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AgriNex: Next-Gen Smart Agriculture with LLM-Integrated UAV-IoT Solutions

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***Abstract*—Emerging smart agriculture is critical for optimizing crop quality and quantity. However, its realization faces significant challenges, particularly the lack of feasible communication infrastructure and poor wireless connectivity in rural areas. This paper presents a novel Unmanned Aerial Vehicle (UAV) assisted two-tier agriculture network architecture to address these issues, where UAVs act as intermediaries between agriculture sensors and cloud servers. Our key innovation is a Large Language Mode (LLM)-based approach for context-aware semantic mapping, introducing an innovative Semantic Criticality Index (SCI) that dynamically assesses the importance of agricultural data. This novel SCI drives our formulation of the agricultural sensor data collection scheduling problem as an optimization problem to minimize energy use in sensors and UAVs, solved using a proposed Semantic-Guided Deep Q-Network (SG-DQN) algorithm that optimizes energy consumption and resource allocation based on semantic context. Simulations using public agricultural datasets show significant improvements over traditional methods in energy efficiency and data classification accuracy.**

***Index Terms*—UAV-assisted smart agriculture, LLM-based data labeling, context-aware semantic mapping, energy-efficient data collection scheduling, and context-aware DQN problem-solving.**

I. Introduction

With global food demand on the rise and environmental challenges intensifying, the agricultural sector faces mounting pressure to increase productivity while minimizing its ecological footprint. To meet these demands, smart agriculture has emerged as a data-driven approach by employing cutting-edge IoT networks to provide real-time data on various parameters such as soil moisture, temperature, and crop health, thus enabling optimized farming practices. Smart agriculture technologies can be divided into sensing, cloud computing, and networking. While sensing and cloud computing have advanced agriculture, networking remains a crucial yet unexplored area, linking sensors to cloud servers for seamless data transmission and decision-making.

Unmanned Aerial Vehicles (UAVs) have been widely utilized in agriculture for tasks such as monitoring, spraying, weeding, sensing, and seed planting. Although UAVs are effective for targeted operations like spraying and planting, ground-based agriculture sensors are often more economical for daily tasks such as continuous monitoring and sensing. However, IoT sensors deployed in rural and large-scale farmlands often face connectivity challenges due to limited infrastructure. To address this gap, this work introduces a novel UAV-assisted communication framework where UAVs function as dynamic data collection and relay nodes, enhancing network coverage and ensuring seamless data transmission. This UAV application scenario leads to two particular challenges, i.e., how to schedule sensor data collection to save crucial energy for UAVs and sensors and how to efficiently route collected sensor data to remote cloud servers for real-time processing and decision-making.

In response to the above-mentioned interconnected challenges, we propose AgriNex, a novel architecture that integrates Large Language Models (LLMs) with UAV-assisted IoT systems to transform smart agriculture operations. Unlike conventional methods that rely on raw data for immediate feedback, AgriNex leverages the semantic depth provided by LLMs to interpret data from diverse agriculture sensors, facilitating context-aware decision-making and dynamic resource management. By prioritizing critical data collection and optimizing energy consumption for both UAVs and sensors, AgriNex ensures timely and efficient responses to evolving agricultural conditions. It effectively captures the multi-dimensional and context-dependent nature of agricultural data, which is often missed by simpler machine learning models [1].

In smart agriculture, data importance is not static but influenced by factors such as seasonal growth requirements, spatial sensor distributions, and environmental conditions. Conventional methods fall short in dynamically prioritizing these data points, potentially missing time-sensitive information [2]. Semantic Criticality Index (SCI), another innovative feature of our AgriNex approach, solves these issues by quantifying data criticality based on crop-specific context and environmental changes, ensuring that UAV resources are focused on high-impact sensors and data collection areas. This adaptation is key for resource optimization in preci-

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sion agriculture, where response times directly affect crop health and energy conservation. To facilitate this adaptive approach, AgriNex introduces a Semantic-Guided Deep Q-Network (SG-DQN) algorithm, which uses the SCI metric to optimize agriculture sensor data collection scheduling and UAV action.

II. Related Works

The work [3] highlights the modernization of traditional agriculture through IoT paradigm. It applies automation and IoT technologies via smart GPS-based remote controlled robot to perform tasks like weeding, spraying, and moisture sensing. The paper [4] offers a precision agriculture concept: a comprehensive meta-review inspiring further research, innovation, and adoption. Recently, agricultural UAVs have gained significant academic interest, playing a key role in precision farming with high-resolution imagery and real-time monitoring [5]. Studies in [6] provides a comprehensive survey of UAV applications in agriculture, including soil analysis, crop monitoring, and weed identification. Research work [7] reviews trends and applications of leading technologies related to agricultural UAVs, control technologies, equipment, and development. Authors in [8] provide an in-depth survey of UAV applications in PA, categorizing them into a) UAV-based applications for tracking, b) UAV-based applications for spraying, and c) Multi-UAV applications. However, they note a shortage of research on multi-UAV applications in agriculture despite the significant potential benefits. LLMs, initially developed for natural language processing, have recently been applied in optimized environmental sensing and agriculture [9]. These models excel at processing large datasets to identify patterns and generate predictions, enhancing semantic understanding in IoT networks and improving data interpretation in agriculture. As energy efficiency remains a key concern for UAV and IoT deployments, the ability of LLMs to optimize data collection and transmission strategies can be especially valuable for sustainable agricultural practices.

III. Smart Agriculture Network Model

This paper presents a novel UAV-assisted two-tier smart agriculture network model illustrated in Fig. 1, comprising agriculture sensors, UAVs and cloud servers for UAV-assisted sensor data collection and routing in agricultural environments, where agriculture sensors communicate through UAVs due to their limited transmission range and cost-efficient design in unlicensed frequency bands. Therefore, agriculture sensors are divided into clusters based on criteria such as spatial distribution where each cluster is managed by at least one UAV, responsible for collecting sensor data and relaying data to cloud servers. Accordingly, the first-tier networks are multi-point-to-point (MP2P) networks, dynamically established by assigning UAVs to sensor clusters for data collection. The second-tier network is a dynamic mesh

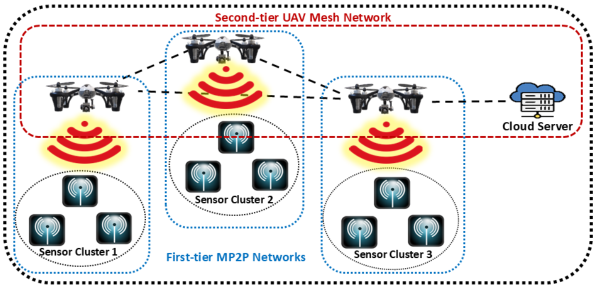

Fig. 1. Two-tier smart agriculture network model

network formed by UAVs and cloud servers for sensor data and analysis information routing. The routing in UAV mesh network can use existing routing schemes in works such as [10] and hence, this work focuses on sensor data collection in the first-tier networks and LLM-based data processing, and decision-making. We consider a sensor cluster comprising N sensors, denoted as $\mathscr{C} = \{1, 2, \ldots, N\}$. Without loss of generality, we assume one UAV u is assigned for the cluster $\mathscr{C}$ to collect data. During a data collection period, the UAV u with capacity constraint U_u^{cap} in communication and storage can only collect data from a subset of the sensors in cluster $\mathscr{C}$ at any time t and thus, needs to make a decision regarding whether or not to serve a sensor n. We denote $U_{u,n,t}$ as action taken by UAV u for the sensor n at time t with $U_{u,n,t} = 1$ indicating sensor n being served and $U_{u,n,t} = 0$ indicating otherwise. The UAV capacity constraint implies that at any time t, $U_{u,n,t}$ must satisfy the constraint $\sum_{n \in \mathscr{C}} U_{u,n,t} \leq U_u^{\text{cap}}$.

IV. LLM-Powered Semantic Labeling of Agricultural Data

Traditional time-series analysis methods often fail to capture the complex, multi-dimensional nature of crop health monitoring [11]. Therefore, AgriNex introduces a novel semantic labeling framework that fundamentally transforms agricultural sensor data interpretation through the novel application of LLMs. The LLMs have shown exceptional performance in natural language processing tasks, and we extend these capabilities to smart agriculture, where sensor data readings, environmental conditions, and crop health indicators form the “language”.

Data Acquisition: UAVs collect sensor data according to data criticality, historical patterns, time elapsed since the last data collection, and environmental triggers that indicate changes in conditions. The raw dataset is formalized as $\mathscr{D} = \{d_1^r, d_2^r, \ldots, d_{|\mathscr{D}|}^r\}$, where each raw data reading d_i^r is a tuple (s_i, t_i, c_i, v_i), s_i is the sensor identifier with location coordinates, t_i is the timestamp, c_i is the cluster identifier, and v_i is a vector of critical agricultural parameters (Nitrogen, Temperature, Humidity, pH, Rainfall, etc.)

Preprocessing: The raw sensor data undergoes preprocessing through a multi-stage pipeline defined as

$$d_i = \text{Norm}(\text{Clean}(v_i)) \circ \text{Context}(s_i, t_i, c_i) \tag{1}$$

where outlier filtering removes anomalies, normalization scales values to a [-1, 1] range, and contextual augmentation incorporates crop-specific thresholds, growth stage, seasonal adjustments, and spatial context.

Semantic Labeling: AgriNex employs fine-tuned Bidirectional Encoder Representations from Transformers (BERT) based models [12] for semantic labeling. Semantic labeling begins with a labeled subset $\mathscr{D}_{\text{labeled}}$, where data is categorized into multiple criticality levels using agricultural expert knowledge. For simplicity, we illustrate our methodology using four criticality levels: "normal," "abnormal," "critical," and "urgent." While these categories may appear simple, their application requires dynamic classifications that adapt to crop-specific and environmental contexts. The BERT model parameters θ are optimized to predict the semantic label y_i for the preprocessed sensor data reading d_i by minimizing the classification loss, as shown below

$$\mathscr{L} = -\frac{1}{N}\sum_{i=1}^{N}\sum_{c\in D_{\text{labeled}}} \mathbb{1}\{y_i = c\}\log P(y_i = c|d_i;\theta), \quad (2)$$

where $\mathbb{1}\{y_i = c\}$ is an indicator function that equals 1 if $y_i = c$ and 0 otherwise, and $P(y_i = c|d_i;\theta)$ is the predicted probability that the data d_i belongs to class c given the collection of all trainable parameters in our fine-tuned BERT model as θ. Techniques like cross-entropy loss and Adam optimization can be employed to fine-tune θ effectively.

Data Level SCI: The Data Level SCI evaluates the criticality of individual sensor readings by measuring their deviation from predefined thresholds, contextualized by crop-specific and environmental factors. To model Data-Level SCI, we use a two-step process that leverages semantic embeddings, context layers, and an attention mechanism.

(1) Semantic Embedding: Each sensor data reading d_i is mapped to a high-dimensional space $E(y_i)$ using corresponding semantic label y_i as

$$E(y_i) = \text{LLM}_{\text{embed}}(y_i, \text{context}), \quad (3)$$

where the term context includes three layers of context: temporal trends from recent historical data, spatial correlations from neighboring sensors, and domain knowledge like crop stage. Hence, the embedding provides feature alignment and contextual enrichment. For example, during critical growth stages, the embedding process prioritizes parameters like temperature and humidity, which may have greater relevance than stable factors such as soil pH.

(2) Contextual Relevance and Attention: To accurately compute the Data-Level SCI, it is essential to incorporate various contextual factors that influence the importance of each sensor reading. Our SCI framework integrates a contextual relevance mechanism inspired by Transformer models, enabling dynamic assessment of each sensor's data based on its relative importance. This mechanism allows the AgriNex system to prioritize high-impact areas and optimize decision-making and resource allocation in smart farming. For a sensor data reading d_i with label y_i, the data-level SCI is computed as

$$I_{\text{SCI}}(y_i) = \text{Attention}(E(y_i), \mathbf{S}_{\text{net}}, \mathbf{H}_{\text{perf}}), \quad (4)$$

where $\mathbf{S}_{\text{net}}$ represents the network state vector and $\mathbf{H}_{\text{perf}}$ represents the historical performance vector. The attention mechanism is defined as

$$\text{Attention}(E(y_i), \mathbf{S}_{\text{net}}, \mathbf{H}_{\text{perf}}) = \sum_k \alpha_k \text{Value}_k, \quad (5)$$

where Value_k represents contextually relevant information derived from $\mathbf{S}_{\text{net}}$ and $\mathbf{H}_{\text{perf}}$, while α_k denotes the attention weight for each contextual component k. The attention weights α_k are computed as

$$\alpha_k = \frac{\exp(\text{Score}(E(y_i), \mathbf{K}_k))}{\sum_l \exp(\text{Score}(E(y_i), \mathbf{K}_l))}, \quad (6)$$

with the score function measuring the relevance of the semantic embedding to the network state and historical performance keys, given by

$$\text{Score}(E(y_i), \mathbf{K}_k) = E(y_i)^\top \mathbf{W}\mathbf{K}_k, \quad (7)$$

where $\mathbf{W}$ is a learnable weight matrix that projects the semantic embedding $E(y_i)$ into the same dimensional space as the keys $\mathbf{K}_k$.

Sensor Level SCI: For a sensor n, we propose an innovative Sensor-Level SCI $\tilde{I}_{\text{SCI}}(n,t)$ that incorporates both the sensor's baseline importance and a Redundancy Index $(\text{RI}(n,t))$ to account for overlapping data. Let $\{d_{n,t}^i\}$ and $D_{\text{h},t}$ be new readings and historical dataset, respectively. Sensor n ultimately yields M_n labels $\{y_{n,1}, y_{n,2}, \ldots, y_{n,M_n}\}$ over a time interval $[T_s, T_e]$. To obtain an overall measure of how important sensor n is, these Data-Level SCIs are averaged to form a baseline Sensor-Level SCI as

$$I_{\text{SCI}}(n,t) = \frac{1}{M_n}\sum_{i=1}^{M_n} I_{\text{SCI}}\big(y_{n,i}\big). \quad (8)$$

A high $I_{\text{SCI}}(n,t)$ indicates that sensor n routinely generates data of substantial significance. However, importance alone does not address overlapping or redundant information. To capture such redundancy, we define a Redundancy Index $\text{RI}(n,t) \in [0,1]$ as

$$\text{RI}(n,t) = \frac{\sum_{i=1}^{M_n} \max_{j\in\{1,\ldots,M_\text{h}\}} \text{sim}\big(d_{n,t}^i, d_{\text{h},t}^j\big)}{|D_{n,t}|}, \quad (9)$$

where $\{d_{n,t}^1, \ldots, d_{n,t}^{M_n}\}$ is the new data from sensor n, $\{d_{\text{h},t}^1, \ldots, d_{\text{h},t}^{M_\text{h}}\}$ is a relevant historical dataset, $|D_{n,t}|$ is the total new-data volume, normalizing the overlap score and $\text{sim}(\cdot)$ is often a Gaussian kernel for measuring data overlap such that

$$\text{sim}(d_{n,t}^i, d_{\text{h},t}^j) = \exp\left(-\frac{\|d_{n,t}^i - d_{\text{h},t}^j\|^2}{2\sigma^2}\right). \quad (10)$$

Finally, we unify sensor's average importance with its novelty by defining the novelty-adjusted Sensor-Level SCI as

$$\tilde{I}_{\text{SCI}}(n,t) = I_{\text{SCI}}(n,t)\big(1 - \text{RI}(n,t)\big). \quad (11)$$

A sensor that is important yet produces highly overlapping data will have its effective SCI penalized, discouraging further resource expenditure on repeated information. Instead, a sensor with both high importance and low redundancy retains a strong $\tilde{I}_{\mathrm{SCI}}(n,t)$, indicating that it should receive higher priority in the data collection process.

By defining $\tilde{I}_{\mathrm{SCI}}(n,t)$ as the definitive sensor-level metric, the system directs its wake-ups and transmissions toward sensors whose data is not only semantically critical but also novel, maximizing useful information gained while minimizing duplication in UAV-assisted agricultural IoT networks. Our LLM-based semantic labeling is described in Algorithm 1. This approach facilitates adaptive and efficient

Algorithm 1: Semantic Labeling with SCI

Input: Preprocessed dataset $\mathscr{D}$, labeled subset $\mathscr{D}_{\text{labeled}}$, fine-tuned LLM model θ
Output: Semantic labels $\mathscr{Y}$, SCI scores $\{I_{\mathrm{SCI}}, \tilde{I}_{\mathrm{SCI}}\}$

```
Fine-tune θ using D_labeled to classify data into
  criticality levels (normal, critical, etc.);
foreach data point x_i ∈ D do
    Predict semantic label y_i: y_i ← arg max P(y|x_i; θ);
    Compute Data-Level SCI:
      I_SCI(y_i) = Attention(E(y_i), S_net, H_perf);
foreach sensor n do
    Compute baseline SCI: I_SCI(n) = (1/M_n) Σ I_SCI(y_{i,n});
    Compute novelty-adjusted SCI:
      Ĩ_SCI(n) = I_SCI(n)(1 − RI(n));
return Y, {I_SCI, Ĩ_SCI}
```

data gathering in agricultural IoT systems by leveraging LLM-derived semantic labels to create a high-level semantic map, allowing for more intelligent decision-making and resource allocation in smart farming.

V. Adaptive Energy Consumption Models

This section presents our context-adaptive energy models.

A. UAV Energy Consumption Model

For the UAV u, its energy consumption can be broadly divided into flight energy and communication energy, modeled as $E_{\mathrm{u}} = E^{u}_{\text{flight}} + E^{u}_{\text{comm}}$.

Flight Energy Consumption: Our work considers UAV flight energy during the sensor data collection period. For the UAV u, its flight energy E^{u}_{flight} is given by

$$E^{u}_{\text{flight}} = \int_{T_c}^{T_c + D(I_{\mathrm{SCI}}(Y(t)))} P_{\text{nav}}(v_u(t))\,dt, \tag{12}$$

where $Y(t)$ is the vector of all distinguished semantic data labels, $P_{\text{nav}}(v(t))$ represents the power required for navigation, T_c and D are data collection starting time and duration.

Communication Energy Consumption: The communication energy of u is modeled as $E^{u}_{\text{comm}} = E^{u}_{\text{tx}} + E^{u}_{\text{rx}}$, where

$$E^{u}_{\text{tx}} = \sum_{n=1}^{N} \int_{0}^{\tau_{\mathrm{u},n}} P_{\text{tx},u}\left(|h_{n,u}(t)|^2\right) dt \tag{13}$$

is control signal transmission energy and

$$E^{u}_{\text{rx}} = \sum_{n=1}^{N} \int_{0}^{\tau_n} P_{\text{rx},u}(t)\,dt \tag{14}$$

covers sensor data reception energy, $P_{\text{tx},u}$ and $P_{\text{rx},u}$ are transmission and reception power levels, respectively, $\tau_{\mathrm{u},n}$ and τ_n are the durations of transmission to sensor n and reception from sensor n, respectively, and $|h_{n,u}(t)|$ denotes the Rician fading channel coefficient between n and u.

B. Sensor Energy Consumption Model

In our UAV-assisted agricultural IoT system, the process of data collection for a sensor n begins when the UAV u sends a wake-up signal to sensor n. Upon receiving this signal, the sensor n transitions from its sleep or listen mode to active wake-up mode, ready to perform its sensing and data transmission tasks. This dynamic interaction between UAV and sensors forms the foundation of our energy-efficient monitoring system.

The energy consumption of the agriculture sensors is a critical factor that directly impacts the efficiency and sustainability of the agricultural IoT network. For a sensor n, its energy consumption can be broadly categorized into sensing energy, transmission energy and sleep energy, modeled as $E_{\mathrm{n}} = E^{\mathrm{n}}_{\text{sensing}} + E^{\mathrm{n}}_{\text{tx}} + E^{\mathrm{n}}_{\text{sleep}}$.

Sensing Energy Consumption: For a sensor n, let t_n, δ_n and τ_n be wake-up time, wake-up duration and data transmission duration, respectively, within a data collection period. Thus, the active sensing interval is $\left[t_n, t_n + \delta_n - \tau_n\right]$ with sensing operation governed by two gating functions:

(i) Sensor-Level Gating Function (α): The gating function $\alpha\left(\tilde{I}_{\mathrm{SCI}}(n,t)\right)$ determines whether sensor n is activated for sensing based on the novelty-adjusted Sensor-Level SCI:

$$\alpha\left(\tilde{I}_{\mathrm{SCI}}(n,t)\right) = \begin{cases} 1, & \tilde{I}_{\mathrm{SCI}}(n,t) \geq \Theta_{\text{sensor}}, \\ 0, & \text{otherwise}, \end{cases} \tag{15}$$

where Θ_{sensor} is the threshold for sensor activation, ensuring that only sensors with sufficiently novel or critical contributions are activated.

(ii) Data-Level Gating Function (β): The data-level gating function $\beta\left(I_{\mathrm{SCI}}(y_i)\right)$ filters individual data readings based on the Data-Level SCI:

$$\beta\left(I_{\mathrm{SCI}}(y_i)\right) = \begin{cases} 1, & I_{\mathrm{SCI}}(y_i) \geq \Theta_{\text{data}}, \\ 0, & \text{otherwise}, \end{cases} \tag{16}$$

where Θ_{data} ensures that only critical data readings exceeding this threshold are considered for further processing or transmission. The sensor consumes energy for sensing only if both the sensor-level and data-level gating conditions are satisfied. The sensing energy is given by

$$E^{n}_{\text{sensing}} = \int_{t_n}^{t_n + \delta_n - \tau_n} \alpha\left(\tilde{I}_{\mathrm{SCI}}(n,t)\right) \beta\left(I_{\mathrm{SCI}}(y_i)\right) P_{\mathrm{s},n}(t)\,dt, \tag{17}$$

where $P_{\mathrm{s},n}(t)$ is the time-varying sensing power of sensor n.

Transmission Energy Consumption: Once the sensor collects data, it transmits only the critical data readings identified by the Data-Level SCI threshold (Θ_{data}). The transmission energy is modeled as

$$E_{\text{tx}}^{n} = \int_{t_n+\delta_n-\tau_n}^{t_n+\delta_n} \beta\left(\tilde{I}_{\text{SCI}}(n,t)\right) P_{\text{tx},n}(t)\, |h_{n,u}(t)|^2\, dt. \tag{18}$$

Sleep Energy Consumption: The energy consumed during sleep mode reflects minimal power usage while maintaining sensor readiness. The sleep energy is modeled as

$$E_{\text{sleep}}^{\text{n}} = \int_{T_s}^{T_e} P_{\text{sleep},n}(t)\chi_{\text{sleep},n}(t)\, dt, \tag{19}$$

where $P_{\text{sleep},n}(t)$ is the time-varying sleep power of sensor n, $\chi_{\text{sleep},n}(t)$ is a binary function that defines the sleep periods of sensor n, given by

$$\chi_{\text{sleep},n}(t) = \begin{cases} 0, & \text{if } t_n \le t < t_n + \delta_n \\ 1, & \text{otherwise} \end{cases} \tag{20}$$

VI. SCI Based Agriculture Sensor Data Collection Scheduling

The sensor data collection occurs between time T_s and T_e, with the collection process starting at T_c for duration D, during which sensors actively gather data while remaining in sleep or sensing mode outside this collection window. At the end of the current collection period, the next data collection period duration D is dynamically adjusted to respond to the varying needs of the system such that

$$D = D_c + \Delta D, \tag{21}$$

where D_c is the duration of the current data collection period and ΔD is calculated to adjust the collection period duration based on the semantic criticality of the data gathered during the current period and to balance the necessity of comprehensive data capture against the imperative of resource conservation. The adjustment factor ΔD is given by

$$\Delta D = D \times (f(I_{\text{SCI}}(Y)) - 1), \tag{22}$$

where Y is the vector of all distinguished semantic data labels and the function $f(I_{\text{SCI}}(Y))$ integrates the semantic criticality indices derived from all sensor data. Using four criticality levels $Y = \{y_{\text{normal}}, y_{\text{abnormal}}, y_{\text{critical}}, y_{\text{urgent}}\}$ as an example, function f can be defined as

$$\begin{aligned} f(I_{SCI}(Y)) = \max\{ & 1 + \gamma_{\text{normal}} \text{avg}\left(I_{\text{SCI}}(y_{\text{normal}})\right), \\ & \exp\left(\gamma_{\text{abnormal}}\left(1 - \max\left(I_{\text{SCI}}(y_{\text{abnormal}})\right)\right)\right), \\ & 1 + \gamma_{\text{critical}}\left(1 - \left[\max\left(I_{\text{SCI}}(y_{\text{critical}})\right)\right]^2\right), \\ & 1 + \frac{\gamma_{\text{urgent}}}{1 + \max\left(I_{\text{SCI}}(y_{\text{urgent}})\right)}\}, \end{aligned} \tag{23}$$

where the scaling factors $\gamma_{\text{normal}}, \gamma_{\text{abnormal}}, \gamma_{\text{critical}}$, and γ_{urgent} are parameters used to modulate the impact of different semantic criticality levels on scheduling duration.

The adjustments on the operational window of sensor n are computed as follows, aligning with UAV availability and ensuring efficient data collection such that

$$\begin{aligned} t_n &= T_c + \Delta t_n, \\ \delta_n &= \delta_n + \Delta\delta_n, \\ \tau_n &= \tau_n + \Delta\tau_n, \end{aligned} \tag{24}$$

where $\Delta t_n, \Delta\delta_n$ and $\Delta\tau_n$ are determined based on the sensor data's semantic criticality, ensuring that each sensor is active only when necessary and transmits the most relevant data.

We formulate the agriculture sensor data collection scheduling problem as an optimization problem that balances energy efficiency with effective scheduling. The primary objective is to minimize the total energy consumption while ensuring successful data transmission. The optimization problem is formally defined as

$$\begin{aligned} \underset{T_c, D, \hat{t}, \hat{d}, \hat{\tau}}{\text{minimize}} \quad & E_{\text{total}} - \omega_{\text{suc}} \sum_{n=1}^{N} P_{\text{success},n,u} \\ \text{subject to} \quad & \text{SNR}_{n,u} \ge \text{SNR}_{\text{threshold}}, \quad \forall n, \\ & 0 \le v_u \le v_{\max}, \\ & T_c \le t_n \le T_c + D - \delta_n, \quad \forall n, \\ & \tau_n \le \delta_n \le D - (t_n - T_c), \quad \forall n, \\ & \sum_{n \in \mathscr{C}} U_{u,n,t} \le U_u^{\text{cap}}, \quad \forall t, \end{aligned} \tag{25}$$

where $P_{\text{success},n,u}$ is the successful packet reception probability at UAV u from sensor n, $\hat{t}, \hat{\delta}, \hat{\tau}$ are vectors of t_n, δ_n, τ_n, respectively, v_u is the velocity of u to maintain the required signal-to-noise ratio (SNR) with sensors, ω_{suc} is a weighting factor to adjust the relative importance of successful data transmission compared to energy conservation, and $E_{\text{total}} = E_{\text{flight}}^{\text{u}} + E_{\text{comm}}^{\text{u}} + \sum_{n=1}^{N}(E_{\text{sensing}}^{\text{n}} + E_{\text{tx}}^{\text{n}} + E_{\text{sleep}}^{\text{n}})$ is total energy.

VII. Semantic-Guided Deep Q-Network (SG-DQN) Algorithm for Optimization Problem

We formulate the scheduling problem (25) as a Markov Decision Process (MDP) and introduce the SG-DQN for it.

State Space S: The state space at time t is defined as $S(t) = \{S_i(t), S_2(t), \cdots, S_N(t), v_u, T_c, D\}$ with $S_n(t) = \{s_n(t), E_n(t), \tilde{I}_{\text{SCI}}(n,t), t_n, \delta_n, \tau_n\}$ being state of the sensor n, where $s_n(t) \in \{\text{sense}, \text{transmit}, \text{sleep}\}$ denotes the operational state of the sensor n, $E_n(t) \in [0, E_{\max}]$ represents the remaining energy of the sensor n.

Action Space A : The action space at time t is defined as $A(t) = \{A_1(t), A_2(t), \cdots, A_N(t)\}$ with $A_n(t) = \{a_n(t) \mid a_n(t) \in \{\text{sense, transmit, sleep}\}, U_{u,n,t}\}$.

State Transition P : The state transition for sensor n is described as follows

$$s_n(t) = \begin{cases} \text{sleep}, & \text{if } T_s \le t < t_n \\ \text{sense}, & \text{if } t_n \le t < t_n + \delta_n - \tau_n \\ \text{transmit}, & \text{if } t_n + \delta_n - \tau_n \le t \le t_n + \delta_n \\ \text{sleep}, & \text{if } t_n + \delta_n \le t \le T_e \end{cases} \tag{26}$$

Reward Function with Penalties: The reward function $R(S(t), A(t))$ at time t is formulated as follows,

$$R(S(t), A(t)) = -E_{\text{total}}(t) - \sum_{i=1}^{5} \lambda_i \max(0, g_i(t)), \tag{27}$$

where the $g_i(t)$ functions are derived directly from the constraints in the optimization problem (25), and λ_i is a penalty coefficient for the i-th constraint, indicating the severity of the penalty for violating this constraint.

Algorithm 2: Training Phase of SG-DQN Algorithm

Input: State $S(t)$, Action $A(t)$, Learning rate η, Discount factor γ, SCI $\tilde{I}_{\text{SCI}}(y,t)$, Exploration rate ε, Crop and environment parameter ρ

Output: Optimal policy $\pi^*(S)$

Initialize Q-network with weights θ, target network with $\theta' = \theta$, and replay buffer $\mathscr{D}$;

for *each episode* $e = 1$ *to* E **do**

  Initialize state $S(0)$;

  for *each time step* $t = 1$ *to* T **do**

    Choose action $A(t)$ using:

$$A(t) = \begin{cases} \arg\max_A \left[Q(S(t), A; \theta) + \rho \tilde{I}_{\text{SCI}}(y,t) \right], \\ \quad \text{with probability } 1 - \varepsilon, \\ \text{random action}, \\ \quad \text{with probability } \varepsilon \end{cases}$$

    Execute $A(t)$, observe reward $R(S(t), A(t))$, and next state $S(t+1)$;

    Store $(S(t), A(t), R(S(t), A(t)), S(t+1))$ in $\mathscr{D}$;

    if *replay buffer is ready for sampling* **then**

      Sample mini-batch from $\mathscr{D}$;

      Compute target $y(t)$:

$$y(t) = R(t) + \gamma \max_{A'} Q(S(t+1), A'; \theta')$$

      Update θ by minimizing the loss function:

$$L(\theta) = \mathbb{E}\left[(y(t) - Q(S(t), A(t); \theta))^2 \right]$$

      Update target network $\theta' \leftarrow \theta$ every C steps;

  Decay ε and adjust ρ as needed;

return $\pi^*(S) = \arg\max_A Q(S, A; \theta)$

Objective: The objective is to find an optimal policy π^* that maximizes the expected cumulative discounted reward for all sensors and is shown as

$$\pi^* = \arg\max_{\pi} E\left[\sum_{t=0}^{\infty} \gamma_d^t R(S(t), A(t)) \right], \tag{28}$$

where $\gamma_d \in [0,1)$ is the discount factor at time t and our proposed SG-DQN approach is described in Algorithm 2.

VIII. Simulation Results and Discussions

We utilized a public dataset Kaggle agriculture [13] to evaluate the performance of our proposed smart agriculture technologies. Our simulation scenario involves one UAV and 20 sensors, with Round Robin, Threshold-Based, Greedy, Weighted Fair Queuing, Earliest Deadline First, and Least Laxity First algorithms serving as benchmarks.

The heatmap in Fig. 2 illustrates the predicted crop conditions based on pairwise combinations of agricultural features. Phosphorus, potassium, and temperature exhibit the strongest positive influence on crop conditions (0.0230 to 0.0360), with rainfall also having a moderate impact, especially when paired with these nutrients. In contrast,

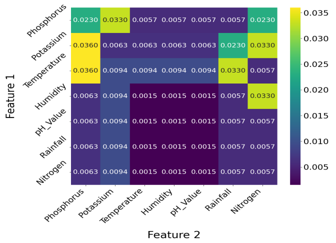

Fig. 2. Heatmap of Predicted Crop Condition

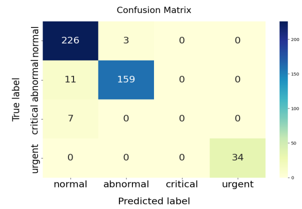

Fig. 3. Confusion Matrix for Data Criticality Classification

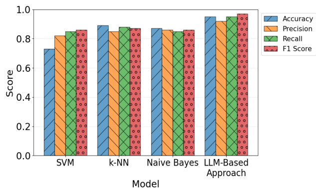

Fig. 4. Performance Comparison of Machine Learning Models

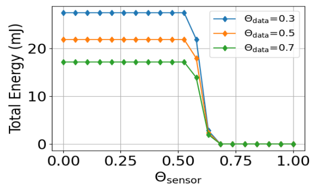

Fig. 5. Energy Consumption vs Sensor-Level SCI Threshold

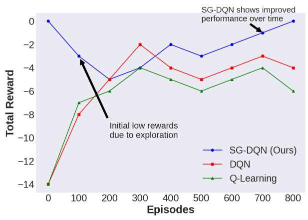

Fig. 6. Total Reward by SG-DQN, DQN and Q-Learning

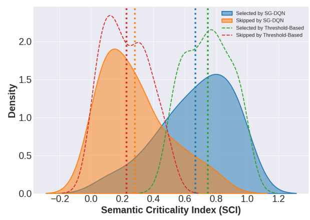

Fig. 7. SCI Distribution for Sensor Selection and Skipping

humidity, pH value, and nitrogen generally show lower predictive power (0.0015 to 0.0094). The confusion matrix in Fig. 3 shows high accuracy in classifying agricultural data, with near-perfect identification of routine and urgent conditions and minimal misclassification in critical cases.

Fig. 4 shows the superior performance of our LLM-based smart agriculture technologies across all metrics, with scores around 0.95 for accuracy, recall, and F1 score, and 0.92 for precision. This significant improvement over SVM, k-NN, and Naive Bayes highlights the effectiveness of integrating LLMs and semantic understanding into smart agricultural systems. Figure 5 depicts the relationship between total energy consumption and the sensor activation threshold (Θ_{sensor}) for three different data thresholds (Θ_{data}). For lower Θ_{sensor}, more sensors are activated, leading to higher energy consumption. As Θ_{sensor} increases, fewer sensors are activated, resulting in a sharp decline in total energy consumption. Beyond a critical Θ_{sensor} value, energy usage drops to nearly zero as no sensors are activated. Lower Θ_{data} values, such as 0.3, result in the transmission of more data, which increases energy consumption. Moreover, higher Θ_{data} values, such as 0.7, filter out moderate sensor readings, thereby reducing transmission energy costs.

Fig. 6 demonstrates the superior performance of our proposed SG-DQN algorithm compared to traditional DQN and Q-Learning algorithms in UAV-assisted smart agriculture systems. After initial exploration, SG-DQN consistently achieves higher total rewards, culminating in a 66% improvement over DQN and 71% over Q-Learning in the final episode. Fig. 7 illustrates the SCI distribution for sensors selected and skipped by our SG-DQN compared to a threshold-based method. Our SG-DQN demonstrates superior discrimination, preferentially selecting sensors with higher SCI values (blue area, peak around 0.8) while skipping lower-value sensors (orange area, peak around 0.15).

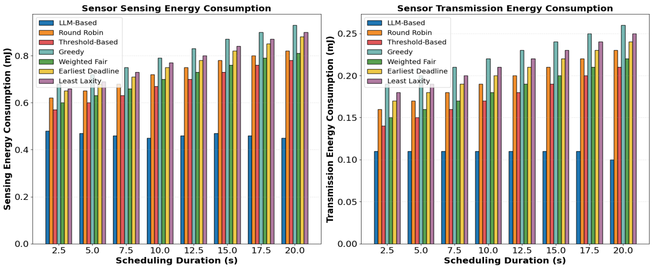

Fig. 8. Sensor Energy Consumption Comparison by Different Scheduling Algorithms

Fig. 8 shows the energy consumption comparison for different scheduling algorithms. Our LLM-based scheduling method consistently demonstrates the lowest energy consumption for sensing and transmission across all scheduling durations. At 20 seconds, the LLM-based method saves up to 50% in sensing and 60% in transmission compared to the next best-performing algorithm.

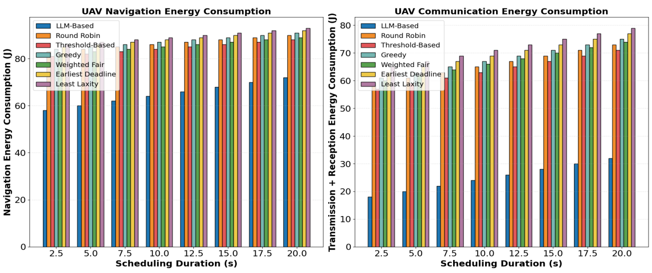

Fig. 9. UAV Energy Consumption Comparison by Different Scheduling Algorithms

Fig. 9 shows UAV energy consumption. For navigation, our LLM-based scheduling consumes up to 58% less energy than other algorithms at longer durations (e.g., 72J vs. 90J+ at 20s). For communication, our LLM-based scheduling uses up to 66% less energy (e.g., 32J vs. 80J+ at 20s). These significant improvements highlight the effectiveness of integrating semantic understanding from LLM with physical energy management in agricultural environments.

IX. Conclusion

In this paper, we proposed AgriNex, a novel UAV-assisted smart agricultural system that integrates UAVs to enable energy-efficient agricultural sensor data collection and data processing. Our approach leverages the power of LLMs to generate a semantic map that identifies sensors of varying importance, enabling adaptive adjustments of signal propagation and energy consumption parameters. We introduced novel energy consumption models tailored for UAVs and agricultural sensors, addressing the critical need for energy efficiency in large-scale farm operations. The agricultural sensor data collection problem was formulated as an optimization challenge to minimize overall system energy consumption. To tackle this, we developed a reinforcement learning-based optimization algorithm that learns optimal data collection intervals and agriculture sensor wake-up interval adjustment policies based on the semantic map and the system's historical performance. Our extensive evaluation using public agricultural datasets demonstrates AgriNex's superior performance, showing significant improvements in both energy efficiency and data classification accuracy compared to conventional approaches, underlining the potential of LLMs and IoT in agricultural practices.

References

[1] N. Islam, M. M. Rashid, F. Pasandideh, B. Ray, S. Moore, and R. Kadel, "A review of applications and communication technologies for internet of things (iot) and unmanned aerial vehicle (uav) based sustainable smart farming," *Sustainability*, vol. 13, no. 4, 2021.

[2] N. Chamara, M. D. Islam, G. F. Bai, Y. Shi, and Y. Ge, "Ag-IoT for crop and environment monitoring: Past, present, and future," *Agricultural systems*, vol. 203, p. 103497, 2022.

[3] S. B. Dhal, S. Mahanta, J. Gumero, N. O'Sullivan, M. Soetan, J. Louis, K. C. Gadepally, S. Mahanta, J. Lusher, and S. Kalafatis, "An IoT-based data-driven real-time monitoring system for control of heavy metals to ensure optimal lettuce growth in hydroponic set-ups," *Sensors*, vol. 23, no. 1, p. 451, 2023.

[4] M. R. B. Júnior, B. R. de Almeida Moreira, V. dos Santos Carreira *et al.*, "Precision agriculture in the united states: A comprehensive meta-review inspiring further research, innovation, and adoption," *Computers and Electronics in Agriculture*, vol. 221, p. 108993, 2024.

[5] S. Zhang, H. Feng, S. Han, Z. Shi, H. Xu, Y. Liu, H. Feng, C. Zhou, and J. Yue, "Monitoring of soybean maturity using uav remote sensing and deep learning," *Agriculture*, vol. 13, no. 1, p. 110, 2022.

[6] A. Rant, A. Chaudhary, N. K. Sinha, M. Mohanty, and R. S. Chaudhary, *Drone: The Green Tetchnology for Future Agriculture*. Harit Dhara Magazine, 2019.

[7] J. Kim, S. Kim, C. Ju, and H. Son, "Unmanned Aerial Vehicles in Agriculture: A Review of Perspective of Platform, Control, and Applications," *IEEE Access*, 2019.

[8] M. Raj, H. N B, S. Gupta, M. Atiquzzaman, O. Rawlley, and L. Goel, "Leveraging Precision Agriculture Techniques using UAVs and Emerging Disruptive Technologies," *Energy Nexus*, vol. 14, 2024.

[9] J. Roberts, T. Lüddecke, R. Sheikh, K. Han, and S. Albanie, "Charting new territories: Exploring the geographic and geospatial capabilities of multimodal llms," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2024, pp. 554–563.

[10] Z. Wang, H. Yao, T. Mai, Z. Xiong, X. Wu, D. Wu, and S. Guo, "Learning to Routing in UAV Swarm Network: A Multi-agent Reinforcement Learning Approach," *IEEE Transactions on Vehicular Technology*, vol. 72, no. 5, pp. 6611–6624, 2023.

[11] M. Arsenovic, M. Karanovic, S. Sladojevic, A. Anderla, and D. Stefanovic, "Solving current limitations of deep learning based approaches for plant disease detection," *Symmetry*, vol. 11, no. 7, 2019.

[12] J. Devlin, M.-W. Chang, K. Lee, and K. N. Toutanova, "BERT: Pre-training of deep bidirectional transformers for language understanding," in *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, 2019.

[13] "Crop Recommendation Dataset," https://www.kaggle.com/datasets/atharvaingle/crop-recommendation-dataset, 2020.