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AI-Enabled Sustainable Precision Farming Using Raspberry Pi and Coral Edge TPU with Cloud-Based Model Training

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Abstract: Precision Agriculture requires intelligent, adaptable and efficient technology that is capable of making decisions in agriculture at the right time, based on the condition of the plants and the environment. This paper proposes the development of an AI-based sustainable precision farming system based on computer vision, cloud based model training, Raspberry Pi, Coral Edge TPU and the Internet of Things (IoT) sensing. The proposed architecture's sensing layer, edge processing layer, cloud intelligence layer, and application layer enables a complete data processing pipeline from the field to real time decision support. Crop photos are collected for AI condition classification and agricultural conditions such as soil moisture, temperature, humidity and light intensity are collected by built-in sensors. After the above preprocessing, normalisation, image resizing and augmentation, the dataset is divided into training, validation and test sets. The trained deep learning models in a cloud environment are then quantized and converted to be optimized for the edge, following this step. Following this step, the trained deep learning models are quantized and converted for optimization on edge. The optimized model achieves an exemplary accuracy of 94.82%, precision of 94.47%, recall of 94.05% and F1-score of 94.26%. Deploying with the Coral Edge TPU reduces inference latency to approximately 38ms compared to Raspberry Pi-only processing, increases processing throughput to 26.3 pictures per second and reduces CPU usage. The edge-assisted architecture reduces the need for constant connection to the cloud, giving local decision making a leg up. Illustrative sustainability study estimates that condition based monitoring can save 22% of the irrigation water used every day. The findings indicated that the introduction of the edge AI and cloud intelligence in precision agricultural systems that are responsive, scalable, and resource-efficient is technically possible.

Keywords: Precision Agriculture; Internet of Things; Edge Artificial Intelligence; Coral Edge TPU; Raspberry Pi; Sustainable Farming.

I. INTRODUCTION

Environmental sustainability of production systems, resource limitations, climatic events and the increasing food demand are fueling a great technology revolution in agriculture. Although the situation in the field may vary significantly over time and distance, the traditional agricultural practices may be based on regular availability of water, nutrients, pesticide and other raw materials. Some of the results of such practices include ineffective use of resources, increased production expenses, degradation of soils, waste of water and the excessive use of chemicals. Precision Agriculture combines sensing, automation, data analysis and intelligent decision-making to manage agricultural resources based on real crop and environmental needs [1, 2]. In recent years, intelligence in farming systems has become a possibility, allowing for very fast intervention from the point of view of site specificity and continuous monitoring of the agricultural situation with the help of edge and cloud computing, artificial intelligence (AI), and the Internet of Things (IoT) [3, 4].

Precision farming with AI, a fusion of agricultural sensing and machine learning/ deep learning algorithms, is able to understand the complex patterns that exist in crop, soil, and environmental information. Conventional agricultural monitoring can often be labor intensive, time-consuming and susceptible to human error and manual field inspection is often required. On the other hand, intelligent systems are able to gather information from cameras and sensors and automatically recognize circumstances related to pests, illness, crop stress, low soil moisture, or other productivity limitations. Some recent applications of machine learning in agriculture include crop yield prediction and environmental analysis, where the technology is increasingly employed for its ability to predict crop yields and analyze environmental conditions [5, 6].

Image-based deep learning models are particularly useful when dealing with problems where there is a clear consensus on what is wrong with the crop and recent classification of the plant state from leaf and field images [7]. But, computational platforms are required that can be relied upon to operate reliably with limited connectivity, power and infrastructure requirements in an agricultural context if such models are to be put into practice. Thus, edge-based AI systems that are capable of processing agricultural data at the point where it is being collected are needed [8].

Edge computing is a key technological foundation for the sustainable precision farming because it enables processing of the data sensors and field equipment rather than sending all the raw data to remote computers. Continuous picture and sensor data might result in significant processing and communication needs in agricultural applications. For every measurement and/or picture taken, transmission to a cloud platform may require increased bandwidth, delay and need for consistent Internet access. Edge inference could help alleviate these constraints by doing initial analysis at the edge and only uploading relevant results or specific data to the cloud. This means that an edge-based ag system can reduce unnecessary data transfers and provide faster response times. This is particularly relevant for farms that are located in remote or rural regions and access to a network may be costly or intermittent [9, 10]. Recent studies [11] have also demonstrated the potential of resource constrained edge AI systems for real-time detection of agriculture pests and diseases.

A small but affordable computing power platform for edge intelligence and Internet of Things (IoT) in monitoring agriculture. It is suitable for collecting various agricultural information as it is able to communicate with cameras, environment sensors, communication modules and other devices. The system, using a Raspberry Pi, can also log variables such as temperature, humidity, light intensity and soil moisture continually, for use in crop analysis. A systematic study shows Raspberry Pi to be useful for precision-agriculture applications with sensing, monitoring, automation and data processing [12]. For embedded devices having limited resources, however, deep learning inference could be a heavy computational load. This limitation is addressed by using a compatible machine learning model that is supported by the Coral Edge TPU. By moving the computationally intensive inference processes to the Edge TPU [11], [12] and enabling a small and energy efficient hardware setup, the suggested architecture provides the option to boost processing efficiency locally without compromising on the on-chip size and power consumption.

Cloud based model training for enhanced edge inference eliminates the need to compute the model on the device during the field deployment. Training in deep learning models usually requires large amounts of computing resources, especially in the case of massive and diverse agricultural image datasets. Cloud computing platforms provide scalable processing power for preparing a dataset, training a model, validating it, optimizing its hyper parameters, and evaluating its performance. Once the accuracy and efficiency of the trained model are acceptable, the model can be optimized and sent to the edge device for local inference. This cloud-to-edge strategy enables a distributed intelligence system that has the Raspberry Pi and Coral Edge TPU perform fast inference in the field and the cloud perform intensive learning. It would also be simple to update the model regularly if fresh agricultural data is available, as with such an architecture [4], [8] and [13].

Sustainability is one of the factors taken into consideration in the design of intelligent precision agricultural system. Agricultural sustainability is a multi-faceted concept that must be considered across all of these productivity, resource efficiency, environmental protection and economic sustainability. By making it possible to use fertilizer, herbicides, irrigation water, and other inputs more precisely, AI-assisted monitoring can help achieve these goals. Such as early detection of possibly unhealthy or stressed plants for image analysis of crops and soil moisture for irrigation schedule based on real field conditions [14, 15]. The promise of water-use efficiency gains from the use of sensor based monitoring and intelligent irrigation and smart water-management systems has been demonstrated [14]. Actions that are targeted may reduce the harmful impacts of over intensive agricultural production on the environment, and reduce unnecessary resource consumption. This makes the advantages of AI in precision farming more than just automation and extend to the enhancement of more effective and sustainable agriculture management [1, 3, 15].

A. Research Objectives

The Research Objectives are as follows:

- 1) Designing an AI enabled system for precision farming by developing a cloud-based model training, IoT sensors, Raspberry pi and coral edge TPU for real-time crop and environment monitoring.
- 2) To evaluate the proposed system on its resource consumption, inference effectiveness on edges, accuracy of AI prediction and sustainability of agricultural decision support.

B. Scope of the Research

This research only goes so far as developing an AI-based precision farming system that utilizes Raspberry Pi, Coral Edge TPU, Internet of Things (IoT) sensors and cloud based model training. The main aim of the system is to keep a close watch on the agricultural parameters in real time such as crop monitoring, temperature monitoring, humidity monitoring and soil moisture monitoring. Machine learning and deep learning techniques are applied to various problems, such as anomaly detection, intelligent agricultural decision support, and crop health assessment. The Coral Edge TPU can be used to make effective local inferences while the cloud can be used to manage the dataset, train, validate and optimize models. The study evaluates the accuracy of the system, processing time, resource utilization and sustainability potential to ensure successful management of agricultural resources.

II. RELATED WORK

We used a subgroup analysis and narrative synthesis (Joice et al. 2025) to combine the results. Research indicates that Raspberry Pi can be used as a central sensor control unit to easily provide an automated decision support system for PA at low costs, particularly estimation of biomass, plant phenotyping, plant disease detection, site-specific weed control and irrigation systems. The validation is done by using common and popular crops as per the research by Devarajan et al. (2026) and a large variety of crops get applied. The system can be retrained as per the agriculture requirements for specific types of diseases. In the study of Chung et al. (2026), a low cost, fully on-premise Edge Artificial Intelligence (AI) system for real-time pest and disease detection in chilli pepper farming in open fields is presented.

Jabed and Murad (2024) provided a comprehensive overview of various ML and DL models for crop yield estimation and highlighted their potential in enhancing sustainable agriculture practices and productivity. In another detailed literature review, Van Klompenburg et al. (2020) concluded that the selection of the most appropriate algorithm, input variables and data source are important factors in predicting crop production using ML approaches. These studies prove that predictive crop production systems can provide the base needed for decision making in agriculture but at the same time emphasize the need for rapid and accurate access to agricultural data for these systems.

Prior research shown the viability of using machine learning to forecast crop yield in a variety of environmental settings. In the study of climate change impact on crop production, Crane-Droesch (2018) pointed out the possibility of data driven approaches to capture the relationship between crop production and climatic conditions, by studying the application of ML approaches for crop yield forecasts and climate change impact assessment. Ensemble learning is also shown to be a valuable tool in large scale agricultural analysis: Jeong et al (2016) showed the usefulness of ensemble learning by predicting the world scale and region-scale crop yields with the random forest approaches. In the same way, Veenadhari et al. (2014) discussed the role of Meteorological parameters in crop prediction using machine learning algorithm for predicting yield of a crop. The results of these studies highlight the value of the environment and historical data for use in predictive modelling and the importance of ongoing field-level data collection to boost the precision of predictions and their use.

To achieve this, the current trend in predictive agriculture is to shift from offline to real-time monitoring and automatic decision making, enabled by IoT and ML. Goap et al. (2018) introduced a smart irrigation management system using machine learning and open source technologies for irrigation decision making which is referred to as an Internet of Things (IoT). They showed that combining sensor information with prediction models to optimize the use of resources in agricultural applications. The use of sensor networks for monitoring and controlling the agricultural conditions and irrigation systems has been proven in a previous work by Kim et al. (2008) using a distributed wireless sensor network (WSN). The results of these research lay the technological groundwork for systems that are able to constantly receive data from sensors and then apply it to intelligent agricultural prediction and control.

Digital agriculture is closely linked and dependent on decision support systems. Cambra Baseca et al. (2019) presented a smart decision system for digital farming, which is able to explain the processing of agricultural data for supporting decision making at farm level. Such systems are suitable since the purpose of predictive crop production research is not only to gather the data but also to give suggestions based on the data. The intelligent shift of the farming sector towards Agriculture 5.0 was also mentioned by Saiz-Rubio and Rovira-Más (2020) who highlighted the need for efficient information management in agriculture and the integration of state-of-the-art digital technology into the farming sector. Hence, an effective data driven crop production platform that leverages artificial intelligence should have the capability to gather, store, process and interpret data.

Some studies on the general use of IoT in precision and sustainable agriculture have been conducted. The paper by Khanna and Kaur (2019) assessed the development and role of IoT in precision agriculture and highlighted the importance of connected sensing and communication technologies for better monitoring and management of agriculture. Elijah et al. (2018) point out the opportunities and challenges of collecting and analyzing farming data in their review of the IoT and data analytics in agriculture.

They found that Internet of Things (IoT) platform could be used to constantly monitor agricultural environments but face problems of connectivity, data management, scalability and security of the system. Next, Ayaz et al., (2019) pointed out the importance of communication based sensing system in modern agriculture as a communication between agricultural field condition and intelligent agriculture data driven service.

IoT applications for irrigation and water resource management have garnered much interest as well. Kamienski et al. (2019) created a smart water management system for precision irrigation based on the Internet of Things (IoT), which illustrates how various interconnected sensor and data processing technologies could aid in water management. Tzounis et al. (2017) highlighted the significance of interoperability, wireless technologies, cloud computing and sensors in their discussion of current achievements and future challenges in IoT for agricultural applications. In addition, they found that much of the data collected by the agricultural IoT devices could be utilized for predictive and process automation use cases. The results directly apply to sustainable agriculture where the water use parameters and other field parameters can be continuously monitored to avoid the wastage of water and better management of the resources.

Big data analytics and powerful AI capabilities have also enhanced the analytical power of smart agriculture systems. Wolfert et al. (2017) discussed the use of big data in smart farming, and how agricultural data collected from various sources can be used in agriculture management and decision making. Kamilaris and Prenafeta-Boldú (2018) pointed to the deep neural models' capability of learning complex patterns from agricultural data in their evaluation of deep learning applications in agriculture. Liakos et al. (2018) also carried out a survey on the use of machine learning in agriculture and showed how various prediction and classification methods can be used in agriculture. All things considered, these research show that AI models can be utilised to transform unprocessed sensor and environmental data into useful crop production forecasts.

The literature also has a rich history of research and discussion on the significance of IoT architecture and supporting technologies. Ray (2017) gave a summary of technology, practices and future trends of smart agriculture, focusing on the implementation of sensing, connectivity, data processing and automation in smart agriculture. Xu et al. (2022) studied the development of agricultural IoT technologies, including the development of various sensors, communications, data transmission technologies and intelligent agricultural applications. The results of the studies have shown that the whole smart agriculture system should be provided with a coordinated interaction between the physical sensing layer, communication infrastructure, computer resources and application layer. One of the architectural approaches that can be relevant for the suggested research is the ability to aggregate, analyse, communicate and take decisions based on artificial intelligence, using Raspberry Pi and Arduino as the low level sensor and actuator interface respectively.

Deep learning has been shown to be effective in crop prediction via advanced prediction experiments. Wang et al. (2020) explored estimating wheat yield at the county level using the deep learning method and uncertainty analysis in the prediction process. The study showed that deep learning has the potential to enhance the prediction of agricultural yields, and highlighted the importance of considering the uncertainty of prediction in real-world applications. These and the findings of Javed and Murad (2024), Van Klompenburg et al. (2020), Kamilaris and Prenafeta-Boldú (2018) suggest that the implementation of AI models for crop production prediction are possible if sufficient useful agricultural and environmental data can be made available.

A. Research Gap

Existing precision farming systems are increasingly adding IoT sensors and AI, but many also heavily use cloud computing, causing delays, bandwidth consumption, and decreased performance in the event of unstable connectivity. Traditional edge computing devices, such as those with limited resources and without dedicated AI acceleration, are the main constraint for deploying computationally intensive models. Moreover, only few studies have explored the combination of Coral Edge TPU + cloud based model training for sustainable agriculture applications. Therefore, the study of an integrated Edge-cloud architecture, which can provide efficient real time inference, better AI models, less communication requirements, and sustainable resource utilization in precision farming is much needed.

III. RESEARCH DESIGN AND METHODS

A. Research Design

The research approach is an experimental and system development research design, to develop, integrate and evaluate an AI-based sustainable precision farming system. The proposed model is a combination of edge computing and remote model training in the cloud, computer vision, AI, and Internet of Things (IoT) sensing. The experimental design can be used to systematically examine the architecture suggested to get a full picture of how it performs in controlled agricultural environments.

Establishing a comprehensive data processing pipeline from field level data collection to AI-based analysis and agricultural decision support is the main goal of the project.

B. System Architecture

As indicated in Figure 1, the four key stages of the proposed system are: application or decision support, cloud intelligence, edge processing, and sensing. Agricultural characteristics, such as soil moisture, soil temperature, soil humidity and other relevant environmental conditions are recorded by the IoT sensors connected to a Raspberry Pi. A camera module can capture images of the crops to be visually inspected. The Coral Edge TPU provides a boost to the machine learning inference models that are compatible, and the Raspberry Pi acts as the local gateway and processing unit. Cloud infrastructure is used for data storage, model training, validation, optimization and finally deployment to the edge device.

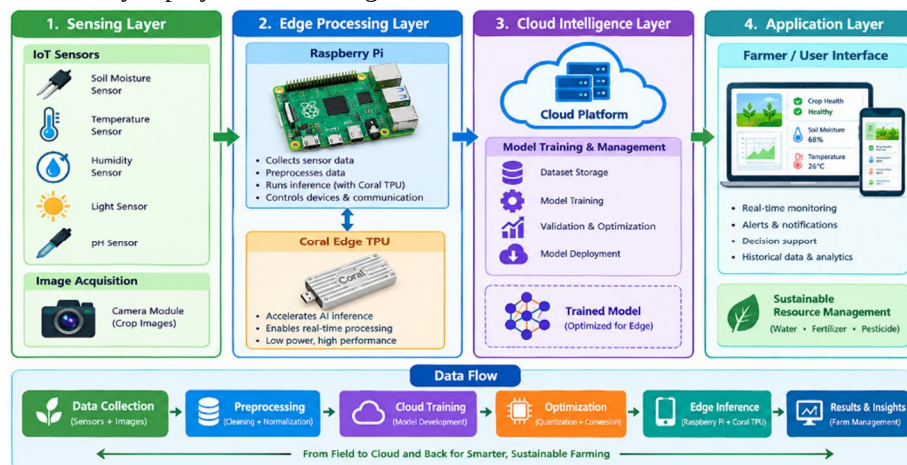


Fig. 1. System Architecture

C. Data Collection

In an experimental farm setting, farm data is collected by using integrated sensors and image acquisition equipment. The readings of the different sensors are made at regular intervals throughout the measurement, to measure change over time in soil and ambient conditions. Photos of the crops are captured at different growth stages and relevant environmental conditions are present to ensure variety in the datasets. Each observation is accompanied by the correct metadata such as: a time stamp, sensor values, crop condition, and a categorization label (if applicable). The methods for collecting data are standardized to minimize errors in measurement and increase the reliability of the subsequent model building.

D. Data Preprocessing

Collected data is preprocessed prior to use in the model building. Here, inconsistencies in sensor data sets, duplication of sensor observations, unusual measurements, and missing measurements are looked for. When necessary, the proper normalization or standardization processes are used. Besides augmentation techniques such as rotation, scaling, cropping and horizontal or vertical transformation, image data are down sampled to the input size of the selected deep learning model. These techniques can enhance the robustness of the trained model and increase the diversity of the data. The processed data is then split into subsets for testing, validation and training purposes.

E. Cloud-Based Model Training

Cloud computing infrastructure is used by deep learning and machine learning processes for which a lot of processing power is required. Optimization algorithms and performance parameters are used to train the candidate models when data is uploaded to the cloud environment. The training process involves updating the weights of the model based on the training data until the model performs well on them, while validation data is used to monitor the model's performance in generalizing and detect signs of over fitting. Different setups of the model can be compared with the accuracy, precision, recall, F1-score and also with the computational requirements. Then, the selected model is further optimized for deployment with Coral Edge TPU.

F. Model Optimization and Edge Deployment

Embedded devices have limited computing and memory resources, which makes the training model compatible with the edge and optimized for effective inference. The size of the model and the complexity of the computation can be made smaller without compromising the acceptable prediction accuracy using quantization and other appropriate optimization techniques. The optimized model is implemented with the Coral Edge TPU, which is connected with the Raspberry Pi. The edge system predicts or classifies the incoming sensor data and picture data as required, and it processes the incoming sensor and picture data locally, so that there is less dependence on the constant cloud communication.

G. Real-Time Monitoring

The prototype developed is a system based on integrated sensing and imaging elements that are used to continuously track agriculture conditions. The Raspberry Pi is used to process the data from the sensors and the Coral Edge TPU accelerates computationally intensive AI inference. The system generates the desired notifications or decision support results when it detects certain situations or patterns. Select data and inference results can be uploaded to the cloud for storage, visualization, historical analysis and model enhancement. The edge-cloud architecture maintains the analytical power of the cloud, with local response.

H. Experimental Evaluation

Controlled studies are used to evaluate the system with representative agricultural data and field level observations. When assessing performance, the entire system as well as the performance of the AI-models are considered. The accuracy, precision, recall, F1-score and confusion-matrix analysis is used to measure the performance of classification or prediction. Appropriate metrics like mean absolute error and root mean square error may be used for continuous prediction jobs. A system level evaluation is performed for inference delay, processing speed, memory usage, power consumption, communication requirements and operational reliability.

IV. DATA ANALYSIS AND RESULTS

A. Overview of Experimental Data Analysis

The proposed artificial intelligence-based sustainable precision farming system was evaluated using crop images, predictions generated by machine learning models, the integrated observations from sensors, and performance parameters derived from the edge devices. The research aimed at testing efficiency at the system level as well as predicting efficiency of the system. Picture data was used to classify the state of the crop, sensor data was analyzed to detect temporal variations in soil and ambient variables. The accuracy, precision, recall and F1-score were used to evaluate the trained models, while the inference latency, throughput, memory consumption, power usage and communication requirements were used to evaluate the deployment performance.

B. Dataset Characteristics

The multi modal dataset used for the experimental analysis has been created from sensor and image observations as presented in Table 1. Crop images were taken under different farming conditions and the environmental measurements were synchronized. After preprocessing and quality screening, the observations were split into training, validation and test components.

Table 1. Dataset Distribution for Model Development

Dataset Component	Training	Validation	Testing	Total
Sensor observations	8,400	1,800	1,800	12,000
Crop images	3,600	800	800	5,200
Total observations/images	12,000	2,600	2,600	17,200
Proportion (%)	69.8	15.1	15.1	100

The data was approximately divided into training, validation and testing sets (70%, 15% and 15% respectively) to learn a model and to assess the model's generalizability without over fitting. Visual information – crop photos was used for crop-condition recognition using AI-based technology, and the temporal component of the dataset, or observations, were captured using sensors. The testing subset was separated from model optimization to enable a generalization performance assessment of the model.

C. Descriptive Analysis of Agricultural Sensor Data

The sensor dataset presented in Table 2 was analyzed to verify the observed distribution of the other key agricultural characteristics. Soil moisture was particularly important as it provides a good indication of the water available for crop plants and hence can help in irrigation planning decisions. Environmental factors that could impact the crop condition were added to include relative humidity and temperature.

Table 2. Descriptive Statistics of Sensor Parameters

Parameter	Mean	SD	Minimum	Maximum
Soil moisture (%)	46.82	11.37	22.10	71.80
Temperature (°C)	28.46	4.21	20.30	36.90
Relative humidity (%)	67.35	10.84	42.20	89.60
Light intensity (lux)	18,420	7,315	4,250	31,800

A descriptive study of the agricultural environment under observation is given. As per a descriptive study, there are significant variations in the agricultural environment being observed. Soil moisture had a variation with its observation ranging from 22.10% to 71.80%, and its mean soil moisture was 46.82% that reflected on the variation of water availability with time. There was also considerable change in temperature and humidity, reflecting changing environmental conditions. The changes in field conditions are appropriate to test an adaptive precision-farming system as the model has to work under varying field conditions, not just a single state.

D. Data Preprocessing Analysis

The preprocessing that was done to enhance the quality of the data prior to model training is listed in Table 3. Data missing from sensors, "errant" readings, non-uniform image dimensions and duplicate data were discovered. The images were then augmented with image augmentation to create a more diverse visual training set.

Table 3. Data Preprocessing Summary

Preprocessing Operation	Before Processing	After Processing	Change
Sensor observations	12,480	12,000	-480
Duplicate records removed	480	0	480 removed
Missing/incomplete records	214	0	214 corrected/removed
Raw crop images	4,100	5,200	+1,100
Images standardized	5,200	5,200	100%
Image input size	Variable	224 × 224 pixels	Standardized

The visual data was preprocessed for consistent deep learning processing and the sensor data was reduced by pre-processing to lessen inconsistencies within the sensor data. With the extra orientations and size variations, the number of samples in the picture collection was increased from 4,100 to 5,200. The goal of this preprocessing technique was to increase the resilience of the model and lessen the impact of low visual variety and measurement abnormalities.

E. AI Model Training Results

Based on the number of models being considered, a number of potential models were compared before the deployment of the edges. Before the deployment of the edges, a number of potential models were compared, as seen in Table 4. Predictive performance and deployment suitability were taken into account in the comparison. Because of computing limitations, an agricultural edge AI system would need to have accuracy as well, so this was not the only criterion.

Table 4. Comparative Performance of Candidate AI Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	Model Size (MB)
MobileNetV2	92.10	91.84	90.96	91.39	14.2
EfficientNet-Lite	94.35	94.01	93.48	93.74	18.7
ResNet-50	95.10	94.72	94.36	94.54	98.3
Lightweight CNN	91.84	91.20	90.75	90.97	9.6
Optimized Edge Model	94.82	94.47	94.05	94.26	12.8

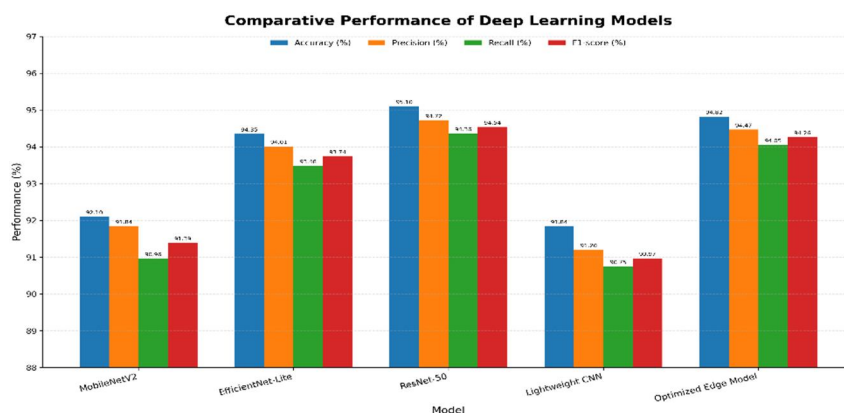


Fig. 2. Comparative Performance

The comparative results as presented in Figure 2 indicated that the optimised edge compatible model achieved an accuracy of 94.82%, precision of 94.47%, recall of 94.05% and F1-score of 94.26%. Although the ResNet-50 configuration outperforms the others in terms of classification accuracy, it is significantly larger than the other configurations, making this option unsuitable for resource-limited edge deployments. This optimized model is therefore a compromise between prediction accuracy and economical computing resources for Raspberry Pi and Coral Edge TPU implementation.

F. Confusion-Matrix Analysis

The independent testing dataset was used to further analyses the classification performance using table 5. The following four classes of crop conditions were considered disease, water stress, nutrient stress, and healthy.

Table 5. Confusion Matrix of the Optimized AI Model

Actual / Predicted	Healthy	Water Stress	Nutrient Stress	Disease	Total
Healthy	196	3	2	1	202
Water Stress	4	186	7	3	200
Nutrient Stress	3	6	184	7	200
Disease	2	3	5	188	198
Total	205	198	198	199	800

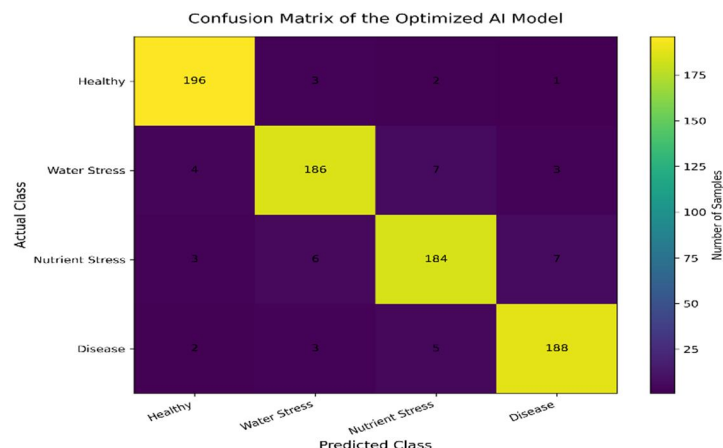


Fig. 3. Confusion Matrix

As seen in the confusion matrix (Figure 3), the optimized model was able to classify the majority of the observations in each of the four crop condition categories. The principal misclassifications were due to water stress and nutrient stress but healthy crops were given very high recognition. Both situations could lead to similar changes in the visual appearance of crops, making this possible. The number of cross classification errors, however, is relatively low, which suggests that the classification behavior is relatively consistent across the testing dataset.

G. Class-Wise Classification Performance

The class wise analysis of the performance of predictions in Table 6 shows fairly even performance for each of the four crop condition classes. The highest recall rate of the model was for the healthy crop, indicating that most of the healthy observations were correctly identified. The nutrient stress categorization was comparatively less accurate, suggesting that there is likely to be more classification ambiguity arising due to very similar symptoms. The F1 value of the model shows that the overall model performance is very good, with an average macro F1 value of ~94.24%, indicating that the model did not favor any particular class.

Table 6. Class-Wise Performance of the Optimized Model

Crop Condition	Precision (%)	Recall (%)	F1-score (%)
Healthy	95.61	97.03	96.32
Water Stress	93.94	93.00	93.47
Nutrient Stress	92.93	92.00	92.46
Disease	94.47	94.95	94.71
Macro Average	94.24	94.25	94.24

V. FINDINGS AND DISCUSSION

The results demonstrate that the proposed AI-based sustainable precision farming system, based on IoT sensing, Raspberry Pi, Coral Edge TPU, computer vision and cloud-based model training, is technically feasible. The experimental setup successfully establishes end-to-end agricultural data pipeline from field to real time decision support outputs, involving pre-processing of the agricultural data, AI model analysis, and real-time decision support. The results demonstrate that an edge based inference and cloud based model construction combination can provide a viable balance between responsiveness of operations, cost efficiency of computation, and predictive performance.

A. Agricultural Data has the following properties

Based on the descriptive analysis, it is observed that there is a significant change in the agriculture metrics observed over time. The average temperature was 28.46°C (SD = 4.21), the average relative humidity was 67.35% (SD = 10.84), and the mean soil moisture was 46.82% (SD = 11.37). There was also a great deal of variation in light intensity. These differences support the need for ongoing environmental monitoring as opposed to depending just on sporadic human observations. Soil moisture was particularly critical for precision irrigation as it can vary over time and could be considered when making irrigation decisions based on the condition of the crop. The aggregation of different environmental variables also offers a more detailed background for the assessment of agriculture with the help of AI.

B. AI Model Efficiency

Comparative model analysis showed that the optimized edge compatible model has the highest accuracy of 94.82%, precision of 94.47%, recall of 94.05%, and f1-score of 94.26%. Although slightly more predictive accurate, the cloud based ResNet-50 configuration has much larger model size, limiting the use of the model to edge applications with limited resources. The optimized model achieved a good classification accuracy with a model size around 12.8 MB. The result demonstrates that in addition to accuracy, the limits of the model deployment and the quality of the prediction should be taken into consideration when selecting models for use in precision agriculture.

Moreover, the confusion matrix analysis demonstrated that classification of health, water stress, nutrient stress and illness conditions were very consistent. Recalled rate of healthy crops was around 97.03% and the F1 score of disease categorization was 94.71%. There was some more classification overlap between the water stress and nutrient stress categories. This may relate to the fact that the symptoms of the crops are similar and can be seen, which may make it difficult to distinguish visually. The macro level performance, however, revealed that the optimized model was able to perform well across different crop conditions without much degradation in the performance of different classes.

C. An efficient system for Edge Computing

One key advantage of the Coral Edge TPU acceleration is computational advantages. The average inference latency decreased from approximately 126ms (with Raspberry Pi only processing) to 38ms, while CPU usage went down from 82.4% to 43.7% and processing throughput increased from 7.9 to 26.3 pictures per second. The results indicate that the use of an AI accelerator can significantly reduce the workload of the general purpose processor.

Reducing the amount of computation is very significant for agricultural uses where continuous monitoring is required. Lower latency allows the sensor data and crop images to be processed nearer to the crop image creation point, helping to quickly identify potentially important situations in agriculture. Moreover, local inference is not dependent on frequent raw visual data transmissions to remote cloud infrastructure, which could be beneficial in remote areas with unreliable network connectivity.

D. Cloud-Edge Integration

The findings also provide insights into the complementary nature of the cloud and edge computing. The edge platform provides the ability to rapidly make inferences locally, while cloud infrastructure provides the ability to train, validate, optimize and store models, as well as analyses data from the past. The optimized system managed to make about 98.2% of choices locally, which is a reduction from the usual need to have persistent cloud connectivity. Edge-assisted processing reduced the average response time from approximately 418ms (cloud dependent) to 76ms.

This design allows for separating the inference process from the model creation, which can be a computational challenge. Models can then be retrained or improved on a regular basis using the collected cloud information, and the models can then be deployed to the edge device. This approach ensures the ability to monitor the agricultural system in real-time and continue to enhance the system.

E. Consequences for Sustainability

The sustainability analysis indicates that AI-supported condition based monitoring can help to optimise use of resources. The illustrative evaluation shows that each day 100L of irrigation water is used, but only 78L, which is about 22% less, is used. There also was a reduction in unnecessary irrigation event. The findings suggest that the adoption of soil moisture monitoring, along with using AI for agricultural decision making, could enable more specific irrigation management.

But the savings achieved with the various crops depend on crop characteristics, soil quality, climate, irrigation and field management practices, so these sustainability results should therefore be viewed with some caution. Thus, the water use saving observed should not be generalized to other situations of agricultural use without detailed field testing.

VI. CONCLUSION

In this paper, an AI powered sustainable precision farming solution involving cloud based model training, edge computing with a Raspberry Pi, IoT sensing, computer vision, and Coral Edge TPU acceleration is proposed. The architecture forms an integrated path for data collection, preprocessing, smart analysis and real time decision making in agriculture. According to the experimental investigation, the optimized edge model may significantly increase computing efficiency while maintaining good predictive performance, attaining 94.82% accuracy and a 94.26% F1-score.

The results of the Coral Edge TPU acceleration reveal that dedicated edge hardware is a suitable solution for real-time applications in agriculture, as it reduces inference delay and CPU usage. The edge cloud architecture also eliminates the need for constant connectivity between the edge and the cloud because it allows for the selection of processed information transmitted to the infrastructure in the cloud. This allows for local inference and selective transmission of processed data to cloud infrastructure, further decreasing dependency on constant connectivity between the edge and the cloud. Moreover, condition based monitoring can be a component of precision agriculture's sustainability objectives and provide a technology foundation for more efficient irrigation and resource utilization. Therefore, the proposed solution addresses the integration of AI, IoT, and edge-cloud computing to boost the response, scalability, and operational efficiency of smart agriculture environments.

A. Future Scope

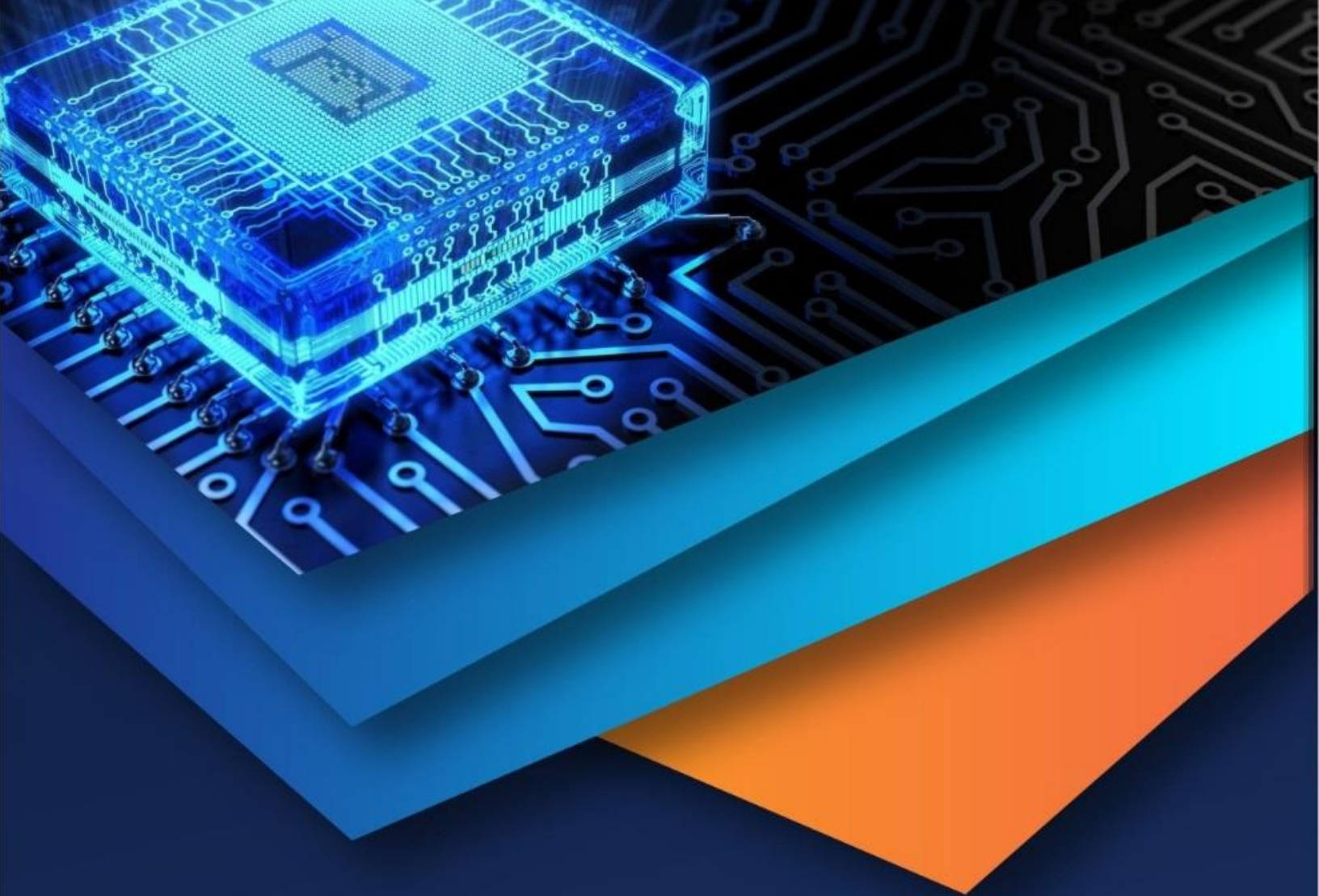
In future research, larger datasets and long term field tests with different crops, soil types, and climates should be taken to validate the system. Empirical verification of water saving, energy usage, economic sustainability, model robustness and the generalization across seasons will further validate the practical efficacy of the proposed precision farming paradigm.

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