https://doi.org/10.65091/icicset.v2i1.23

An Integrated System of IoT-based Agriculture, Disease Detection and News Classification

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***Abstract*—Smart agriculture systems are becoming more and more integrated based on IoT and artificial intelligence to aid farm monitoring and decision-making, but most current solutions support the assessment of single elements and are studied in laboratory settings, restricting their practical implementation. The current paper introduces a highly integrated, end-to-end smart farming system which incorporates the real-time sensing of the physical environment, automated irrigation management, AI-based detection of plant diseases, and provision of information to farmers into a single, low-cost system. The system is clearly aimed at managing the practical deployment limitations such as latency, energy efficiency, reliability of connectivity and scalability in agricultural settings with resource limitation. In order to accomplish the deployment-oriented challenges, a comparative analysis of the convolutional neural networks namely ResNet-50, DenseNet-201 and MobileNet-V2 are performed using a large scale data set. DenseNet-201 is more accurate however, MobileNet-V2 is chosen to deploy on the field due to its much low inference time and model size, which is more applicable in limited resources of agriculture facilities. In addition, an agricultural news classification module is incorporated to filter domain-specific information for farmers, with limitations in dataset size and generalization explicitly discussed. Experimental data prove that the proposed system effectively balances sensing, computation and automation requirements, bridging the gap between laboratory-level performance and practical smart agriculture deployment.**

***Index Terms*—Smart irrigation, Crop monitoring system, Plant disease detection, Real-time monitoring, Agricultural automation, News Classification, Deployment-Oriented.**

I. Introduction

Agriculture continues to be the mainstay of the Nepal economy supporting livelihoods, food security and rural employment of a significant percentage of the population. Nevertheless, the industry lacks systemic water management efficiency: just a part of agricultural land is supplied with consistent irrigation, the irrigation systems used are outdated in most parts of the country and the efficiency of water use is low[1].

Most of the current irrigation systems, especially the traditional and farmer operated irrigation systems cannot ensure supply throughout the year because they rely on seasonal rainfall and natural water courses, prone to climate changes and real time monitoring is not possible [2]. This will usually result in wastage of water, unequal allocation of water (particularly to the mid- and tail-end farms) and decreased agricultural productivity [1].

Furthermore, in addition to irrigation, Nepali farmers usually do not have the means to monitor the state of soil and plants in real time. Thus, applying reactive and not proactive crop management. This absence of an integrated technological support adds to inefficiencies in the use of water, declines the yield and limits sustainable development of agriculture. [2]

These difficulties have created an increasing necessity of low-cost, accessible and integrated farming solutions that could address the efficient control of water in addition to real-time environmental tracking and smart agricultural health diagnosis as per the agro-ecological and socio-economic situation in Nepal. As an illustration, Patil et al. state that precision irrigation with the use of IoT is more efficient in terms of water-use because it automates irrigation according to soil moisture and other environmental conditions [3].

The further development of smart irrigation and monitoring technologies favors the need to use IoT and sensor networks to monitor farms in real time. Sarker et al. thoroughly discuss the

[1]Nepal: Irrigation and Water Resource Management
[2]Present Status of Irrigation in Nepal

design of the systems of IoT-based smart greenhouses including the ability of the environmental sensors and automated controls to ensure the most favorable environment in which crops can grow [4]. Additionally, [5] refer to the usefulness of IoT-based solutions in ensuring sustainable irrigation and crop protection, and the solutions are applicable to the situation of smallholder farming . All these works show that intelligent sensing and automation can have a profound effect on the results of farming processes.

At the specific case of Nepal, there is some limited adoption of digital technologies in agriculture analyze the perspectives of smart farming system regarding the detection of disease and crop protection in Nepal and note that there is a high potential with little implementation owing to cost, shortage of technical skills and insufficient infrastructure [6]. Also, farmers in Nepal are struggling to access efficient irrigation systems and smart and decentralized solutions should be considered to meet the needs of the local community [7]. These results correspond with the necessity to have an integrated, inexpensive, and easy-to-use smart agriculture system that should be thought-out in terms of Nepalese limitations.

Recent surveys and empirical studies have demonstrated the growing potential of deep learning and Internet of Things (IoT) technologies in modern agriculture. [22] highlighted that while deep learning has achieved promising results in agricultural applications such as crop disease detection, most systems are evaluated under controlled settings and lack consideration of real-world deployment constraints, including scalability, computational efficiency and integration with sensing and actuation mechanisms. Similarly, the comparative study by [23] showed that fine-tuned deep convolutional neural networks can achieve high accuracy for plant disease identification. However, the analysis primarily focused on classification performance, with limited emphasis on inference latency, model complexity and practical deployment feasibility.

Most existing research studies IoT-based irrigation systems and plant disease detection separately, rather than as a single integrated system. Very few works combine real-time sensing, automated irrigation and AI-based disease diagnosis in a practical, low-cost framework that can work under real-world conditions. Challenges such as unreliable internet connectivity, sensor inaccuracies, system delay and scalability are often ignored, even though they are critical in smallholder farming environments like Nepal.

In addition, many plant disease detection studies focus mainly on achieving high accuracy using deep learning models, without considering how fast the model runs or how large it is. Lightweight models that are better suited for real-time and low-resource agricultural deployment are not sufficiently explored. This creates a gap between results obtained in laboratory settings and what is practical for real-world agricultural use.

To address these gaps, the present work proposes an integrated smart agriculture framework that combines IoT-based sensing and automated irrigation with deep learning–based plant disease detection. In contrast to prior studies, this paper emphasizes not only classification accuracy but also inference efficiency and model complexity through a comparative evaluation of deep and lightweight CNN architectures. This approach bridges the gap between algorithmic performance and real-world agricultural deployment requirements, with particular relevance to resource-limited farming environments.

This research will have the following objectives:

- To design and validate a tightly coupled farm monitoring and control system in which sensing, processing, monitoring, and actuation are closely integrated to ensure reliable and practical field operation.
- To conduct a deployment-oriented evaluation of lightweight convolutional neural network (CNN) models for plant disease detection by comparing accuracy, inference latency, and model complexity.
- To develop an integrated farm management solution incoporating smart irrigation, integrated backend- mobile application ecosystem and farm monitoring.
- To design agricultural news classification module filtering agriculture-related information for farmer oriented information delivery.

II. System Design and Architecture

The system design and architecture aims to describe the system's design and architecture integrating IoT-based environmental sensing, automated irrigation control and AI-driven decision support within a unified smart agriculture framework. As illustrated in Fig. 1 the architecture have the objective of outlining the design, its functional and physical attributes.

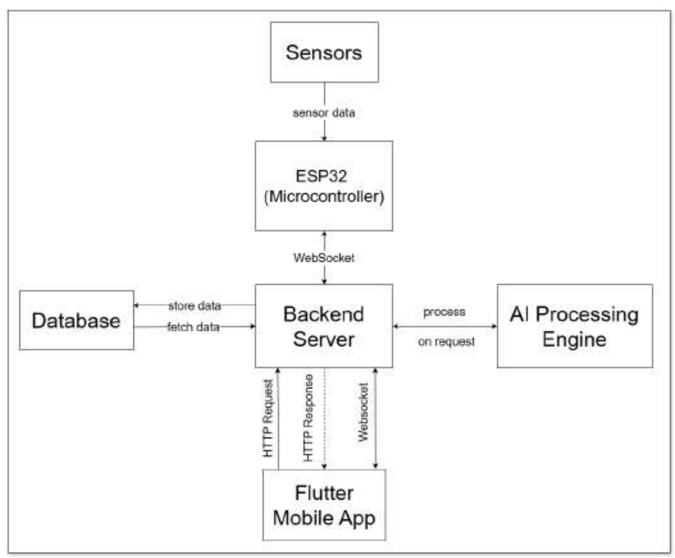

Fig. 1: System Architecture of the IoT-AI Smart Irrigation System

At the sensing layer, low-cost IoT sensors continuously monitor key environmental parameters such as soil moisture, temperature, and humidity. The sensor values are passed to a processing layer via lightweight communication protocols appropriate to unreliable or bandwidth constrained communication. All the sensors used in the system which are shown in Fig 2.

Fig. 2: IoT Device and Microcontroller Interaction.

The decision layer incorporates two modules which are an automated irrigation control system that activates irrigation according to real-time sensor values and a plant disease detection system that examines the images of leaves with the help of deep learning models. Inference of disease is done without consideration of the sensing pipeline, allowing it to be deployed on edge or cloud platforms based on the available resources.

The application layer offers the delivery of information and interchanges with users such as parameters like soil moisture, temperature, humidity, irrigation status monitor, disease diagnosis details as well as advisory notifications and agricultural related news. This layered separation is what makes sensing, inference and actuation loosely coupled to provide better system scale and maintenance.

Unlike existing approaches that focus on isolated components, the presented architecture characterizes end-to-end integration with the deliberate focus on deployment-related constraints (latency, computational overhead and scalability of the system). This design allows the practical implementation in the smallholder farming setting, where low-cost hardware usage, a lack of infrastructures and real-time responsiveness are essential.

III. Methodological Framework

The proposed system is designed in such a way that its methodology revolves around the essential functional features that have been created in the project. Every feature is backed by a certain piece of hardware, software, communication protocols and computational methods to create a complete and working smart agriculture platform. The exposition of the methodology in these characteristics makes the design highly consistent with the target application of the Nepalese farmers. Fig. 3 shows the physical implementation of the hardware setup used for system deployment, including the ESP32 controller, sensor modules, relay-based pump control, IR sensor and power supply.

Fig. 3: Experimental Hardware Setup Used for System Deployment

A. Irrigation Control Module

The Intelligent Irrigation Control Module is designed to automate water delivery based on real-time soil and micro-environmental conditions. Soil moisture is monitored using a capacitive soil moisture sensor, which measures changes in the soil's dielectric permittivity and outputs a corresponding voltage to the ESP32's ADC. This serves as the primary input for irrigation decisions.

Irrigation water availability is monitored using a simple mechanical float sensor that acts as a safety switch, ensuring the pump is never activated when the water reservoir is low [10]. Environmental temperature and humidity are measured using a DHT11 sensor. The DHT11 transmits a fixed 40-bit frame consisting of humidity (integer + decimal), temperature (integer + decimal), and a checksum for data integrity. Internally, it uses a thermistor for temperature and a polymer capacitive element for humidity measurement. In outdoor agricultural conditions, relative humidity typically ranges between 50–90% in summer and 30–70% in winter, and the temperature–humidity relationship influences moisture retention in soil. These readings are therefore used as a secondary factor; when ambient humidity is very low, the irrigation frequency is increased. A manual mode for controlling the pump is also made available in the mobile app, where triggering the pump function and timing turns the pump motor on and off based on the app user's command.

Pump actuation is handled through an L298N H-Bridge motor driver. The ESP32 controls the driver by sending HIGH/LOW logic signals to enable or disable the pump based on a combination of soil moisture levels, float-sensor status, and DHT11 feedback. This ensures safe, automated, and condition-aware water delivery. This setup enables a closedloop automated irrigation system that is responsive to both soil and environmental conditions.

B. Real-Time Environmental Monitoring Module

The Real-Time Environmental Monitoring Module continuously tracks soil, water, and environmental parameters across the farm. Soil and irrigation water pH are measured using standard glass-electrode pH probes. Raw probe outputs range from approximately +414 mV at pH 0 to –414 mV at pH 14, making them unsuitable for direct ADC sampling [11]. Therefore, an onboard pH interface module amplifies and level-shifts these signals to a usable range (approximately 3.0 V at pH 0, 2.5 V at pH 7 and 2.0 V at pH 14) [12]. The ESP32 ADC digitizes the conditioned signal. Direct soil pH serves as the primary fertility indicator, while irrigation water pH is used as a secondary reference when water mixes with the soil. Because pH sensors drift over time and are temperature-dependent, calibration is performed through the module's trimmer capacitors and the probe is kept wet to maintain accuracy.

Environmental parameters including soil moisture, temperature and humidity are also monitored using the capacitive soil sensor and the DHT11. The ESP32 decodes the DHT11's 40-bit data frame to obtain temperature and humidity values, which are used to characterize microclimatic conditions and identify periods of extreme dryness that could influence irrigation demand. The float sensor is again used here to continuously check irrigation water availability.

For farm safety, an IR flame detection system is included. The IR module is tuned to the 760–1100 nm spectral band, which corresponds to the characteristic infrared emissions of open flames. To avoid false alarms caused by brief IR reflections or sunlight flashes, temporal filtering is applied: the system only triggers an alert when the IR sensor maintains a high signal for a consistent duration rather than reacting to a single short spike.

Additional security functionality is provided through a laser-based intrusion detection system composed of a laser pointer aligned with a photoresistor. Any interruption of the beam indicates potential animal or human intrusion, which is logged by the ESP32. When an intrusion is detected or when triggered the system activates a flashing LED and buzzer to produce light and sound deterrence, helping protect the field.

All sensor data from this module are coordinated by the ESP32 and transmitted to a Node.js server over WebSockets, enabling real-time visualization and continuous environmental awareness throughout the farm which is shown in Fig 4

C. AI-Based Plant Disease Detection Module

This system focuses on image-based plant disease detection using deep learning models, with particular emphasis on model generalization, inference efficiency and deployment suitability for agricultural environments.

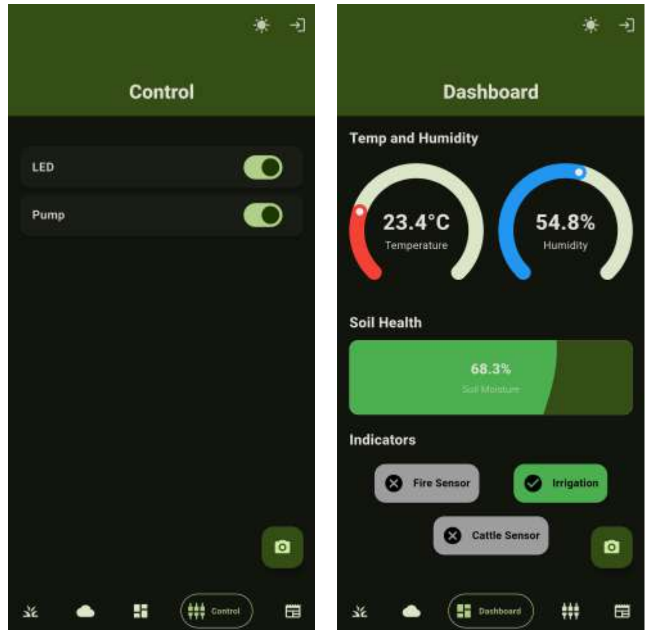

Fig. 4: Control features and Dashboard

1) Dataset and Preprocessing: The experiments is conducted using the publicly available New Plant Diseases Dataset. The dataset contains images of healthy and diseased plant leaves across 38 classes. A total of 63,266 images are used for model training, while 17,572 images are reserved as an independent test set to evaluate generalization performance. From the training data, 10% of the samples are further separated as a validation set to monitor performance during training and prevent overfitting. This data split ensures a sufficiently large and diverse test set, enabling a more reliable assessment of real-world performance.

All images are resized to 224 × 224 pixels. To mitigate overfitting and improve model generalization, data augmentation techniques such as random resized cropping, horizontal flipping and color jittering is applied to the training data. Validation and test datasets are processed using deterministic resizing and normalization.

2) Model Architectures: Three convolutional neural network architectures are evaluated as they represent state-of-the-art convolutional neural network architectures that have been widely and successfully applied to plant disease detection and classification tasks [4].

- ResNet-50
- DenseNet-201
- MobileNet-V2

All models are initialized with ImageNet pre-trained weights. The final classification layers is replaced to match the number of plant disease classes. Fine-tuning is performed on the augmented plant disease dataset.

3) Training Configuration: All models are trained for five epochs using the Adam optimizer with a learning rate of 2 ×

10^{-4} and a batch size of 32. Cross-entropy loss is used as the optimization objective. Validation accuracy is computed after each epoch and the model achieving the highest validation accuracy is saved for final evaluation.

The fine-tuned hyperparameter values used for training the model are summarized in Table I

TABLE I: Hyperparameter Configuration for Plant Disease Detection

Hyperparameter	**Value**
Input image size	224×224
Batch size	32
Number of epochs	6
Optimizer	Adam
learning rate	2×10^{-4}
Loss function	Cross-Entropy Loss

4) Evaluation Metrics: Performance is evaluated using classification accuracy on validation and test sets. In addition, inference time per image and model complexity (number of trainable parameters) are measured to assess deployment feasibility. This multi-criteria evaluation ensures that accuracy gains do not come at the cost of excessive computational overhead.

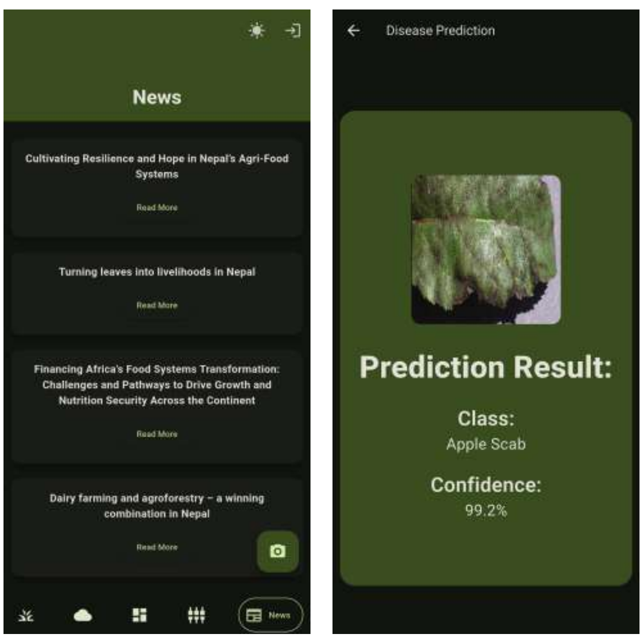

Fig. 5: News and Disease Detection Visual

D. Agricultural News Classification Module

Agricultural news classification module is designed to automatically collect farm headlines of big Nepali online newspapers and focus on the delivery of updates on their agriculture to the farmers with the aid of the mobile app. Due to the absence of the publicly available dataset on agriculture-specific Nepali news, a dataset is built by means of systematic web scraping. The titles of the articles are picked up out of the major national news websites such as The Kathmandu Post, The Himalayan Times, My Republica, Nepali Times and The Rising Nepal.

The headlines gathered are then systematically put into two of the categories of the supervised dataset by hand. Agricultural, climate, weather, crop, market, irrigation and farming policy headlines are classified under class 1. The label of class 0 are used to the headlines that refer to other fields like politics, entertainment, sports, technology and crime which has been publicly released on the authors' Kaggle profile to support transparency and reproducibility of the research [17]. The final dataset had 270 labeled headlines which has 155 as label 1 (related to agriculture) and 115 as label 0 which is shown in Fig 6

Fig. 6: Distribution of Data Labels

The textual preprocessing steps were done before training the model that includs lowercasing, punctuations, stop-word and tokenization. The embedding method Term Frequency-Inverse Document Frequency (TF-IDF) is used to convert the processed text into numerical vectors. It is especially helpful with short, information-dense text (e.g. news titles) where slight variations in language (e.g. harvest, monsoon, pesticide, yield, weather alert, farmer subsidy) are highly predictive of the agricultural sector [18] [19]. WordCloud of the all the news title present in dataset is shown in Fig 7

In the case of the classification model, a Logistic Regression classifier is used. The reason behind the selection of the Logistic Regression is its robustness, interpretability and the high efficacy in cases of sparse and high-dimensional text representations based on the TF-IDF embeddings [20]. It is computational light which is why it can be used in a system that needs to process incoming news information on a daily basis with minimum latency. The logistic regression model is optimized in training the decision boundary separating the agriculture related headlines (class 1) and the general news headlines (class 0) and the best parameter choosen are given in table II.

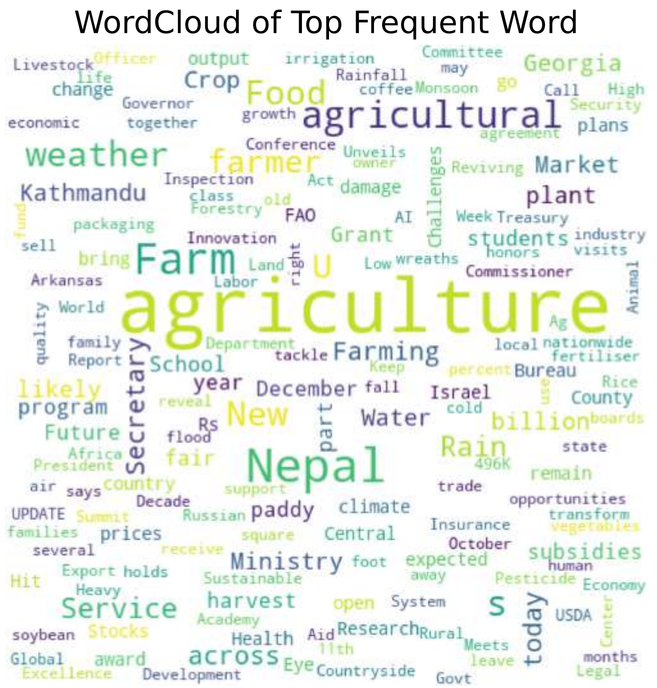

Fig. 7: Visualization of Most Common Words from News Headlines

TABLE II: Hyperparameter Configuration for Logistic Regression

Parameter	Best Value
C	10
Penalty	L1
Solver	liblinear
Cross-Validation Folds	5
Scoring Metric	accuracy

The classifier deployed as an active inference service in the backend server after training. The system uses automated web scraping to update itself with new headlines of the same news sources on a regular basis. All incoming headlines are sent through the preprocessing pipeline, transformed into a TF-IDF vector and sent to the logistic regression classifier. In case the model detects the headline as one that is related to agriculture, the system saves the headline and sends it to the mobile application and display in screen shown in Fig. 5. The unrelated headlines are thrown away.

E. Deployment and System Integration

The IoT sensing and control unit is deployed directly in the agricultural field of size 1100 - 1500 square meter with careful consideration of sensor placement, environmental exposure and ease of maintenance [24]. The soil pH sensor is installed in a ponded or standing-water zone where irrigation water remains stagnant for a period of time, enabling continuous monitoring of water acidity during irrigation cycles. The soil moisture sensor is placed in the middle region of the field, where water infiltration occurs gradually, providing a realistic approximation of the average soil moisture condition rather than localized saturation near the irrigation source. This deployment strategy ensures that irrigation decisions are based on representative field conditions [25].

The temperature and humidity sensor is mounted slightly above ground level inside a hollow PVC enclosure to protect it from rain, dust, and direct sunlight while allowing ambient air to pass through. The enclosure consists of a 110 mm PVC pipe with ventilation holes and a removable top lid, providing a simple, low-cost, and weather-resistant housing. The ESP32 microcontroller and supporting electronics are installed inside this PVC pipe, forming a compact and integrated field node. An infrared (IR) sensor is mounted on the outer side of the enclosure and oriented toward the open field to detect potential fire or abnormal heat events.

Electrical wiring from the PVC enclosure is routed across the field to connect the pH sensor, float sensor, and water pump. The pH sensor cable and float sensor wire are laid along the field surface and irrigation channel with protective insulation to minimize damage from moisture, soil movement, and farming activities and irrigation pump is powered though external power source. The float sensor is installed inside the irrigation channel to monitor water availability and prevent dry running of the pump. The water pump itself is placed directly within the irrigation channel and is connected to the control unit through a motor driver powered by external power line for pumping water, allowing automated irrigation based on sensor readings and system logic.

Power management is designed to support long-term field operation with minimal maintenance. A small solar panel is mounted on the top lid of the PVC enclosure and is used to charge a Li-ion battery pack housed inside the pipe. The power subsystem consists of two 3.3 V with 3000-4000 mAh capacity Li-ion cells with an integrated voltage regulation stage that provides a stable 5 V supply to the ESP32 . To further reduce energy consumption, the ESP32 operates using scheduled wake-up cycles and deep-sleep modes, activating in around every 2 hours during which data collection, transmission, and sensing is done. In this cycle when ESP32 wakes up it connects to WiFi, gathers sensor information, sends it and gathers input commands at the same time for irrigation control. This low-power design enables the system to operate for more than a week without manual charging, even under limited solar conditions. Recent work highlights the use of photovoltaic-powered IoT sensor nodes for sustainable irrigation automation in off-grid agricultural settings [25].

System integration is achieved through wireless communication between the field node and a mobile application using WebSocket-based data transfer over Wi-Fi. Although Wi-Fi connectivity is temporarily made available in the field for real-time monitoring, the system architecture is designed to support future replacement with LoRa-based communication modules deployed at both the field and farmer's home for long-range, low-power data transmission. Beyond sensor monitoring and irrigation automation, the mobile application integrates additional farm management features such as camera-based plant leaf disease detection, expense tracking for cultivation inputs, and classification of agriculture-related news. The combination of robust field deployment, efficient power management, and integrated digital services makes the proposed system effective, low-cost, and practical for adoption by farmers.

Fig. 8: Weather Forecasting and Farm Management

IV. Results And Discussion

The findings of both IoT and AI systems are explained below, focusing on energy efficiency and practical implementation in agricultural conditions.

A. Energy Efficiency and Deployment Constraints

To accomplish high energy efficiency when used in constant field deployment, the deployed IoT node is run on the basis of periodic wake-up and deep-sleep operation. In the active mode, the ESP32 uses about 120-180 mA to drive the soil moisture sensor, pH sensor interface, DHT11 sensor, IR sensor, and float sensor and send the data to the mobile application via Wi-Fi connection.The water pump is powered by external power line to the motor driver. The period of each active cycle after wake-up is about 30-50 seconds. In the deep-sleep mode, the ESP32 power consumption is minimal and about 40-60 micro ampere when all sensors are turned off. The average system current consumption of 8-12 mA is attained with a constant wake-up time of 2 hours, this is a balance between the frequency of monitoring and power use with 2 hours not influencing the accuracy of the irrigation decision.

Besides energy efficiency, the spatial coverage of the sensing node dictates its applicability in the actual implementation of farm deployment. The existing system is in the form of a single-point monitoring unit, and as such it does not present distributed measures rather approximates of the average field conditions. Having the soil moisture sensor at a representative mid-field position and the pH sensor placed inside the irrigation water channel, the system could effectively be used to measure the agricultural plots in the area of about 1100 -1500 square meter when the soil was uniform and the irrigation water was uniform. This is suitable coverage in small size farms usually found in the rural farming context.

The power system comprising of two 3.3 V Li-ion battery and small solar cell, on which under normal day-light, the solar-charging made up the daily energy usage, thus allowing the long-term continuous functioning of the power system without human intercession of up to 15-20 days under normal day-light conditions. The current deployment is supported by Wi-Fi communication to facilitate real-time WebSocket-based data transmission.

In system integration terms, the time lag in communication between sensor data collection at the ESP32 and data visualisation in the mobile application is always low. The mean end-to-end latency, sensor sampling time, data packet assembly, WebSocket transmission, backend processing, and mobile application display is between 130 and 180 ms when Wi-Fi conditions are stable. Such latency is good enough to make near real-time monitoring and timely irrigation feedback, which makes soon the conditions of the sensed fields to be presented promptly in the user interface without impacting decision-making or responsiveness of control. In general, the measured cost, power consumption, communication, and stability of the operation of the system prove that the proposed system is suitable to be used in practice on farms and to be operated in the everyday working conditions of real farms.

B. Plant Disease Detection Accuracy

To ensure a deployment-oriented evaluation, multiple deep learning models like ResNet-50, DenseNet-201 and MobileNet-V2 are comparatively analyzed using three key criteria: classification accuracy, inference time and model complexity. Based on the combined findings from these metrics, the final model selection is made by balancing predictive performance with computational efficiency.

1) Classification Performance: Table III summarizes the final test accuracy achieved by the evaluated models.

TABLE III: Classification Accuracy Comparison of Evaluated Models on the Test Dataset

Model	**Test Accuracy (%)**
ResNet-50	98.77
DenseNet-201	99.23
MobileNet-V2	98.94

DenseNet-201 achieved the highest accuracy; however, the performance difference among the three models was marginal (less than 0.3%). This indicates that all models are capable of learning discriminative plant disease features effectively.

2) Inference Time Analysis: Inference time is critical for real-time agricultural applications. Figure 9 illustrates the average inference time per image for each model. MobileNet-V2 achieved the fastest inference (1.05 ms/image), significantly outperforming ResNet-50 and DenseNet-201. This result highlights the suitability of lightweight architectures for time-sensitive agricultural decision-making.

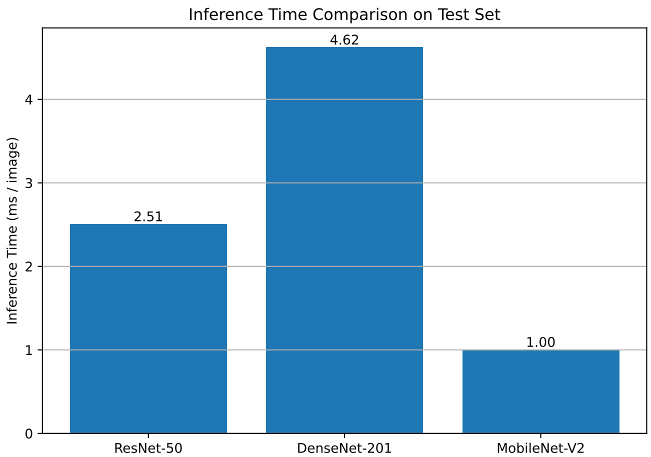

Fig. 9: Average inference time per image for all models

3) Model Complexity: Figure 10 compares the number of trainable parameters across models. MobileNet-V2 required only 2.27 million parameters, compared to 23.59 million for ResNet-50 and 18.17 million for DenseNet-201. Reduced model complexity translates to lower memory usage and energy consumption, which is essential for edge and mobile deployment.

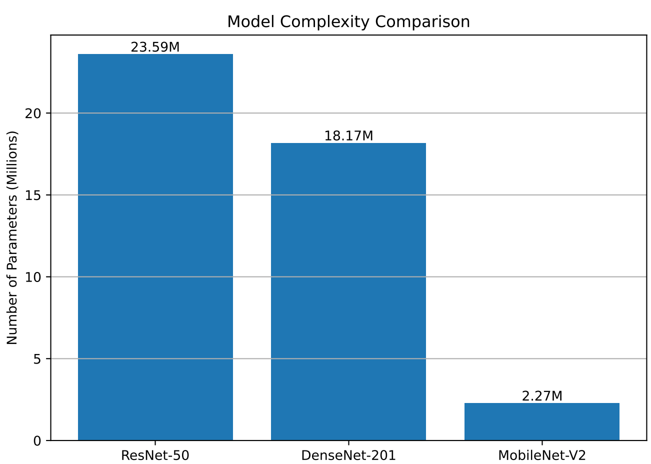

Fig. 10: Comparison of model complexity in terms of the number of trainable parameters

4) Model Selection Justification: Although DenseNet-201 achieved the highest accuracy, MobileNet-V2 is selected as the final model due to the following reasons:

- Low inference time, enabling real-time disease detection.
- Low model complexity, reducing storage and computational requirements.
- Minimal accuracy trade-off, with less than 0.29% reduction compared to the best-performing model.

These characteristics are especially important in agricultural scenarios, where disease detection systems are often deployed on mobile devices or edge hardware with limited computational resources and power availability. Prior studies have also emphasized that lightweight models are more suitable for precision agriculture and field-level decision support systems [21].

Overall, the results demonstrate that MobileNet-V2 provides the best balance between accuracy, efficiency and practicality making it an appropriate choice for deployment in smart agriculture systems.

C. News Classification Performance Results

The agricultural news classification module carried out well on the annotated Nepali news headline dataset. The system performed well with high accuracy and unanimous class-dependent discrimination of agriculture-related and non-agriculture headlines using TF-IDF embeddings and a Logistic Regression classifier. The model had an accuracy of 0.9630, precision of 0.9653, recall of 0.9630 and an F1-score of 0.9628, which is a good balance of both classes. These findings indicate that the classifier is very useful in terms of detecting agricultural contents with the lowest false positives and false negatives. The confusion matrix attached separately further attests the high prediction power of the model, as it will be suitable to be incorporated into the pipeline of real-time news filtering employed by the mobile application. A confusion matrix is created to visualize the performance which is shown in Fig 11

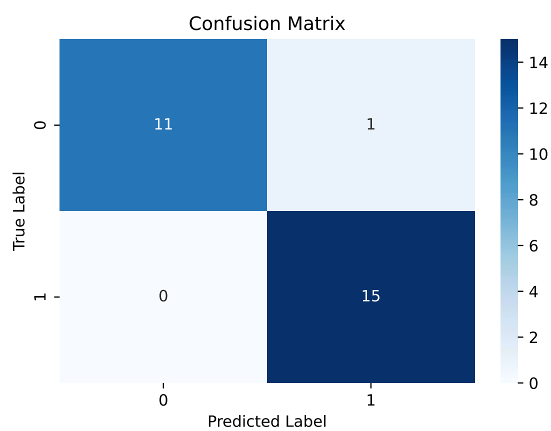

Fig. 11: Confusion Matrix for News Classificatio

D. Limitations of the System

The system might fail to be deployed in areas with unreliable or inexistent Internet connectivity. Resilience could be improved by adding alternative communication protocols such as the GSM or LoRaWAN. The accuracy should be maintained at long-term levels by periodical recalibration. Multiple sensor probe can be used for further increasing the accuracy of data readings. AI disease detection model is constrained by its training set. It can confuse the situation with a region-specific disease that is not included in the data set and may not fully reflect performance under diverse real-field conditions such as varying lighting, occlusion on background noise. The news classification module is trained on a relatively small dataset, potentially limiting its generalization to broader news sources and emerging topics.

V. Conclusion

The current paper introduces a single architecture of an IoT-AI-driven smart agriculture system that combines real-time reading of environmental conditions, automatic control of irrigation, identifying the occurrence of plant disea A comparative evaluation of deep and lightweight CNN models demonstrated that while high accuracy is achievable, inference latency and model complexity are critical factors for practical field deployment. MobileNet-V2 is used as the most appropriate model based on this finding because it has low inference time and a small architecture. On the whole, the given system has solved the major gaps between the performance of laboratory-level performance and the actual needs of the farming sector, making it a practical and scalable solution for resource-constrained farming environments.

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