# IoT-UAV enabled Intelligent Resource Management in low-carbon Smart Agriculture using Federated Reinforcement Learning

Nada Alasbali, Fahad Masood, Noha Alnazzawi, Wad Ghaban, Abdulwahab Alazeb, Shadi Basurra, Faisal Saeed

*Abstract*—**The Internet of Things (IoT) and unmanned aerial vehicles (UAVs) continue to advance the low-carbon smart agriculture technologies for next-generation consumer electronics and unlock more informed agricultural practices. Reinforcement learning (RL), federated learning (FL), and federated reinforcement learning (FRL) have demonstrated notable achievements in resolving complex problems, including resource allocation, energy efficiency, anomaly detection, and bandwidth utilization for multimodal tasks. This research explores multimodal data analysis and resource optimization using FRL for agricultural consumer electronics. The proposed framework employs IoT devices to monitor temperature, humidity, soil temperature, and soil moisture in real time, while UAVs provide aerial imagery for soil moisture, crop growth, and pest identification across three fields. This framework supports distributed learning, which trains local RL models on each node and combines them into the global model. The proposed FRL model demonstrated significant enhancements, including a 17% reduction in energy consumption for IoT devices and a 15% reduction for UAVs compared to non-FRL methods. This research emphasizes the effectiveness of FRL in integrating IoT and UAV for efficient resource allocation, energy efficiency, and reduced carbon emissions for low-carbon agricultural consumer electronics.**

*Index Terms*—**Federated Reinforcement Learning, IoT, UAV, Energy Efficiency, Agriculture Consumer Electronics.**

## I. Introduction

The Next-generation low-carbon technologies and sustainable computing are transforming modern industries, including agriculture and consumer electronics [1], [2], [3]. Precision farming and smart consumer applications have been revolutionized with the growth of these technologies. Real-time data accumulation, effective resource usage, and environmentally conscious actions have enabled these technologies to promote carbon reduction and sustainability. The development of cutting-edge technologies in various innovative systems, including smart cities and agriculture, has gained more research interest in recent years [4], [5].

Smart agriculture enables precise farming using real-time data collection and automated decisions. Resources, including fertilizers, water, and pesticides can be used efficiently for precision farming. Integrating the Internet of Things (IoT) and Unmanned Aerial Vehicles (UAVs) has offered multimodal data handling to optimize agricultural practices, such as precise irrigation, pest control, and soil health monitoring for low-carbon agricultural consumer electronics [6]. Several key parameters, such as temperature, soil moisture, soil temperature, and humidity, can be monitored using IoT sensors, while aerial supervision can be performed using UAVs. Resource allocation, bandwidth optimization, energy consumption, and anomaly detection are crucial challenges in precision agriculture.

Advanced computational techniques are required to address the challenges of low-carbon smart agriculture systems to improve performance and sustainability [7]. Federated reinforcement learning (FRL) involves the strength of both federated learning (FL) and reinforcement learning (RL), which has emerged as a transformative technology for addressing challenges in IoT and UAV networks [8], [9], [10], [11]. Promoting local learning and model updates controls communication overhead, minimizes energy consumption, and increases scalability in precise low-carbon agriculture [12].

Data reliability and resource management are vital in anomaly detection environments as system disruption can be controlled for sustainable and reliable operations [13]. Advanced machine learning methods can offer strong solutions for outlier identification in IoT-UAV networks. Each IoT node can independently perform local RL training to optimize resource allocation and anomaly detection, resulting in enhancing the system's resilience.

The main aim of this study is to investigate the applications of FRL in integrating IoT and UAV to enhance the performance of low-carbon agricultural consumer electronics. This approach contributes to the progression of innovative technologies that focus on the importance of reliability, efficiency, and environmental awareness in next-generation smart agriculture.

In this article, Section II presents the review of the literature

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highlighting the key challenges in smart agriculture and related works, Section III provides brief details of the proposed methodology followed by the results and discussion in Section IV. The conclusion and future work are discussed in Section V.

## II. Related Works

The Internet of Things (IoT) is a technological innovation that is widely used for improving efficiency and accelerating development toward the goal of low-carbon smart agriculture. AI methods, including machine learning (ML) and deep learning (DL), are the key enablers for shifting farming toward agriculture 5.0. A TinyML framework assisted by UAVs has been presented in [14]. This framework focused on the measurement of soil moisture by IoT and UAVs using long short-term memory (LSTM) and deep neural networks (DNNs).

The estimation of root-zone soil moisture has been done using ML methods applied to the ground penetrating radar (GPR) signals in [15]. The model was validated by comparing the synthetic and real-time data for enhancing the estimation accuracy. IoT, blockchain, and DL were integrated for pest detection and identification in [16], [17]. This improvement helped the dual purpose of protective health and supporting farming sustainability. The high achieved accuracy (98.91% ) of pest detection highlights the effectiveness of the proposed DL model.

The use of blockchain technology enhances the privacy and reliability of data transmission, whereas the decision-making progression for pest identification is enhanced by using IoT with a response time of 1.71 s. IoT and images are integrated into poultry farming to enhance farm management and increase livestock [18].

Real-time data monitoring was performed for disease detection in chickens. The integration of IoT with advanced imaging techniques not only demonstrates a high accuracy rate of 99% in disease detection but also shows a significant improvement in overall poultry health by 35%.

Multimodal data analysis in smart agriculture has an essential impact on abnormal crop identification. A novel Internet of Agriculture Things (IoAT) framework has been proposed for image acquisition based on static-motion and edge intelligence strategy [19], [20]. Similar studies have been performed for accurate crop customized recommendations [21], [22]. The proposed approaches employed a systematic fusion of several patterns and components, including S-transform, frequency, and entropy patterns extracted from different data sources. Results reveal that crop recommendations were enhanced using these features.

Mobile edge computing (EC) combined with IoT and UAVs has also shown progressive results for task offloading in smart agriculture [23]. A multi-agent RL layout has been implemented for offloading decisions to improve system stability and minimize loss and delay. A multi-access EC using UAV as a flying charger for energy harvesting has been used to address energy issues in [24]. They aimed to reduce the age of information (AoI) and increase energy efficiency by mutually enhancing the UAV paths and data offloading. Markov decision process (MDP) and a stochastic game model were applied for handling complex and dynamic data and achieved high-efficiency rates of up to 95.5%.

Other studies for low carbon green communication, improved energy efficiency, and secure agriculture systems have been performed using multimodal systems with EC, and advanced AI models [25], [26], [27], [28], [29], [30], [31], [32], [33].

## III. Methodology

This research aims to develop an efficient and intelligent resource allocation framework for IoT-UAV enabled smart agricultural consumer electronics (SACE) environment using federated reinforcement learning (FRL). An interconnected network of IoT sensors through agricultural fields has been developed to monitor environmental factors, including temperature, soil moisture, soil temperature, and humidity. UAVs were placed to capture high-resolution images for soil moisture, crop growth, and pest identification at regular intervals in three crop areas. Convolutional Neural Networks (CNNs) have been used for image analysis, and data is then transmitted to the edge server for efficient local processing. The learning process is formalized by the Markov Decision Process (MDP), which implements and learns ideal actions using reinforcement learning (RL) and assigns rewards. The locally trained model is sent to the central server by the edge server for global model aggregation using federated learning (FL). The individual local models are combined into a global model that highlights collective learning across the network, maintaining each local dataset's privacy. A priority weight aggregation is applied by the central server, giving more importance to the anomalous and critical data. The updated model is returned to each edge server after the model update, thus enhancing the decision-making for the next data collection round and resource management.

### A. Data Collection

Data collection for this research was performed over four months from December 2023 to March 2024 in Peshawar, Pakistan, corresponding to the wheat crop's growth. A three-layered IoT-UAV network was established for real-time multimodal data collection for monitoring environmental conditions and efficient resource management. IoT sensors were positioned for collecting vital environmental data, including temperature, soil moisture, soil temperature, and humidity, while UAVs were used for aerial inspection for soil moisture, crop growth, and pest identification. Raspberry Pi 4 was used as a local processing hub at the edge layer to run a local FRL model for instant response. The central server layer was responsible for refining global processing sent back to the edge layer. The dataset can be accessed at (https://github.com/researchcsaup/research024.git)

### B. CNN for UAV images in SACE

Convolutional Neural Networks (CNN) have been implemented to analyze UAV-captured images across three fields.

The high-resolution images have been collected for detecting soil moisture, pest identification, and crop growth. The obtained images have been pre-processed, normalized, and augmented by resizing them into a uniform resolution to improve the model's resilience. The multiple convolutional layers structure the CNN architecture for capturing sufficient details. Max pooling layers were used to reduce dimensionality to improve computational efficiency without affecting the spatial information. The ReLU activation function with fully connected layers was also included for non-linear transformation, and the Adam optimizer for balanced updates. The convolutional layer was the core part of a CNN for feature extraction by applying filters across the input image. Mathematically,

$$\text{Feature Map}_{i,j}^{(l)} = \sum_{m=0}^{M-1}\sum_{n=0}^{N-1} \text{Image Pixel}_{(i+m)(j+n)}^{(l-1)} \cdot \text{Kernel}_{m,n}^{(l)} + b^{(l)} \tag{1}$$

where Feature $\text{Map}_{i,j}^{(l)}$ represents the output feature map at layer $l$ at position $(i, j)$, Image $\text{Pixel}_{(i+m)(j+n)}^{(l-1)}$ shows the input UAV image pixel from the previous layer $(l-1)$ at offset $(i+m, j+n)$, $\text{Kernel}_{m,n}^{(l)}$ is the filter for pest-specific filter extraction at layer $l$, $b^{(l)}$ is the bias term for layer $l$, $M$ and $N$ are the dimension of the filter i.e., 3x3. An activation function, Rectified Linear Unit (ReLU), is applied for non-linearity after convolution.

$$\text{ReLU}(x) = \max(0, x) \tag{2}$$

ReLU replaces all negative values with zero for each element $x$ in the feature map. The spatial dimensions of the feature maps are reduced using max-pooling layers. The pooled features are expressed as,

$$\text{Pooled Feature}_{i,j}^{(l)} = \max_{\substack{0\le m<M\\ 0\le n<N}} \text{Feature Map}_{(i+m)(j+n)}^{(l)} \tag{3}$$

and the average pooling is given as,

$$\text{Pooled Feature}_{i,j}^{(l)} = \frac{1}{M \times N}\sum_{m=0}^{M-1}\sum_{n=0}^{N-1} \text{Feature Map}_{(i+m)(j+n)}^{(l)} \tag{4}$$

where Pooled $\text{Feature}_{i,j}^{(l)}$ represents the pooled value at $(i, j)$, $M$ and $N$ are the pooling window dimensions, and Feature $\text{Map}_{(i+m)(j+n)}^{(l)}$ is the value within the pooling window. The resulting feature maps are then flattened into a single vector and fed into the fully connected dense layer. The output of a fully connected layer in terms of the flattened vector $\mathbf{f} = [f_1, f_2, \ldots, f_n]$ is given as,

$$\text{Output}_k = \sum_{j=1}^{n} f_j \cdot w_{j,k} + b_k \tag{5}$$

where $\text{Output}_k$ is the output of the $k$-th neuron denoting the pest class in the fully connected layer, $f_j$ is the $j$-th feature in the flattened vector, $w_{j,k}$ is the weight connecting feature $j$ to neuron $k$, and $b_k$ is the bias for neuron $k$. The output layer applies the softmax function to convert the final outputs into probabilities for each class, given as,

$$\text{Softmax}(z_i) = \frac{e^{z_i}}{\sum_{j=1}^{C} e^{z_j}} \tag{6}$$

where $z_i$ is the output of the $i$-th neuron in the final layer, and $C$ is the total number of classes. Table I shows the parameters used for CNN implementation.

TABLE I
PARAMETERS FOR CNN IMPLEMENTATION

| Parameter | Value |
|---|---|
| Image Resolution | 224x224 pixels |
| Number of filters | 32, 64, 128 |
| Filter Size | 3x3 |
| Pool Size | 2x2 |
| Batch Size | 32 |
| Epochs | 50 |
| Learning Rate | 0.001 |
| Optimizer | Adam |

## C. RL in SACE

Reinforcement Learning (RL) enables the nodes for local training using the Markov Decision Process (MDP), where each node works as an independent RL agent. The UAV imagery and the sensor readings act as multimodal data sources for resource optimization. The states $s_t$, actions $a_t$, and rewards $r_t$ define an MDP, where actions represent decisions, and the reward defines the action quality. The policy $\pi$ is learned to map states and actions for maximizing the expected reward. Mathematically,

$$J(\pi) = \mathbb{E}_{\pi}\left[\sum_{t=0}^{T} \gamma^t r_t\right] \tag{7}$$

Where $\gamma \in [0, 1]$ represents the discount factor to balance the rewards and T denotes the time horizon. The action-value function $Q(s_t, a_t)$ derives the optimal policy which satisfies the Bellman equation:

$$Q^*(s_t, a_t) = \mathbb{E}_{s_{t+1}}\left[r_t + \gamma \max_{a_{t+1}} Q^*(s_{t+1}, a_{t+1})\right] \tag{8}$$

The actions are evaluated and improved by the above relation. The complexity of the multimodal data is handled using Deep Q- Learning (DQL), which uses a neural network $Q(s, a; \theta)$ for action-value function approximation. $\theta$ denotes the network's parameters, which are updated by reducing the temporal difference (TD) error

$$\delta = \left[r_t + \gamma \max_{a_{t+1}} Q(s_{t+1}, a_{t+1}; \theta') - Q(s_t, a_t; \theta)\right]^2 \tag{9}$$

$\theta$ is updated in the optimization step with the learning rate as, $\theta \leftarrow \theta - \alpha\nabla_\theta \delta$, The multiple objectives, including anomaly detection, resource optimization, and system controls, are balanced using the reward function as

$$r_t = w_1 R_{\text{resource}} + w_2 R_{\text{anomaly}} - w_3 C_{\text{energy}} - w_4 C_{\text{delay}} \tag{10}$$

The action space is explored by the agent with an $\epsilon$ greedy policy as,

$$a_t = \begin{cases} \text{random action} & \text{with probability } \epsilon \\ \arg\max_a Q(s_t, a) & \text{with probability } 1-\epsilon \end{cases} \tag{11}$$

In the local training process, the episode begins with initializing the state $s_0$. $a_t$ is selected at time step t by the agent, which observes the $r_t$ and $s_{t+1}$, updates the Q-network, and stores the transitions $(s_t, a_t, r_t, s_{t+1})$ in a replay buffer.

### D. FL in SACE

Federated Learning (FL) permits multiple IoT and UAV nodes to collectively learn a global model without sharing their data. It helps control privacy and ensure efficient communication during the learning process in distributed environments. The simulation parameters for model implementation is shown in Table II. The training is performed locally at each node, which is then updated at the central aggregator. Local model training, central aggregation, and updating of the global model are the three key steps in the FL process. Each input node $k$ trains a local RL model, and after the training iteration $t_{th}$, the model parameters are denoted as,

$$\theta_k^{(t+1)} = \arg\min_\theta \frac{1}{n_k} \sum_{i=1}^{n_k} \mathcal{L}(\theta; x_i, y_i) \tag{12}$$

where $\mathcal{L}(\cdot)$ denotes the local loss function, $n_k$ represents the number of samples at $k$ for the data samples $(x_i, y_i)$. The updated model parameter $\theta_k^{(t+1)}$ is sent to the central aggregator after local training and can be represented in terms of the total number of nodes K, the total number of samples across all the nodes $(\sum_{k=1}^{K} n_k)$, as,

$$\theta^{(t+1)} = \sum_{k=1}^{K} \frac{n_k}{n} \theta_k^{(t+1)} \tag{13}$$

where $\frac{n_k}{n}$ represents the assigned weight to node k and $\theta^{(t+1)}$ is sent to all the nodes for the next local training. The updated global model is given as,

$$\theta_k^{(t+1)} \leftarrow \theta^{(t+1)} \tag{14}$$

The energy consumption, network bandwidth usage, and resource allocation over communication rounds have been expressed as,

$$E_c(k) = \alpha \cdot d_u(k) + E_{\text{comm}}(k) + E_{\text{comp}}(k) \tag{15}$$

Where $\alpha$ is the energy per unit distance (Joules/m), $d_u(k)$ is the distance covered by UAVs in round $k$, $E_{\text{comm}}(k)$ is the communication energy in round $k$, and $E_{\text{comp}}(k)$ is the computation energy in round $k$.

$$B_w(k) = N \cdot (S_{\text{uplink}} + S_{\text{downlink}}) \tag{16}$$

$S_{\text{uplink}}$ is data sent by devices to the central server (MB), and $S_{\text{downlink}}$is the data sent by the server to devices(MB).

$$R_a(k) = R_{\text{base}} + \Delta R \cdot f(k) \tag{17}$$

Where $R_{\text{base}}$ is the base resource allocation, $\Delta R$ is the additional resources allocated dynamically, and $f(k)$ is the resource adjustment factor. Algorithm 1 and 2 show the algorithm details for the proposed framework, presenting the local training and federated learning for all the IoT devices and UAVs.

TABLE II
PARAMETERS FOR FRL IMPLEMENTATION

| Parameter | Value |
|---|---|
| Communication Rounds ($K$) | 50 |
| Local Training Iterations ($T$) | 30 |
| Learning Rate ($\alpha$) | 0.001 |
| Discount Factor ($\gamma$) | 0.95 |
| Exploration Rate ($\epsilon$) | Decay from 1.0 to 0.1 |
| Batch Size | 64 |
| Reward Function | $+10$ for optimal actions; $-5$ for inefficiencies |

**Algorithm 1** Local Training at IoT and UAV Devices

**Initialize:** Initialize local model parameters $\theta_i \leftarrow \theta_{\text{global}}$, replay memory $\mathcal{D}_i$, exploration rate $\epsilon$, discount factor $\gamma$, and learning rate $\alpha$.
**for** each local training iteration $t = 1$ to $T$ **do State Observation:** Extract multimodal state $s_t$ from dataset $D_i$.
**CNN Classification:** Process images to classify crop health and pest presence.
**Action Selection:** Generate a random number $u_t \sim U(0, 1)$.
  **if** $u_t < \epsilon$ **then** Select random action $a_t$ (exploration).
  **else**Select $a_t = \arg\max_a Q(s_t, a; \theta_i)$ (exploitation).
  **end if**
**Execute Action:** Apply $a_t$ and observe reward $r_t$ and next state $s_{t+1}$.
Store $(s_t, a_t, r_t, s_{t+1})$ in replay memory $\mathcal{D}_i$.
**Replay Sampling:** Sample minibatch $\{(s_j, a_j, r_j, s_{j+1})\}$ from $\mathcal{D}_i$.
  **for** each experience $(s_j, a_j, r_j, s_{j+1})$ **do Q-value Update:**
    **if** $s_{j+1}$ is terminal **then** $y_j = r_j$.
    **else**$y_j = r_j + \gamma \max_{a'} Q(s_{j+1}, a'; \theta_i)$.
    **end if**Update Q-network by minimizing:

$$L(\theta_i) = \frac{1}{M} \sum_j (y_j - Q(s_j, a_j; \theta_i))^2$$

  **end for**
Compute local model update:

$$\theta_i^{(t+1)} = \arg\min_\theta \frac{1}{|D_i|} \sum_{x \in D_i} \mathcal{L}(\theta; x)$$

**end for**
**Output:** Updated local model $\theta_i$.

## IV. RESULTS AND DISCUSSION

This section provides a comprehensive results analysis of the proposed federated reinforcement learning framework for IoT-UAV-enabled smart agriculture across three agriculture fields. The performance of the proposed models was analyzed in terms of various Quality of Service (QoS) parameters, including classification accuracy, reward calculation, and energy efficiency. The advantage of FRL in resource allocation and decision-making was observed for UAV-based crop growth monitoring, soil moisture detection, and pest identification.

The results further demonstrated the effectiveness of FRL and non-FRL-based approaches using several performance metrics.

Figure 1 shows the model convergence in terms of average loss for training rounds in all the fields. An initial high loss in Field 3 has been observed for both IoT devices and UAVs, which steadily drops as the model learns from the data. Field 2 showed faster loss reduction compared to Field 3, which suggests more structured data collection from the devices. In Field 1, both IoT devices and UAVs lead to the lowest loss values and faster convergence. The higher loss and slower convergence were due to more training challenges for both IoT devices and UAVs. The UAVs resisted crop growth accuracy due to several parameters, including discrepancies in environmental conditions, while the IoT devices revealed variations in multiple parameters, which delayed model convergence.

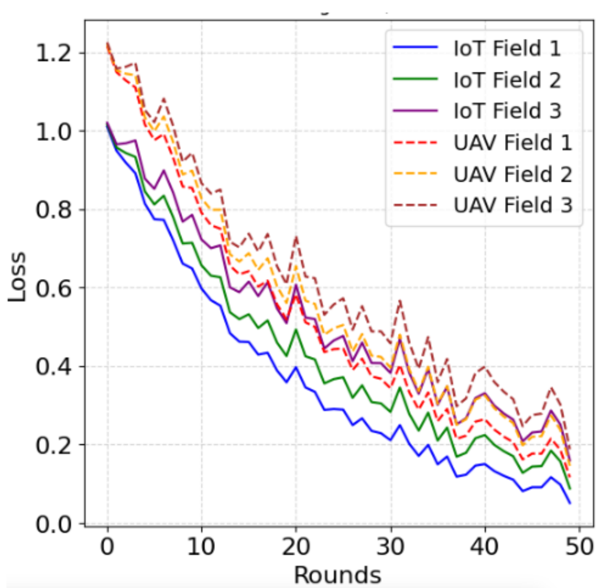


Fig. 1. Average convergence over communication rounds for all IoT Devices and UAVs across three fields.

**Algorithm 2** Federated Learning: Global Model Aggregation

**Initialize:** Initialize global model $\theta_{\text{global}}$, total rounds $K$, number of devices $N$.

**for** each communication round $k = 1$ to $K$ **do** Broadcast $\theta_{\text{global}}$ to all IoT and UAV devices.

**for** each device $i = 1$ to $N$ **do** Receive updated local model $\theta_i^{(t+1)}$ from device $i$.

**end for**

**Global Model Aggregation:**

$$\theta_{\text{global}}^{(t+1)} = \frac{\sum_{i=1}^{N} |D_i| \cdot \theta_i^{(t+1)}}{\sum_{i=1}^{N} |D_i|}$$

Broadcast $\theta_{\text{global}}^{(t+1)}$ to all devices.

**end for**

**Output:** Optimized global model $\theta_{\text{global}}$.

The reward values are the indication of resource allocation optimization over time. Figure 2 shows the average reward values of both IoT devices and UAVs obtained over training rounds across all the fields. The highest reward values were observed at the initial stages of the training in Field 3, middle in Field 2, and low values in Field 1. The low reward values in the earlier stages for IoT devices are due to several environmental conditions and data availability. The UAVs in the early stages also struggle with optimal flight paths, which leads to low reward values. A significant and rapid shift in the reward values was observed as the training progresses across the three fields. The improvements in the reward values indicate that the model successfully learned during the training rounds, and maintained reliable performance.

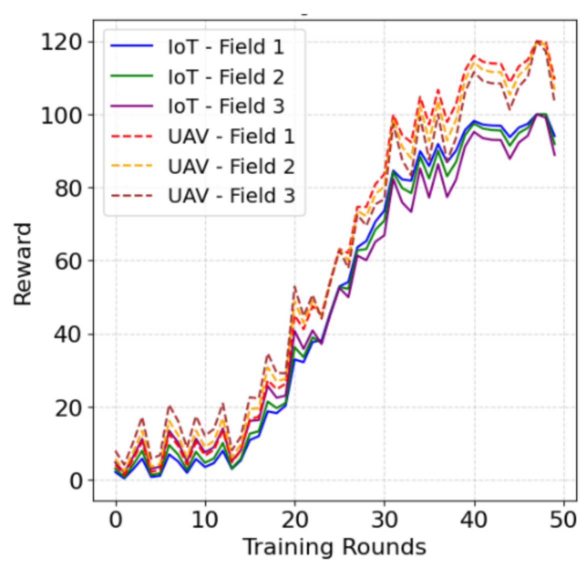


Fig. 2. Average rewards over communication rounds for all IoT Devices and UAVs across three fields.

The efficiency of IoT devices and UAVs can be evaluated by energy consumption for effective resource allocation. Figure 3 shows the energy consumption for all IoT devices and UAVs, and it is found that the energy consumption was reduced using FRL across all the fields. The FRL can dynamically optimize the resources, including the reduction of redundant data transmission, sensor activation, and controlled UAV flight paths. The energy consumption without FRL is significantly high due to the lack of adaptive learning in resource allocation. In addition, the experimental results showed that UAVs consumed more energy than the IoT devices in both FRL and non-FRL cases. The energy consumption was reduced by up to 15% for UAVs and 17% for IoT devices, indicating that FRL effectively reduces unnecessary UAV flights and controls sensor data transmission.

Figure 4 shows the heatmap for the energy consumption of both the IoT devices and UAVs across the three fields. The energy consumption percentage for UAV1 in all fields was measured between 76.4-78.7, for UAV2 it was 79.6-77.0, and 80.1-75.5 for UAV3. Similarly, the energy consumption for the temperature sensor was measured between 81.1-75.7, for the soil moisture sensor 83.1-84.5, for the soil temperature sensor

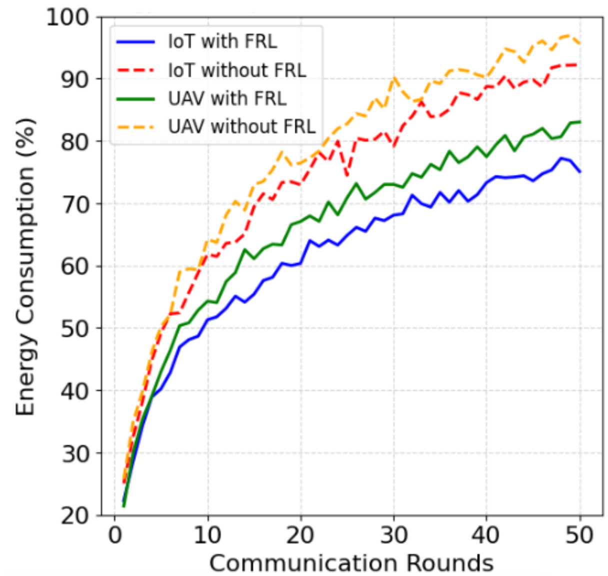


Fig. 3. Comparison of average energy consumption for UAVS and IoT devices over communication rounds across the three fields with FRL and non-FRL.

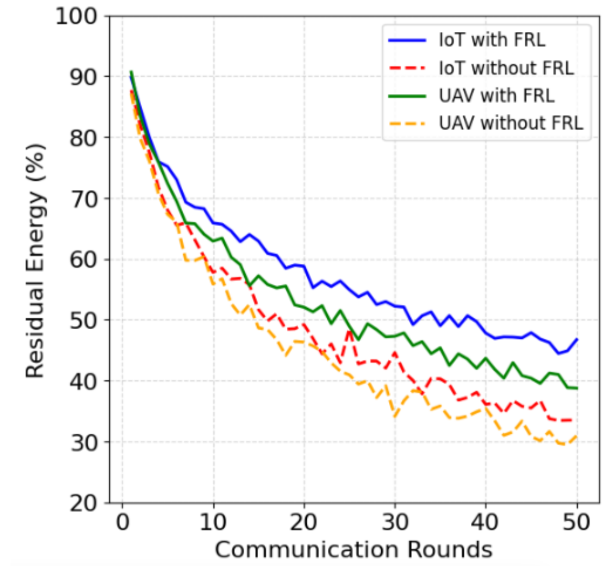


Fig. 5. Comparison of average residual energy over communication rounds for UAVs and IoT devices across the three fields with FRL and non-FRL.

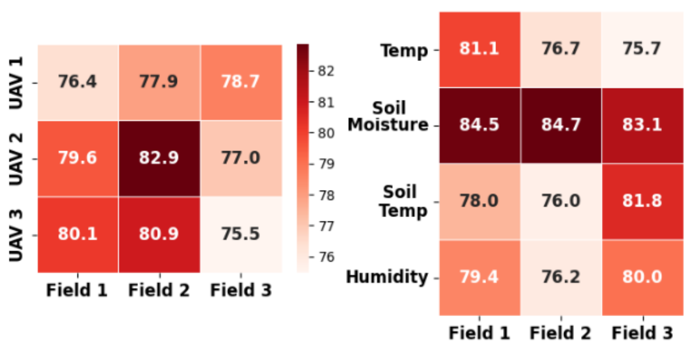


Fig. 4. Percentage distribution of average energy consumption of UAVs and IoT devices in the three fields.

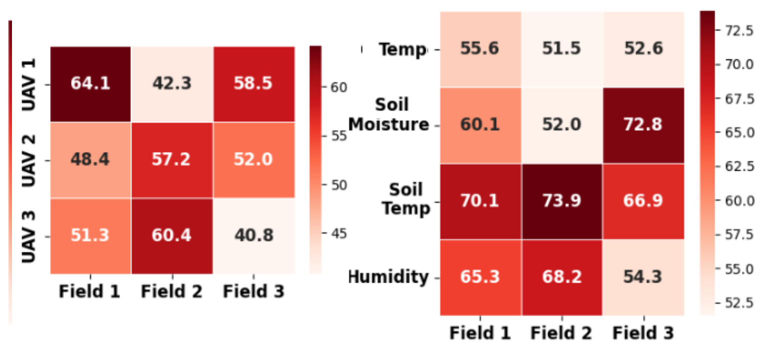


Fig. 6. Percentage distribution of average residual energy of IoT devices and UAVs for all the fields.

78.0 - 81.8, and for the humidity sensor 79.4- 80.0.

Figure 5 shows the comparison results of Residual Energy (RE) for the IoT devices and UAVs with and without FRL across the fields. Results show that the RE with FRL was relatively high when compared with the non-FRL implementation. The percentage of the RE for both the IoT and UAVs without FRL was 35% and 30%, while with FRL, it was increased to 49% and 40%. The increase in the percentage of RE indicates the effectiveness of the FRL implementation. This increase proposes that FRL minimizes redundant processes and ensures optimal operations. Figure 6 shows the heatmap of average RE for the IoT devices and UAVs across the three fields. UAV1 values range from 42-64 in all the fields, 48-57 for UAV2, and 40-60 for UAV3. The values for temperature sensors range from 51-57 for all the fields, 52-78 for soil moisture, 67-74 for soil temperature, and 54-68 for the humidity.

Figure 7 shows the percentage of resource allocation for all the IoT devices and UAVs. The overall results indicate that the percentage of resource allocation for both IoT devices and UAVs was optimized using FRL. The IoT devices performed several tasks, including monitoring temperature, soil moisture, soil temperature, and humidity. UAVs performed tasks including soil moisture analysis, crop growth, and pest identification for low-carbon smart agriculture. The average percentage of the resource allocation for the IoT devices using FRL was 85 and 80 for that of UAVs. The average percentage of the resource allocation for the IoT devices without FRL was 62 and 65 for that of UAVs.

Figure 8 shows the heatmap results of the resource allocation for the IoT devices and UAVs across the three fields. The percentage of the success rate of UAVs ranges between 75 and 95, which indicates generally a high performance. The low success rate indicates environmental interference, communication latency, and substandard task assignments. Similarly the percentage of efficiency rate for the IoT devices ranges from 70 to 90. The results imply that the adaptive task scheduling using FRL maximized the performance and data reliability in a smart agriculture environment.

Table III shows the comparison of the accuracies of soil moisture, crop growth, and pest identification in various fields. It is noticeable that pest identification has the highest accuracy

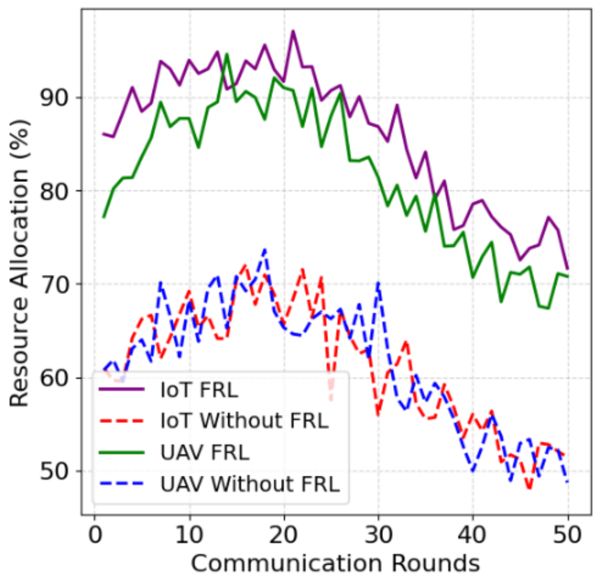


Fig. 7. Comparison of average resource allocation over communication rounds for UAVs and IoT devices across the three fields with FRL and non-FRL.

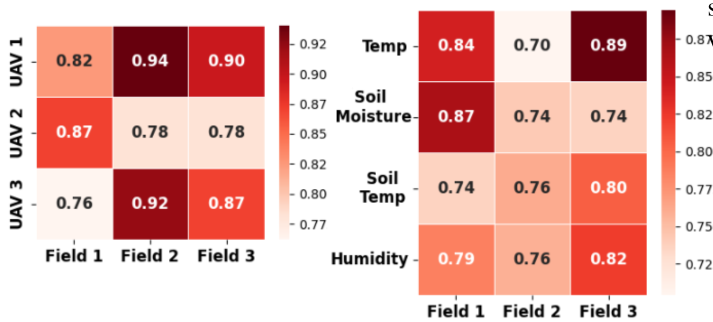


Fig. 8. Percentage distribution of average resource allocation of IoT devices and UAVs across the three locations.

among the three parameters. The accuracy in Field 2 is higher than the others, which shows that the image contrast and pest visibility are optimal in this location. The accuracy of soil moisture detection was observed above 90%. It shows efficient capturing of infrared and multispectral images by UAVs, which shows reliable detection of soil moisture variations. Accuracy for the crop growth monitoring was slightly lower as compared to the other two parameters. The highest accuracy in Field 2 was observed, which can be due to uniform crop structure.

TABLE III
COMPARISON OF ACCURACY FOR SOIL MOISTURE, CROP GROWTH, AND PEST IDENTIFICATION AT VARIOUS FIELDS

| | Feild 1 | Field 2 | Field 3 |
|---|---|---|---|
| Soil Moisture | 0.92 | 0.94 | 0.93 |
| Crop Growth | 0.89 | 0.91 | 0.90 |
| Pest Identification | 0.94 | 0.96 | 0.93 |

Table IV shows correlation data analysis of different features in various fields. A strong correlation was observed between UAV and IoT soil moisture, with little difference. The dissimilarities may arise due to evaporation, UAV image resolution, or shading effect. The pest infestation detected by the UAV seems to be influenced by temperature and humidity levels observed by IoT sensors. The pest infestation was high in Field 3, which coincides with the highest humidity (65 %). This shows that high humidity and low temperature make favorable conditions for pests. In contrast, Field 2 has low pest infestation and high temperature, which may decrease pest existence. Crop growth detection using UAV was directly influenced by soil moisture measured by the IoT sensor. The highest crop growth and well-balanced IoT soil moisture values were analyzed for Field 2, while the lowest values were measured for Field 3. It indicates that maintaining the soil moisture level at optimal levels is an important factor for crop growth in smart agriculture.

Figure 9 shows the comparison results of the proposed model for Field 1 in terms of various performance metrics. A high accuracy (0.94) was achieved for pest identification compared to that of soil moisture (0.92) and crop growth (0.89). The high recall for pest identification indicates that the pest infestation was identified with minimum false negatives. The lower crop growth values for precision and recall show that some misclassification occurred in plant growth assessment. It was noticed that UAV1 performed well for pest detection.

TABLE IV
UAV AND IoT CORRELATION DATA ANALYSIS FOR VARIOUS LOCATIONS

| | Field 1 | Field 2 | Field 3 |
|---|---|---|---|
| **UAV Soil Moisture (%)** | 35 | 42 | 30 |
| **UAV Crop Growth (%)** | 70 | 85 | 65 |
| **UAV Pest Infestation (0-1)** | 0.2 | 0.1 | 0.4 |
| **IoT Temperature (°C)** | 28 | 30 | 27 |
| **IoT Humidity (%)** | 60 | 55 | 65 |
| **IoT Soil Temperature (°C)** | 22 | 24 | 21 |
| **IoT Soil Moisture (%)** | 34 | 40 | 28 |

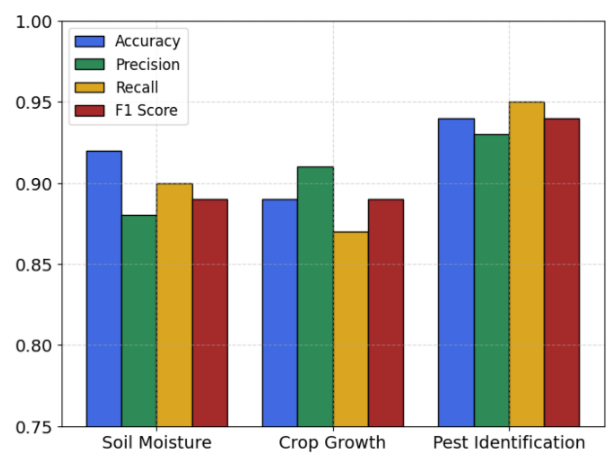


Fig. 9. Comparison results of various performance metrics for soil moisture, crop growth, and pest identification at field 1.

Figure 10 shows the comparison results of the proposed model for Field 2 in terms of various performance metrics. The results indicate that UAVs in Field 2 outclass other UAVs, achieving the highest accuracies from pest identification (0.96), soil moisture (0.94), and crop growth (0.91). The false positives were also minimized, which was represented by higher precision values. In addition, the higher recall values for soil moisture indicate that UAV2 has taken most variations in moisture level.

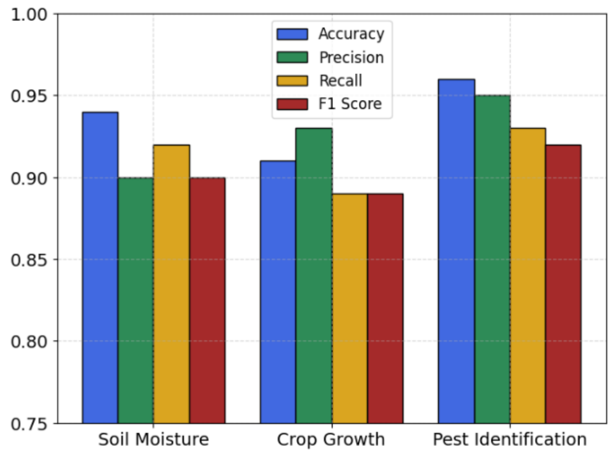


Fig. 10. Comparison results of various performance metrics for soil moisture, crop growth, and pest identification at field 2.

Figure 11 shows the comparison results of the proposed model for Field 3 in terms of various performance metrics. The accuracy for UAV3 is comparatively high, yet marginally lower than UAV2. The recall value was the lowest among all the UAVs for crop growth, which indicates that UAV3 missed certain crop health differences. The precision values for soil moisture were also the lowest, which suggests higher false positive rates in soil moisture detection. However, the pest identification by UAV3 performed well, as represented by the highest recall values.

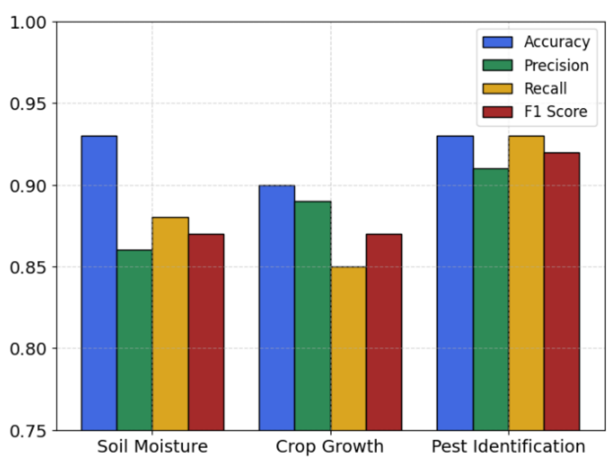


Fig. 11. Comparison results of various performance metrics for soil moisture, crop growth, and pest identification at field 3.

## V. Conclusion

In this research, a federated reinforcement learning framework has been proposed for low-carbon smart agriculture consumer electronics that integrates the Internet of Things (IoT) and Unmanned Aerial Vehicles (UAVs) for energy efficiency and resource management. Environmental and agricultural conditions, including humidity, temperature, soil moisture, soil temperature, crop growth, and pest identification, were observed using IoT sensors and unmanned aerial vehicles (UAVs). The FRL framework enables dynamic decision-making across multiple devices, ensuring data privacy and efficient resource management. The experimental results showed that the proposed model achieved better performance results in terms of energy efficiency, bandwidth utilization, and resource allocation. The framework can further be extended with additional modalities, including climate data over a long network range for a more sustainable and efficient smart agriculture system.

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