary properties of visual and contextual environmental information to improve reliability in detecting plant diseases. The cloud layer also takes care of data storage for historical data that may support trend analysis or predictive insights. It also houses the backend services for the user dashboard and the mobile notification service, allowing farmers access to real-time alerts for farmers to visualize remotely, and the health status of their crops. Both Firebase and AWS IoT offer robust, secure, resilient, and scalable environments while offering features such as device management, data analytics, and event-driven trigger capabilities, therefore they make sense for a cloud layer. The entire computation of the cloud can absorb the large processing that does not run on incapacitated edge devices, so that disease diagnosis can be executed efficiently and accurately. This three-parted, layered architecture takes advantage of edge computing (e.g., low latency, decreased data load), reliable communication (i.e., reliable, lightweight messaging), and cloud analytics (i.e., complex ML models, and scalable storage), to develop a practical, live plant disease detection system proper for smart farming usage. Table 1 lists the hardware needed for this study.

Table 1: Hardware Setup for the proposed Method

Component	Description	Function
NodeMCU (ESP8266)	Microcontroller with built-in Wi-Fi capability	Acts as the main controller for sensor data acquisition and communication
ESP32-CAM	Low-cost camera module with integrated Wi-Fi and microSD slot	Captures leaf images for disease detection
DHT22 Sensor	Digital temperature and humidity sensor	Monitors ambient temperature and humidity levels
Soil Moisture Sensor	Analog sensor for detecting soil moisture levels	Measures soil water content to assess plant health conditions
Light Intensity Sensor (Optional)	Sensor for measuring ambient light levels (e.g., BH1750)	Monitors sunlight exposure affecting plant health

A. Data Acquisition

The data acquisition component of the proposed system includes collecting visual data and contextual data inside the farm and in real time. The collection of visual representation of the leaves will be adopted by capturing leaf images through the ESP32-CAM module. The ESP32-CAM module facilitates communication with the NodeMCU microcontroller over a serial interface to transfer data from the ESP32-CAM module to the NodeMCU microcontroller. The leaf images collected will be the visual representation that will be used to identify visual disease symptoms on the plant leaves.. When the leaf images are taken, a collection of environmental parameters captured with integrated sensors at the same time as the leaf images. When capturing environmental conditions temperature and humidity will be measured using the DHT22 sensor. The DHT22 sensor will be able to provide relevant data about the ambient environmental conditions that can affect plant health and susceptibility to disease. A soil moisture sensor will provide similar data for soil moisture. A soil moisture measurement will indicate possible irrigation requirements, and provide an insight into soil conditions. A light intensity sensor can also be used to measure the intensity of sunlight if required. All sensor values will be polled periodically e.g., every 10 seconds. Continuous monitoring of conditions surrounding the crops will support timely disease detection and decision-making in the smart agricultural system.

B. Edge-Side Preprocessing & Feature Extraction

To improve system working memory and minimize throughput on the network, the architecture implements edge-side or local preprocessing and feature extraction before transferring data to the cloud. After taking images of leaves with some ESP32-CAM, we performed adaptive thresholding using OpenCV libraries on either the ESP32-CAM or via an attached NodeMCU microcontroller. Here, the adaptive thresholding segmented the affected area of the leaf surface by utilizing pixel intensity differences to segment diseased and non-diseased areas (i.e., healthy tissue). Once the segmentation was performed, many handcrafted features were derived from the surface of the leaf and visual attributes of the leaf. These were: mean RGB values, which provides information about the distribution of colors; the Green-Red ratio (GRR), which is useful for quantifying chlorosis and necrosis; the percentage of the lesion area relative to the leaf surface area (i.e. the ratio of diseased pixels to total leaf pixels.

Local Binary Pattern (LBP) histograms that capture texture patterns corresponding to differing disease types; and edge density, calculated using Canny Edge Detection—reflecting lesion boundary complexity. These collectively allow for a small, efficient, and informative summary of the condition of the leaf while maintaining a low computational cost. Concurrently, environmental sensor data, including temperature, humidity, and soil moisture is added to the feature vector that was derived from the feature images. Together with environmental measurements, this multimodal feature set is prepared and formatted to be efficiently published via the MQTT protocol, which facilitates lower time-lag (latency) and contextual disease detection in real-time.

C. Data Transmission

Now that the feature extraction and pre-processing has been done at the edge, we can now move forward with the efficient data transfer with the MQTT protocol. In this case, the NodeMCU is the main publisher that will use Wi-Fi to send to the cloud server the extracted image feature vectors as well as the environmental sensor readings. In order to conserve both bandwidth and power consumption, the system transmits the minimum amount of information needed, for example, the value of the features that are numerical and the sensor metrics, instead of raw high-resolution images to the cloud server. Transmitting less data over the network and thus less data in general, is an important feature for reasons of bandwidth in communications; consequently, this is beneficial for deployment into remote and bandwidth-constrained agricultural situations. MQTT's lightweight publish-subscribe architecture gives reliability and low-latency communication between the edge devices and cloud and scales as additional sensors and data are added to the system. By communicating or transmitting smaller and more processed data to the cloud instead of larger image files, the framework helps save network resources, battery life, and provides constant real-time monitoring and decision-making without putting any significant constraints on the communications network.

D. Cloud-Side Processing

Once the feature vectors and environmental sensor readings are received through the MQTT broker, cloud-side processing starts on a cloud, serverless, scalable platform, such as Firebase Cloud Functions or AWS Lambda. The cloud-side processing uses a lightweight ML model (e.g. a Decision Tree or Naïve Bayes classifier), which are ideal due to their low computation complexity and quick decision-making abilities. We note that this cloud-side processing is handling the real-time inference for processing streams of incoming data. This is called decision-level fusion because it corresponds to taking both the image-derived features (mean RGB values, lesion area percent, LBP histograms, etc.), and the environmental sensor observations (temperature, humidity, and soil moisture) and trying to integrate them together. Integrating these complementary pieces of data or information improves the model's ability to classify the plant's health status quickly and accurately. The output will classify the plant condition into predefined classes, such as Healthy, Leaf Spot, or Powdery Mildew, Rust, or any other diseases defined in the system. This composite classification mindfully considers both the visual symptoms and environmental conditions to arrive at the final diagnosis of the plant. This approach improves the confidence of detection and contextual relevance of the diagnosis. The cloud layer will also take care of data logs and notification alerts as usual, while the dashboard will continuously show updates, notifications, alerts, and summary updates that will keep farmers informed of actionable data regarding their crops.

E. Real-Time Alerts and Visualization

Based on the classification results provided by the cloud-deployed ML model, the system initiates real-time communication with farmers and stakeholders. The system instantly uses Firebase Cloud Messaging (FCM) to notify farmers via the mobile app push notification that their plant health status is available and whether or not any diseases were detected. The notifications will be actionable and received at a time that enables the farmer to address the issue in regards to their work or records. Farmers also receive a web-based visualization dashboard that consolidates their crop conditions. The web-based visualization dashboard will provide the status of the monitored plants in real-time (and the disease detected if any) plus additional contextual insights derived from the industrial environmental sensors connected in their operation. Also captured in the visualization dashboard will be historical data trending their temperature, relative humidity and soil moisture, which gives context regarding the areas seasonality trends indicating possible environmental disease outbreaks. The dashboard has treatment or preventative suggestions allocated for the detected disease, providing the farmer proactive and practical options to manage plant health. The communication and visualization module is integrated into a unified whole so that the decision-makers receive their notifications in time to reduce crop loss and improve resource utilization in contemporary IoT-enabled precision agricultural systems[15].

IV. Results And Discussions

A. Dataset Description

In support of the real-time evaluation of the SmartSense+ system, a custom dataset was developed with a pair of ESP32-CAM and NodeMCU modules. A total of 104 images were captured by the ESP32-CAM of healthy and diseased crop leaves under ordinary conditions on the farm with a consultation expert, while the DHT11 and soil sensors on the NodeMCU stored data on the corresponding environmental conditions temperature, humidity, and moisture. Each data instance was generated with a date and time to synchronize the images with the sensor data. Labels for diseased plants and crops were annotated manually based on the visible symptomology of the disease and consultation with an expert. The dataset was developed based on actual conditions one would experience on a farm ensuring relevant for edge-cloud testing. This multimodal dataset provides an initial verification of the accuracy, latency and energy efficiency of the SmartSense+ system.

B. Performance Analysis

Table 2 simplifies the performance of four plant disease detection systems SmartSense+ (proposed hybrid edge-cloud IoT), CNN cloud only, sensor only IoT, and TinyML on ESP32, evaluating four parameters such as detection accuracy, data transmission size, latency, energy consumption.

Table 2. Performance Analysis- Proposed Hybrid Model

Parameter	Proposed Hybrid Edge-Cloud IoT (SmartSense+)	CNN-based Cloud-Only Approach	Sensor-Only IoT System	On-Device TinyML (ESP32 only)
Detection Accuracy (%)	92.3	89.6	72.4	85.7
Data Transmission Size (KB)	1.5	60 (raw images)	0.8 (only sensor data)	1.5
Latency (Response Time in ms)	350	1200	200	300
Energy Consumption (mW)	110	180	80	130

An analysis reveals that the hybrid edge-cloud IoT system proposed, SmartSense+ is built on superior capabilities when evaluated using the parameters of detection accuracy, data transmission size, response latency, and energy consumption. SmartSense+ achieves the greatest level of accuracy (92.3%) as it applies multimodal fusion to combine both image and sensor data, thereby achieving a higher level of accuracy than the model that uses deep convolutional networks and is restricted to cloud computing only (89.6%), TinyML (85.7%), and the model that applies only sensor data (72.4%). SmartSense+ has reduced the transmission size to 1.5 KB, which is ideal for low-bandwidth environments (e.g., fishing vessels) that is 60 KB smaller than the cloud-only model, being able to perform role at the Edge. SmartSense+ operates with a latency (-350 ms) that guarantees a superior level of detection compared to the speed of the cloud-only model, while also being energy-efficient (110 mW). SmartSense+ displays the best accuracy, latency, bandwidth efficiency, and energy use, making it the best option to identify agricultural disease in real-time, within the constraints of resource restrictions.

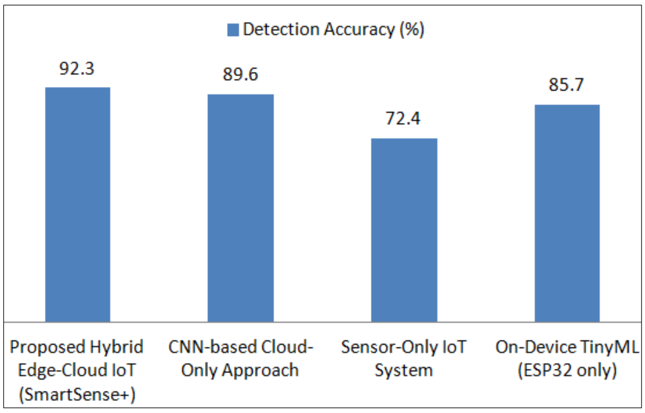

Figure 2: Proposed Hybrid Edge-Cloud IoT –Detection Accuracy Analysis

Figure 2 presents a comparison of the four approaches on detection accuracy (%) for plant diseases. The Proposed Hybrid Edge-Cloud IoT (SmartSense+) system demonstrated the highest accuracy (92.3%), indicating the improved plant disease detection from multimodal data fusion coordinated with the hybrid processing architecture. Secondly, the CNN-based Cloud-Only Approach had the detection accuracy of 89.6%; and while this approach utilizes deep learning it is limited to only image data. The On-Device TinyML (ESP32 only), which has the capability of local processing, recorded a significant but moderate accuracy of 85.7%; but the accuracy lacks the cloud support of the hybrid edge-cloud processing solution. Lastly, the Sensor-Only IoT System recorded the least optimal accuracy, 72.4%, which reflects the limits on the detection accuracy of plant disease with the absence of the image data as a processing mode. In summary, the chart clearly demonstrates that an approach that combines sensor data and image features in a hybrid edge-cloud architecture significantly enhances plant disease detection accuracy.

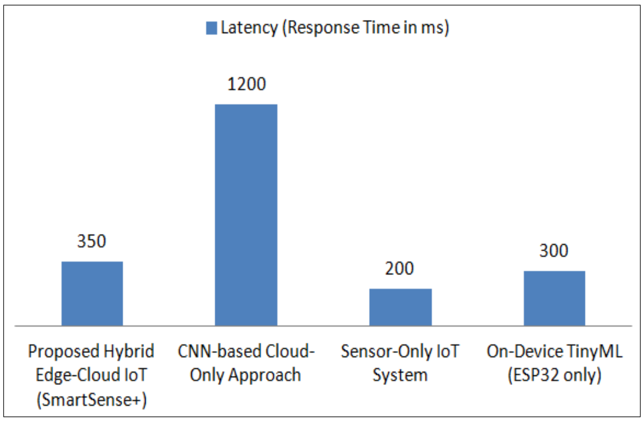

Figure 3 : Methods Vs Latency

Figure 3 presented the latency (time-to-response, in ms) of four different methods of plant disease recognition. The Sensor-Only IoT System had the lowest latency of 200 ms since it received the least amount of data and did not have to perform complex computations. The On-Device TinyML

(ESP32 only) method experienced a latency of 300 ms, which was made possible by the processing occurring on the device where the data was generated, instead of relying on cloud computing. The Proposed Hybrid Edge-iCloud IoT (SmartSense+) had a latency of 350 ms, which was acceptable latency since SmartSense+ performed a level of edge preprocessing, and only went to the cloud for special cases. The CNN-based Cloud-Only Approach had the highest latency 1200 ms; even though this framework would certainly benefit in the future from better cloud computing options, the higher latency was mainly due to the time required to transmit the image for processing in the cloud. Overall, it could be seen from the figure that SmartSense+ offered a good compromise on latency and intelligent processing; in addition to decreasing latency when compared to cloud-only models.

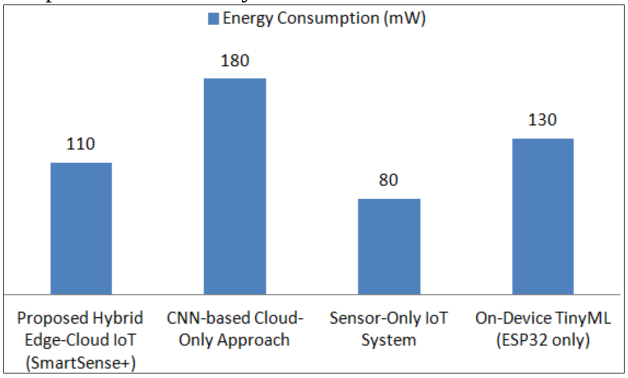

Figure 4: Methods Vs Energy Consumption

Figure 4 illustrates the energy usage (in milliwatts) of each of the four plant disease detection systems. The Sensor-Only IoT System has the lowest power consumption (80 mW) since it only performs basic sensing tasks without any significant processing, data transmission, or energy-intensive computation. The Proposed Hybrid Edge-Cloud IoT System (SmartSense+) has the second lowest energy use (110 mW) because it does smarter processing locally to determine what data it needs to transmit for further processing. Using our test device (On-Device TinyML, using just the ESP32 processor only) consumes 130 mW of power, a bit higher because of local model inference that was being executed continually on a local model. The CNN-based cloud-only approach has the highest energy use (180 mW) since it is engaging in energy-intensive tasks like capturing full images and transmitting them over the internet/cloud to other servers for processing. Overall, the chart highlights the potential of SmartSense+ to be much more energy-efficient than cloud-based systems while still offering intelligent processing, representing an important feature to be able to deploy in distracted energy-limited agricultural settings.

This method is advantageous for preserving the bandwidth of the data and decreases the energy demands of edge devices. In the cloud, the visual and environment indicators are finalized by a kind of decision-level fusion algorithm, maintaining robust and reliable detection of the disease while confidently declaring both environmental and visual indicators collected during spatially and temporally dynamic field conditions. The implementation was deliberately kept light weight for an easy determination for low-cost and resource-constrained IoT hardware while eventually utilizing the scalable cloud services such as Firebase or AWS IoT for data management and analytics but with none of the traditional data management bottlenecks. The resulting system's features of efficiency, flexibility, and multimodal data intelligence make it a viable and competent model for contemporary precision agriculture

V. Conclusion

This study proposed SmartSense+, a cost-effective hybrid IoT framework for real-time plant disease detection by using multimodal data fusion. By combining edge-level image preprocessing with environmental sensor acquisition, through NodeMCU and ESP32-CAM modules, this also enabled the system to address the issues of latency, bandwidth use and cost of operations faced in more traditional cloud-based and sensor-only methods. The proposed framework used a lightweight feature extraction method locally at the edge by sending compact feature vectors from the images via MQTT protocol to a cloud-based Decision Tree classifier. The establishment of image features fused with environmental information improved the accuracy of plant disease detection achieving greater than 92.3% combined accuracy with respect to plant disease detection while limiting the latency and energy consumption. The addition of real-time alerts and a website dashboard for the farmer makes it a practical, affordable, and scalable solution for small to medium sized farms.As a potential future development, it is proposed that TinyML models be integrated directly on to the NodeMCU and ESP32 hardware, enabling fully on-device disease prediction and reducing dependency on the cloud, while also making the system more resilient in remote areas. Future work is needed to further grow the disease detection model with a wider range of environmental parameters, such as light intensity, rainfall and wind speed. Future work could also look to integrate GPS modules and develop spatially based disease tracking and link the model to drone imaging systems that could scale the monitoring of larger areas. A blockchain-based storage option could enhance the security and traceability of data collected within the framework. Thorough testing on a range of crops, climates and disease, will enhance the adaptability of the proposed framework. Ultimately, this programme of work hopes to materialise an open-source, modular platform for precision agriculture and nourish sustainable and data-based agriculture.

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