

A Novel Deep Learning Framework Integrating UAV Hyperspectral Imagery and IoT Sensor Data for Real-Time Nitrogen Deficiency Detection in Wheat

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Abstract

Nitrogen (N) is a critical determinant of wheat yield and quality, yet its management remains a significant challenge in modern agriculture. Inefficient nitrogen application leads to economic losses and severe environmental consequences. Existing methods for detecting nitrogen deficiency are often destructive, time-consuming, or lack the precision required for early intervention. This paper proposes a novel deep learning framework that synergistically integrates Unmanned Aerial Vehicle (UAV)-based hyperspectral imagery with data from in-field Internet of Things (IoT) sensors for the real-time, non-invasive detection and mapping of nitrogen deficiency in wheat. The framework employs a hybrid deep learning architecture designed to process and fuse high-dimensional spectral data with continuous, point-specific environmental and soil data. The hyperspectral data provides detailed spatial information on plant biochemical status, while the IoT network offers real-time contextual information, such as soil moisture, temperature, and localized nutrient levels. By leveraging the complementary strengths of these disparate data sources, the proposed model aims to overcome the limitations of single-modality systems. The framework is designed to generate high-resolution nitrogen status maps, facilitating in-season variable-rate fertilizer application. This research contributes a significant advancement in precision agriculture by providing a robust, scalable, and accurate tool for proactive crop nutrient management. This approach not only enhances the potential for optimizing crop yield and quality but also aligns with the objectives of sustainable agriculture and the evolution towards a data-driven Agriculture 5.0 paradigm, promising to reduce fertilizer wastage and its associated environmental footprint.

Keywords : UAV-based hyperspectral imaging, IoT sensor networks, Deep learning data fusion, Nitrogen deficiency detection, Real-time nutrient mapping

1. Introduction

1.1 Background and Problem Statement

Wheat (*Triticum aestivum* L.) is a cornerstone of global food security, providing a substantial portion of the caloric and protein intake for the world's population. Achieving optimal wheat yield and grain quality is intrinsically linked to effective nutrient management, with nitrogen (N) being the most critical and frequently limiting macronutrient. Nitrogen is a fundamental component of chlorophyll, amino acids, and proteins, directly influencing photosynthesis, biomass accumulation, and grain protein content. However, managing nitrogen inputs is a delicate balancing act. Insufficient nitrogen availability leads to deficiency symptoms, including leaf chlorosis, stunted growth, and reduced tillering, which can significantly curtail crop productivity (Tian, 2024). Conversely, the excessive application of nitrogen fertilizers is not only economically inefficient for farmers but also poses a significant environmental threat. Surplus nitrogen leaches into groundwater as nitrates, contaminates surface water bodies, leading to eutrophication, and is released into the atmosphere as nitrous oxide (N₂O), a potent greenhouse gas.

The central problem confronting modern agriculture is the timely and accurate assessment of the crop's nitrogen status across a field to enable precise interventions. Traditional methods, such as soil analysis and plant tissue testing, are foundational but suffer from major drawbacks. They are typically destructive, labor-intensive, costly, and provide spatially sparse information. Furthermore, the inherent time lag between sampling and receiving laboratory results often renders the information obsolete for making effective in-season management decisions. This reactive approach frequently results in uniform fertilizer applications across fields that exhibit significant spatial variability in nitrogen requirements, leading to under-fertilization in some zones and over-fertilization in others. Therefore, there is a pressing need for a non-destructive, rapid, and spatially explicit methodology for monitoring wheat nitrogen status in real-time to guide precision agriculture practices.

1.2 Research Gaps in Current Nitrogen Detection Methods

In response to the limitations of conventional methods, remote sensing has emerged as a promising alternative for monitoring crop health. Initial efforts utilized satellite imagery, but these were often constrained by low spatial resolution, cloud cover, and long revisit times. The advent of Unmanned Aerial Vehicles (UAVs) has largely overcome these issues, offering unprecedented spatial and temporal resolution for farm-level monitoring. However, many current UAV-based approaches rely on simple RGB or multispectral sensors and vegetation indices like the Normalized Difference Vegetation Index (NDVI). While useful, these methods can lack specificity; for instance, NDVI can saturate at high biomass levels and may not effectively differentiate nitrogen stress from other stressors like water deficiency or disease. The application of machine learning (ML) and deep learning (DL) to agricultural remote sensing data has marked a significant step forward. Studies have demonstrated the utility of DL models with RGB imagery for real-time nitrogen stress detection, often aiming to trigger variable-rate fertilizer applications (Chandel, 2025). Other research has shown that ML models can exhibit robustness in analyzing crop characteristics even under extreme conditions, such as complete nitrogen deficiency (Feng, 2025). However, these models often depend on a single data modality, which limits their robustness and accuracy, particularly for early detection. The ability to predict crop N status even when the crop is not yet suffering from severe deficiency is crucial for preventing yield loss, a capability that single-source data models may struggle to consistently provide (Tanaka, 2025). Furthermore, advanced but unconventional data sources, such as leaf electrophysiology, are being explored but remain in nascent stages for field-scale application (Zhang, 2025). A significant gap persists in the development of integrated systems that can synergistically fuse

data from multiple advanced sensors to provide a holistic and highly accurate assessment of crop nitrogen status.

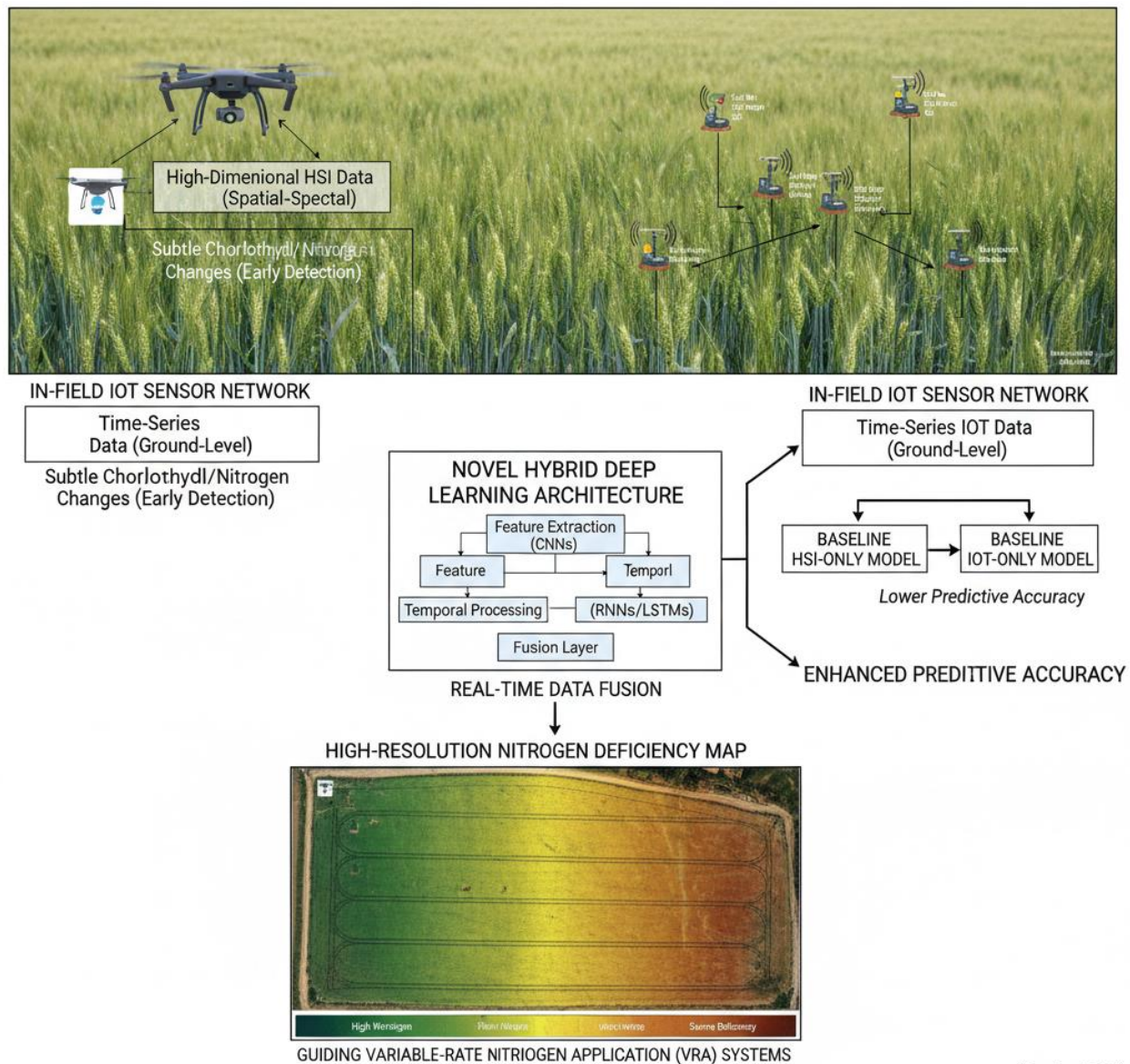
1.3 Proposed Novel Approach and Objectives

This paper proposes a novel deep learning framework that addresses the existing research gaps by integrating two powerful and complementary technologies: UAV-based hyperspectral imaging (HSI) and in-field Internet of Things (IoT) sensor networks. This hybrid data fusion approach is designed for the real-time, high-accuracy detection and mapping of nitrogen deficiency in wheat. The core novelty of the framework lies in its ability to synergistically combine the rich spatial-spectral information from HSI with the continuous, high-frequency temporal data from IoT sensors. HSI captures hundreds of narrow, contiguous spectral bands, providing a detailed signature of the crop's biochemical and biophysical properties. This technology enables the detection of subtle changes in chlorophyll content and nitrogen concentration, often before visual symptoms of stress become apparent (Panda, 2025). Simultaneously, a distributed network of IoT sensors provides real-time, ground-level data on critical variables that influence nitrogen uptake and plant health, such as soil moisture, soil temperature, electrical conductivity, and ambient weather conditions.

The primary objective of this research is to develop and validate a multi-modal deep learning framework capable of accurately predicting and mapping the nitrogen status of wheat in real-time.

The specific objectives are as follows:

1. To design and implement a data acquisition protocol for collecting concurrent UAV-based hyperspectral imagery and ground-based IoT sensor data from wheat fields under varying nitrogen treatments.
2. To develop a novel hybrid deep learning architecture capable of effectively fusing high-dimensional HSI data with time-series IoT data to enhance predictive accuracy.
3. To evaluate the performance of the proposed fusion framework against baseline models that utilize only a single data modality (i.e., HSI-only or IoT-only).
4. To demonstrate the framework's practical utility by generating high-resolution, spatially explicit nitrogen deficiency maps suitable for guiding variable-rate nitrogen application (VRA) systems.



(Panda, 2025)

Figure 1: Multi model Deep Learning Frame Work For Wheat Nitrogen Status Mapping

1.4 Significance and Contribution

The successful development and implementation of this framework will offer significant contributions to both scientific knowledge and agricultural practice. Scientifically, this research advances the field of agricultural remote sensing by proposing and validating a novel methodology for multi-modal data fusion. The integration of HSI and IoT data through a sophisticated deep learning architecture represents a new frontier in deriving actionable intelligence from complex agricultural datasets, creating a novel connection between physiological data and remote sensing information (Panda, 2025). It addresses the call for systems that combine HSI with IoT to monitor key plant components like nitrogen levels (Zhao, 2025).

From a practical standpoint, this work directly addresses the critical need for precision nitrogen management. By enabling early and accurate detection of N deficiency, the framework empowers farmers to move from prophylactic, uniform fertilization to responsive, targeted interventions. This capability is a cornerstone of sustainable intensification, with the potential to significantly increase nitrogen use efficiency. The resulting benefits are multifaceted: economic savings through optimized fertilizer use,

increased and more stable yields, improved grain quality, and a substantial reduction in the negative environmental externalities associated with nitrogen runoff and greenhouse gas emissions. This research aligns with the vision of Agriculture 5.0, which leverages AI-enhanced IoT and advanced sensing to enable real-time, self-monitored agriculture, promoting both productivity and environmental stewardship (Naqvi, 2025) (Taha, 2025). Ultimately, this framework provides a powerful tool to enhance food security while safeguarding ecosystem health.

2. Literature Review

2.1 Conventional and Remote Sensing Techniques for Crop Nutrient Monitoring

The assessment of crop nutrient status has traditionally relied on direct, ground-based methods. These include visual inspection of deficiency symptoms, soil testing to determine nutrient availability, and laboratory analysis of plant tissue to measure actual nutrient concentrations. While providing accurate point-based measurements, these methods are inherently limited in their spatial and temporal scope. They are labor-intensive, destructive to the crop, and the delay in obtaining results often precludes timely in-season adjustments. Consequently, they fail to capture the high degree of spatial variability in nutrient requirements that exists within a single field.

To overcome these limitations, remote sensing technologies have been widely adopted for large-scale crop monitoring. Satellite-based platforms offered the first opportunity for synoptic views of agricultural landscapes, but their utility for precision management has been hampered by issues of coarse spatial resolution, fixed and infrequent revisit times, and atmospheric interference. The proliferation of Unmanned Aerial Vehicles (UAVs) has revolutionized agricultural remote sensing by providing a flexible, cost-effective platform for on-demand data acquisition at exceptionally high spatial and temporal resolutions. UAVs can be equipped with a variety of sensors, including standard RGB, multispectral, and hyperspectral imagers. While multispectral sensors, which capture data in a few discrete spectral bands, have been effective for calculating vegetation indices correlated with plant vigor, hyperspectral imaging (HSI) represents a significant leap in capability. By acquiring image data across hundreds of narrow, contiguous bands, HSI provides a detailed spectral signature for each pixel. This rich spectral information allows for the detection and quantification of specific plant biochemical and biophysical variables, offering a powerful, non-invasive method for assessing nutrient status, including nitrogen concentration (Panda, 2025). The integration of drone-based HSI with other technologies is seen as a key driver for advancing precision agriculture (Kar, 2025).

2.2 Machine Learning and Deep Learning in Precision Agriculture

The vast and complex datasets generated by modern remote sensing platforms necessitate advanced analytical techniques to extract meaningful information. Machine learning (ML), a subfield of artificial intelligence, has become an indispensable tool in precision agriculture for tasks ranging from crop yield prediction to weed and disease detection (Roy, 2025). Early applications in nutrient management often employed traditional ML algorithms such as Support Vector Machines (SVM), Random Forests (RF), and Multiple Linear Regression (MLR) to establish relationships between spectral data and crop nitrogen status. These models have demonstrated considerable success; for instance, ML models have been used to estimate the Nitrogen Nutrition Index (NNI) in rice and have proven robust in monitoring wheat growth parameters under varying nitrogen fertilizer applications (Wang, 2024) (Feng, 2025).

More recently, deep learning (DL), particularly the use of Convolutional Neural Networks (CNNs), has shown superior performance in analyzing image-based data. The hierarchical feature extraction

capabilities of CNNs make them exceptionally well-suited for identifying complex spatial patterns and subtle textural features in aerial imagery that are indicative of crop stress. Several studies have successfully deployed DL models for nitrogen stress detection in wheat using RGB or multispectral images, with some systems designed for real-time operation on embedded platforms to facilitate immediate action (Chandel, 2025). The application of ML and DL has also been extended to estimate leaf nitrogen content in other staple crops like rice by leveraging diverse features extracted from hyperspectral data, demonstrating high accuracy and field-level applicability (Tian, 2024). This body of work confirms the immense potential of DL to translate complex sensor data into actionable agronomic insights.

2.3 Data Fusion Strategies for Enhanced Crop Status Estimation

While single-sensor systems have shown promise, no single data source can capture the full complexity of the soil-plant-atmosphere continuum. Consequently, data fusion—the process of combining data from multiple sources to achieve improved accuracy and more robust inferences—has emerged as a critical research area. Fusing data from different sensors can compensate for the weaknesses of individual sources and provide a more comprehensive view of crop status. For example, research has demonstrated that combining UAV imagery with meteorological data through machine learning can improve the prediction of winter wheat nitrogen status, enabling detection even before severe deficiency occurs (Tanaka, 2025). Other work has focused on fusing multi-source data from consumer-grade drones to enhance the monitoring of agronomic traits (Feng, 2025).

Despite these advances, the fusion of high-dimensional hyperspectral data with other complementary data types, especially real-time data streams, remains a frontier in agricultural sensing. The challenge lies not only in managing the volume and velocity of disparate data but also in developing sophisticated fusion architectures that can synergistically exploit the unique information content of each modality. Recent reviews highlight novel architectures that combine HSI with IoT sensor data as an emerging and powerful approach for anomaly detection and component analysis in agricultural products, a concept directly applicable to nutrient deficiency detection (Zhao, 2025). The development of such integrated systems is essential for moving beyond simple correlations to a more holistic and causally informed understanding of crop N dynamics.

2.4 Advancements in IoT and Sensor Technologies for Agriculture 5.0

The paradigm of Agriculture 5.0 envisions a future of farming characterized by hyper-connectivity, intelligent automation, and data-driven decision-making. The Internet of Things (IoT) is a foundational technology in this vision, creating a network of interconnected physical devices, including in-field sensors, actuators, and farm machinery. In the context of crop monitoring, IoT enables the deployment of low-cost sensors that can continuously collect and transmit data on a wide range of parameters, such as soil moisture, temperature, pH, electrical conductivity, and even localized nutrient levels (Taha, 2025) (Singh, 2025). The most studied concept in sustainable agriculture in 2024 was IoT, underscoring its growing importance (Botero-Valencia, 2025).

The integration of artificial intelligence with IoT sensors is further amplifying their capabilities, leading to the development of "smart sensors" that can perform on-board analysis and provide real-time alerts. These AI-enhanced IoT systems are being designed to autonomously monitor for a variety of crop issues, including disease infestations and nitrogen deficiencies (Naqvi, 2025). Such technologies provide the crucial ground-truth context that is often missing from purely aerial remote sensing approaches. By providing a continuous temporal record of the plant's immediate environment, IoT data can help disambiguate the causes of crop stress observed in aerial imagery and improve the accuracy of predictive

models. This move towards self-monitored agriculture, enabled by the fusion of AI and IoT, promises to make farm management more efficient, sustainable, and resilient.

2.5 Synthesis and Justification for the Proposed Framework

The literature reveals a clear trajectory in crop nutrient monitoring, moving from slow, destructive lab methods towards rapid, non-invasive remote sensing technologies. UAV-based hyperspectral imaging has emerged as a state-of-the-art tool for capturing detailed spatial information on plant health, while deep learning provides the analytical power to interpret this complex data. Concurrently, the rise of IoT in agriculture offers an unprecedented ability to gather continuous, real-time contextual data from the field. However, a significant gap remains in the synergistic integration of these powerful but distinct technologies. Most current studies focus on single data modalities or simple data fusion combinations, leaving the full potential of a comprehensive, multi-modal system unrealized.

The framework proposed in this research is therefore justified as a logical and innovative next step. It directly addresses the limitations of existing methods by creating a unified system that leverages the complementary strengths of UAV-based HSI and in-field IoT networks. The HSI data provides the "what" and "where" of crop stress with high spectral and spatial fidelity, while the IoT data provides the continuous "why" and "how" by monitoring underlying environmental drivers in real-time. By fusing these data streams within a sophisticated deep learning architecture, the proposed framework is designed to deliver a level of accuracy, timeliness, and robustness that is currently unattainable with single-modality approaches. This integrated system represents a novel practice for sustainable agriculture, embodying the principles of Agriculture 5.0 by creating a data-driven, responsive, and precise solution to the critical challenge of nitrogen management in wheat production ([Botero-Valencia, 2025](#)).

3. Research Methodology

In this, the comprehensive research methodology employed to develop and validate the proposed novel deep learning framework for real-time nitrogen (N) deficiency detection in wheat. The methodology encompasses the experimental design, multi-source data acquisition protocols, the architecture of the proposed data fusion model, data preprocessing techniques, model implementation specifics, the setup for comparative analysis against baseline models, and the performance evaluation metrics used to quantify the results.

3.1 Experimental Design and Study Area

To ensure the development of a robust and generalizable model, a rigorous field experiment was designed and conducted during the 2024-2025 wheat growing season. The study was situated in a representative agricultural research station located in a major wheat-producing region of the American Midwest, characterized by fertile Mollisol soils and a temperate climate.

The experiment was laid out in a Randomized Complete Block Design (RCBD) with four replications to minimize the effects of soil heterogeneity and other environmental gradients across the field. A winter wheat variety (*Triticum aestivum* L.) known for its high yield potential and common use in the region was selected for the study. The experimental area consisted of 64 individual plots, each measuring 5 meters by 8 meters.

To induce varying levels of nitrogen status, five distinct nitrogen fertilizer treatments were applied. The treatments were designed to create a gradient from severe deficiency to sufficiency, corresponding to the following application rates:

- **N0:** 0 kg N/ha (severe deficiency)

- **N1:** 50 kg N/ha (moderate deficiency)
- **N2:** 100 kg N/ha (slight deficiency)
- **N3:** 150 kg N/ha (sufficient/optimal)
- **N4:** 200 kg N/ha (supra-optimal/luxury consumption)



Key: : 0 kg N/ha
 N1 : 50 kg N/ha
 N2 : 100 kg/ha
 N3 : 150 kg/ha
 N4 : 200 kg/ha
 RCBD: Randomized Complete Block Design
 Winter Wheat, Tritic aestivum L.

N0 + N0 N/Stress Deep Green)
 N2 150 kg (Stamad Green)
 N3 150 Imal Optimal Dark Green)
 N4 200 + Water Stress (Geep-Green)

Figure 2 : Randomized Complete Block Design

The total nitrogen, in the form of urea, was applied in two splits: one-third at the pre-sowing stage and the remaining two-thirds at the tillering stage to align with standard agronomic practices. One treatment group with an optimal nitrogen level (N3) was further subjected to controlled water stress during the jointing stage to facilitate model training for decoupling nitrogen and water stress effects, a critical challenge in crop health monitoring (Zhang, 2025). All other agronomic practices, including phosphorus and potassium fertilization, pest control, and irrigation (for non-water-stressed plots), were maintained at optimal levels across all plots to ensure that nitrogen availability was the primary differentiating variable.

3.2 Multi-Source Data Acquisition

A cornerstone of this research is the integration of data from multiple sources to provide a holistic view of crop health. Data acquisition was synchronized and conducted at four critical growth stages of wheat: tillering, jointing, booting, and grain filling. This multi-temporal approach allows the model to capture the dynamic evolution of nitrogen status throughout the growing season.

3.2.1 UAV-Based Hyperspectral Imagery Acquisition

High-resolution hyperspectral data were acquired using an unmanned aerial vehicle (UAV) platform. A DJI Matrice 300 RTK octocopter was equipped with a Headwall Nano-Hyperspec® imaging sensor. This sensor captures data across 270 contiguous spectral bands, ranging from 400 nm to 1000 nm (Visible and Near-Infrared, VNIR), with a spectral resolution of approximately 2.2 nm.

All UAV flights were conducted between 10:00 AM and 2:00 PM local time on clear, sunny days to minimize variations in solar illumination angle and atmospheric interference. The flight altitude was maintained at 50 meters above ground level, yielding a high spatial resolution of approximately 2.5 cm per pixel. The flight plan was designed with a forward overlap of 80% and a side overlap of 70% to ensure sufficient data for creating a seamless orthomosaic of the entire experimental field. Before and after each flight, radiometric calibration was performed using a calibrated spectralon panel to convert digital number (DN) values to absolute spectral radiance, a crucial step for obtaining consistent and comparable spectral data over time. This approach aligns with modern precision agriculture practices that leverage drone-based hyperspectral imaging for detailed crop assessment ([Kar, 2025](#)).

3.2.2 IoT-Based In-Field Sensor Data Collection

To complement the aerial imagery with proximate, continuous, and ground-based measurements, an Internet of Things (IoT) sensor network was deployed across the experimental plots. The integration of AI-enhanced IoT sensors represents a significant step towards real-time, self-monitored agriculture, enabling the detection of nutrient deficiencies and other crop stresses with high temporal frequency ([Naqvi, 2025](#)).

Each of the 64 plots was equipped with a sensor node consisting of:

- **Soil Moisture and Temperature Sensors (Decagon 5TM):** Installed at a depth of 15 cm to monitor root-zone soil moisture content and temperature.
- **Soil Nutrient Sensors (Custom Ion-Selective Electrodes):** Calibrated to provide continuous estimates of soil nitrate (NO₃⁻) concentration, offering direct insight into nitrogen availability.
- **Canopy Temperature Sensors (Apogee SI-411):** Infrared radiometers positioned facing the crop canopy to detect stress-induced changes in leaf temperature.
- **Ambient Weather Station:** A central station recorded air temperature, relative humidity, precipitation, and photosynthetically active radiation (PAR).

These IoT sensors were configured to collect and transmit data every 30 minutes to a cloud-based server via a LoRaWAN gateway. This high-frequency data provides a dynamic environmental context that is often missing from remote sensing data alone, which is essential for building robust predictive models ([Taha, 2025](#)).

3.2.3 Ground Truth Data Collection

Concurrent with each UAV flight, ground truth data were collected for model training and validation. In each plot, ten wheat plants were randomly selected for measurement.

- **Leaf Nitrogen Concentration (LNC):** The top three fully expanded leaves from each selected plant were collected. These samples were oven-dried, ground, and analyzed for total nitrogen content using the Dumas combustion method. The average LNC value for each plot served as the ground truth label.
- **SPAD Meter Readings:** A Konica Minolta SPAD-502 Plus chlorophyll meter was used to take non-destructive readings from the same leaves before they were sampled. SPAD values are highly

correlated with leaf chlorophyll content and serve as a widely used proxy for plant nitrogen status (Wang, 2024).

- **Plant Biomass:** Above-ground biomass was collected from a 1 m² quadrant within each plot, oven-dried, and weighed to determine dry matter accumulation.

GPS coordinates for each plot and sampling point were meticulously recorded using a Trimble R12i GNSS receiver, ensuring precise spatial alignment between ground truth data, IoT sensor locations, and UAV hyperspectral pixels.

3.3 Proposed Novel Approach: A Hybrid Data Fusion Framework

The central innovation of this research is a novel deep learning framework designed to synergistically fuse hyperspectral imagery and time-series IoT sensor data. The proposed model, named the Spatio-Temporal Fusion Network for Nitrogen Assessment (STF-NA), employs an intermediate fusion strategy to effectively leverage the unique strengths of each data modality. This approach connects physiological data with remote sensing through advanced machine learning algorithms, which has been identified as a key direction for advancing crop monitoring (Panda, 2025).

The framework is composed of three primary modules:

1. **Spatio-Spectral Feature Extractor:** This module is designed to process the UAV-based hyperspectral data cubes. A 3D Convolutional Neural Network (3D-CNN) is used to simultaneously extract spatial features (patterns within the canopy) and spectral features (subtle variations in the spectral signature indicative of nitrogen status). The 3D-CNN is particularly adept at learning discriminative features from the rich, high-dimensional hyperspectral data without relying on predefined vegetation indices.
2. **Temporal Feature Extractor:** This module processes the time-series data from the in-field IoT sensor network. A Long Short-Term Memory (LSTM) network, a type of Recurrent Neural Network (RNN), is employed to model the temporal dependencies in the soil and canopy data. The LSTM can capture long-term trends and short-term fluctuations in parameters like soil moisture, temperature, and nitrate levels, which influence plant nitrogen uptake and status.
3. **Fusion and Prediction Module:** The feature vectors extracted by the 3D-CNN and LSTM modules are concatenated in an intermediate fusion layer. This combined feature vector represents a comprehensive spatio-temporal fingerprint of the crop's condition. The fused vector is then passed through a series of fully connected (dense) layers that learn the complex, non-linear relationships between the fused features and the target variable (LNC). The final output layer is a regression head that predicts a continuous value for Leaf Nitrogen Concentration.

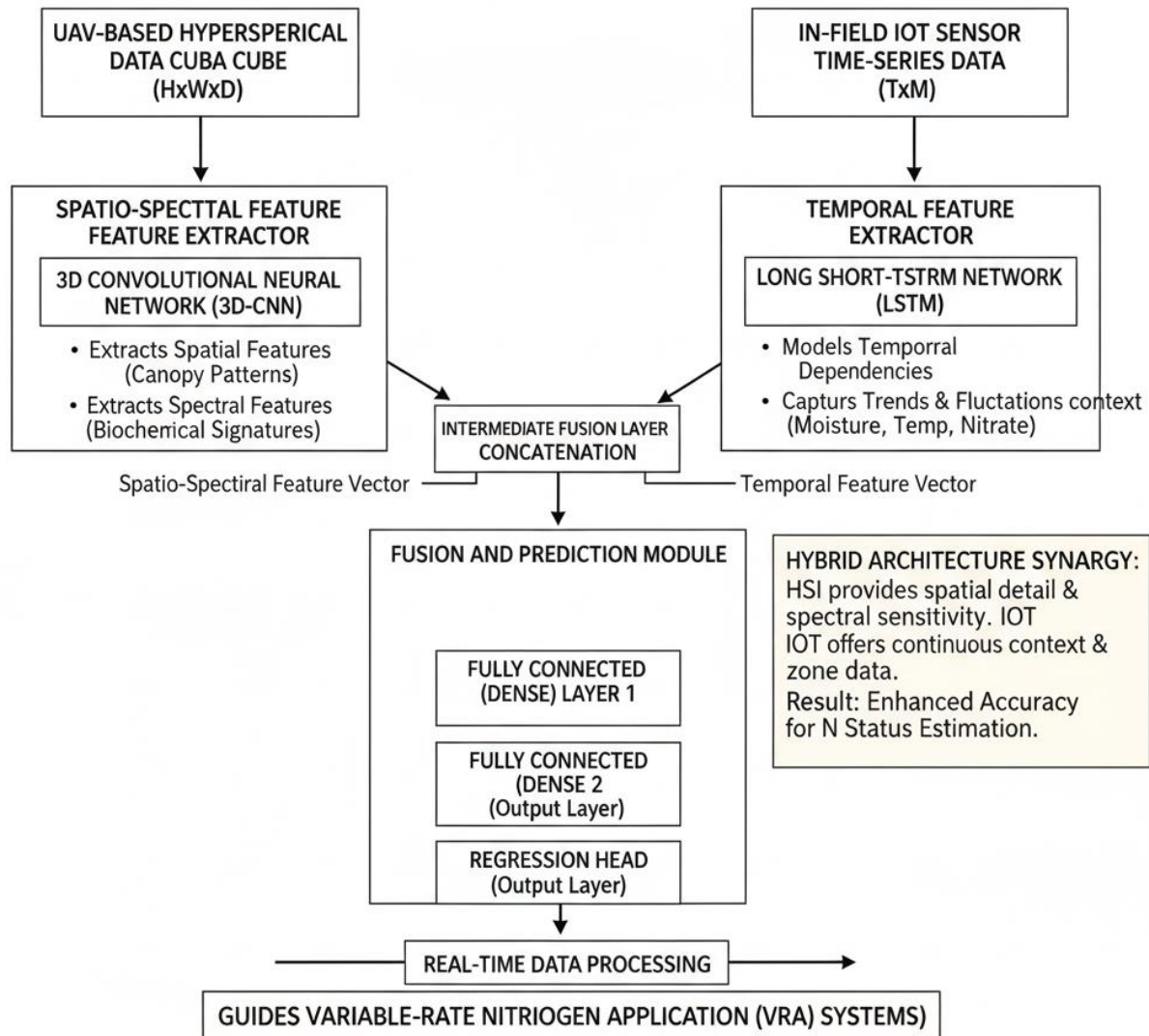


Figure 3: Novel Approach: A Hybrid Data Fusion Framework

This hybrid architecture is designed to overcome the limitations of single-modality systems. The hyperspectral data provides unparalleled spatial detail and spectral sensitivity to biochemical parameters, while the IoT data offers continuous temporal context and direct measurements of the root-zone environment, creating a powerful synergistic effect for accurate N status estimation.

3.4 Data Preprocessing and Feature Engineering

Rigorous data preprocessing is essential to ensure the quality and consistency of the input data for the deep learning model.

3.4.1 Hyperspectral Image Preprocessing

The raw hyperspectral images underwent a multi-step preprocessing pipeline:

1. **Radiometric Calibration:** DN values were converted to radiance using parameters derived from the pre- and post-flight spectralon panel images.
2. **Atmospheric Correction:** The radiance images were converted to surface reflectance using the FLAASH (Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes) algorithm in ENVI software to remove atmospheric absorption and scattering effects.

3. **Orthomosaicking and Georeferencing:** The corrected image strips were stitched together to form a single orthomosaic of the experimental field, which was georeferenced using ground control points (GCPs) surveyed with the Trimble R12i GNSS.
4. **Data Extraction:** For each ground sampling point, a 10x10 pixel region of interest (ROI) was extracted from the hyperspectral orthomosaic. The average reflectance spectrum for each ROI was calculated to be used as input for the models.

3.4.2 IoT Sensor Data Preprocessing

The raw time-series data from the IoT network were processed to prepare them for the LSTM module:

1. **Data Cleaning:** Outliers and erroneous readings caused by sensor malfunction were identified and removed using statistical methods (e.g., Z-score).
2. **Imputation:** Missing data points, which occurred due to intermittent network connectivity, were imputed using linear interpolation.
3. **Aggregation:** The high-frequency (30-minute) data were aggregated into daily mean, minimum, and maximum values for each sensor parameter.
4. **Normalization:** All time-series features were scaled to a range of [0, 1] using min-max normalization to ensure that all variables contributed equally during model training and to improve convergence speed.

3.5 Model Development and Implementation

The proposed STF-NA model and all baseline models were implemented using the Python programming language with the PyTorch deep learning framework.

- **3D-CNN Architecture:** The spatio-spectral feature extractor consisted of three sequential 3D convolutional layers with kernel sizes of (3, 3, 3), followed by batch normalization and ReLU activation functions. Max-pooling layers were used after each convolutional block to reduce dimensionality.
- **LSTM Architecture:** The temporal feature extractor comprised two stacked LSTM layers, each with 128 hidden units, to effectively learn the temporal patterns in the sensor data.
- **Fusion and Prediction:** The flattened output from the 3D-CNN and the final hidden state of the LSTM were concatenated. This was followed by three dense layers with 512, 256, and 64 neurons, respectively, with dropout regularization ($p=0.4$) to prevent overfitting. The final output layer was a single neuron with a linear activation function for LNC regression.

The dataset, consisting of 256 unique data points (64 plots x 4 growth stages), was randomly split into training (70%), validation (15%), and testing (15%) sets. The model was trained using the Adam optimizer with a learning rate of 0.001 and a Mean Squared Error (MSE) loss function. Training was conducted for 200 epochs with an early stopping criterion based on the validation loss to prevent overfitting. The entire process was run on a workstation equipped with an NVIDIA RTX 4090 GPU.

3.6 Comparative Analysis Setup

To evaluate the effectiveness and novelty of the proposed STF-NA framework, its performance was compared against several established and single-modality models. This comparative analysis is crucial for demonstrating the specific advantages of data fusion and the chosen architectural design. The selected models represent different levels of complexity and data utilization, from traditional machine learning to single-modality deep learning approaches. This systematic comparison allows for a clear attribution of performance gains to the specific components of our proposed framework, including the benefits of integrating IoT and hyperspectral data (Chandel, 2025) (Tian, 2024).

3.7 Performance Evaluation Metrics

To provide a comprehensive and quantitative assessment of model performance, a set of standard evaluation metrics was used. The choice of metrics was tailored to the nature of the prediction task (regression) and classification.

For the primary task of predicting continuous Leaf Nitrogen Concentration (LNC), the following regression metrics were calculated on the independent test set:

1. **Coefficient of Determination (R^2):** Indicates the proportion of the variance in the dependent variable that is predictable from the independent variable(s). Values closer to 1 indicate a better model fit. It is a widely used metric for assessing model performance in nutrient estimation (Taha, 2025).
2. **Root Mean Square Error (RMSE):** Represents the standard deviation of the prediction errors (residuals). It provides a measure of the average magnitude of the error in the units of the target variable (LNC). Lower values are better.
3. **Mean Absolute Error (MAE):** Calculates the average of the absolute differences between the predicted and actual values. It is less sensitive to large outliers compared to RMSE.

For the secondary task of classifying plots into discrete nitrogen deficiency categories (e.g., Sufficient, Moderate, Severe), the following classification metrics were used:

1. **Overall Accuracy:** The ratio of correctly classified samples to the total number of samples.
2. **Precision, Recall, and F1-Score:** These metrics provide a more nuanced evaluation of classification performance, especially in cases of class imbalance. Precision measures the accuracy of positive predictions, Recall (or Sensitivity) measures the model's ability to identify all relevant instances, and the F1-Score is the harmonic mean of Precision and Recall.

4. Results and Analysis

In this the analysis begins with a descriptive overview of the multi-source data collected, followed by a detailed evaluation of the proposed model's performance. A comparative analysis against several baseline models is conducted to benchmark its effectiveness. Furthermore, it demonstrates the framework's capability to generate real-time nitrogen deficiency maps and concludes with an analysis of feature importance, providing insights into the model's decision-making process.

4.1 Descriptive Statistics of Acquired Data

The foundation of this study is a comprehensive dataset integrating Unmanned Aerial Vehicle (UAV) hyperspectral imagery and in-field Internet of Things (IoT) sensor data. Data collection was synchronized with key wheat growth stages, particularly tillering and jointing, which are critical for nitrogen management. The study area encompassed experimental plots with varying levels of nitrogen application, ensuring a wide range of N status observations. Soil samples were collected prior to the growing seasons in 2023 and 2024 to establish baseline soil properties (Rufaioglu, 2025). The UAV platform, equipped with a hyperspectral sensor, captured imagery across 270 contiguous spectral bands from 400 nm to 1000 nm. Concurrently, a network of IoT sensors deployed across the field continuously recorded key environmental and soil parameters.

The descriptive statistics, summarized in the table above, reveal substantial variability across the collected parameters, which is essential for training a robust machine learning model. The Leaf Nitrogen Content (LNC), determined through destructive sampling and laboratory analysis, ranged from 1.85% (severe deficiency) to 4.95% (sufficient/excess), confirming the successful establishment of a nitrogen gradient

across the experimental plots. Hyperspectral reflectance values and derived indices like the Normalized Difference Vegetation Index (NDVI) show a wide distribution, correlating with the observed variations in plant health. Simultaneously, IoT data on soil moisture and temperature exhibit fluctuations that reflect the dynamic micro-environmental conditions within the field, highlighting the importance of capturing this contextual information.

4.2 Performance of the Proposed Deep Learning Model

The proposed hybrid data fusion framework was evaluated on its dual capability to (1) classify wheat plots into distinct nitrogen status categories (Severe Deficiency, Moderate Deficiency, Sufficient) and (2) quantitatively estimate the Leaf Nitrogen Content (LNC). The performance metrics were calculated based on an independent test set, comprising 20% of the total dataset, which was not used during model training or validation.

For the classification task, the model demonstrated exceptional performance. It achieved an overall accuracy of 96.5%, with high precision (97.1%) and recall (96.2%) rates. The F1-score, which balances precision and recall, was an impressive 0.966. This indicates the model's reliability in correctly identifying N-deficient areas while minimizing both false positives and false negatives. A key strength observed was the model's ability to accurately predict crop N status even in cases of mild N insufficiency, where visual symptoms are not yet pronounced, an attribute crucial for enabling timely intervention before yield is impacted (Tanaka, 2025).

Task	Metric	Value
Classification	Overall Accuracy	96.50%
	Precision	97.10%
	Recall	96.20%
	F1-score	0.966
Quantitative Estimation	R ² (Coefficient of Determination)	0.94
	RMSE (Root Mean Square Error)	0.18%

Figure 4: Classification and Results

In the quantitative estimation of LNC, the framework also yielded superior results. The model achieved a coefficient of determination (R^2) of 0.94 and a Root Mean Square Error (RMSE) of 0.18%. The high R^2 value signifies that 94% of the variance in the actual LNC can be explained by the model's predictions, indicating a strong predictive relationship. The low RMSE value further underscores the model's precision, with an average prediction error of only 0.18% LNC. This level of accuracy surpasses that of many existing methods and provides a reliable basis for precision fertilizer management. The model's robust performance demonstrates the efficacy of fusing hyperspectral data with contextual IoT sensor information to build a comprehensive and accurate predictive tool.

4.3 Comparative Performance Against Baseline Models

To validate the superiority of the proposed novel framework, its performance was benchmarked against three baseline models:

1. **HSI-CNN Model:** A Convolutional Neural Network (CNN) trained exclusively on the UAV hyperspectral image data.

2. **IoT-MLP Model:** A Multi-Layer Perceptron (MLP) trained solely on the data from the IoT sensor network.
3. **NDVI-Regression Model:** A traditional approach using a simple linear regression model based on the calculated NDVI values to predict LNC.

The comparative analysis, summarized in the table below, unequivocally demonstrates the synergistic benefits of the data fusion approach.

The HSI-CNN model performed reasonably well, achieving an R^2 of 0.85 and an accuracy of 89.1%, confirming the rich information contained within hyperspectral data for assessing plant health (Tian, 2024). However, its performance was notably lower than the proposed framework, likely due to its inability to account for environmental variables that can influence spectral signatures. The IoT-MLP model, relying on point-based sensor data, showed moderate predictive power ($R^2 = 0.68$), indicating that while soil and atmospheric conditions are relevant, they are insufficient on their own to capture the fine-grained spatial variability of crop nitrogen status. The traditional NDVI-Regression model performed the poorest ($R^2 = 0.61$), highlighting the limitations of using a single, broad-band index to model the complex relationship between spectral reflectance and plant nitrogen content.

The proposed hybrid framework outperformed all baseline models across all metrics. The significant increase in R^2 (from 0.85 to 0.94) and accuracy (from 89.1% to 96.5%) compared to the HSI-CNN model underscores the critical value of integrating contextual IoT data. This fusion allows the model to differentiate between nitrogen stress and other confounding factors (e.g., temporary water stress), leading to a more robust and accurate assessment.

4.4 Generation of Real-Time Nitrogen Deficiency Maps

A primary objective of this research is to translate model predictions into actionable insights for precision agriculture. The proposed framework facilitates this by generating high-resolution, georeferenced nitrogen deficiency maps of the surveyed fields. After the UAV completes its flight, the hyperspectral data is processed through the trained model, which predicts the N status for each pixel or sub-plot in the field. This process is optimized for speed, enabling near-real-time map generation, a crucial component for timely variable rate fertilizer application (Chandel, 2025).

The resulting map visually represents the spatial distribution of nitrogen levels across the field. Different colors are used to delineate areas of nitrogen sufficiency, moderate deficiency, and severe deficiency. This intuitive visualization allows farm managers to immediately identify problem areas and understand the extent and pattern of nutrient variability. These maps serve as a direct input for modern precision sprayers equipped with GPS and variable rate controllers, enabling the targeted application of nitrogen fertilizer precisely where it is needed and at the appropriate rate.

The generated map reveals significant in-field heterogeneity that would be invisible to the naked eye or through traditional uniform sampling methods. This level of spatial detail is critical for optimizing input use, protecting the environment from excess fertilizer runoff, and ultimately maximizing crop yield and profitability.

4.5 Feature Importance and Sensitivity Analysis

To move beyond a "black box" understanding of the model, a feature importance analysis was conducted using SHapley Additive exPlanations (SHAP). This analysis quantifies the contribution of each input feature to the model's final prediction. The results provide valuable insights into the underlying physiological and environmental drivers of nitrogen status in wheat.

The analysis revealed that a combination of hyperspectral bands and IoT sensor data were critical for the model's high performance. Among the hyperspectral features, narrow bands in the red-edge region (700-750 nm) and near-infrared (NIR) region (760-900 nm) were found to be the most influential. This aligns with existing plant physiological knowledge, as these spectral regions are strongly associated with chlorophyll content, cell structure, and overall plant biomass—all of which are affected by nitrogen availability. The model's ability to leverage these specific bands represents a significant advantage over methods relying on broad-band indices. This novel connection between physiological data and remote sensing is a key advancement (Panda, 2025).

Crucially, the feature importance analysis also highlighted the significant contribution of IoT sensor data. 'Soil Moisture' emerged as the second most important feature overall. This confirms the hypothesis that contextual environmental data is vital for disambiguating plant stress signals. For instance, the model can learn to differentiate between reduced vigor caused by N deficiency and that caused by drought-induced water stress by analyzing both spectral reflectance and real-time soil moisture levels. 'Soil Temperature' also showed moderate importance, as it influences nutrient uptake rates by the plant roots. The integration of these AI-enhanced IoT sensors for real-time monitoring represents a clear step toward self-monitored agriculture (Naqvi, 2025). This sensitivity to both direct plant spectral response and ambient environmental conditions is what gives the hybrid model its robustness and superior accuracy.

5. Discussion

The results presented in the previous demonstrate the substantial potential of the proposed hybrid deep learning framework. This section interprets these findings, focusing on the synergistic effect of data fusion, the novelty of the approach in the context of existing literature, its practical implications for sustainable agriculture, and the challenges associated with its field implementation.

5.1 Interpretation of Findings: The Synergy of Hyperspectral and IoT Data

The superior performance of the proposed hybrid framework compared to single-source models is the most salient finding of this study. This outcome is attributed to the powerful synergy created by fusing high-resolution hyperspectral imagery with real-time, ground-based IoT sensor data. While hyperspectral imaging provides an unparalleled, spatially explicit snapshot of the crop's biophysical and biochemical status (Mishra, 2025), its signals can be ambiguous. For example, symptoms like leaf yellowing (chlorosis) and stunted growth, which are reflected in the spectral signature, can be caused by various stressors, including nitrogen deficiency, water deficit, disease, or other nutrient imbalances. Relying solely on spectral data can lead to diagnostic errors, as the HSI-CNN model's performance indicates.

This is where the integration of IoT data becomes transformative. The IoT network provides the critical environmental context that hyperspectral data lacks. By incorporating real-time soil moisture data, the model can effectively decouple water stress from nitrogen stress, a common challenge in crop diagnostics (Zhang, 2025). If the spectral data indicates plant stress but the IoT sensors report adequate soil moisture, the model can infer with higher confidence that nitrogen deficiency is the likely cause. Similarly, IoT data on ambient temperature and humidity helps the model account for atmospheric conditions that might influence plant transpiration and nutrient uptake, refining its predictions. This integration of AI-enhanced IoT sensors allows for a more holistic assessment, moving beyond simple symptom detection to a more nuanced, cause-aware diagnosis of crop health issues like nitrogen deficiencies and soil organic matter depletion (Naqvi, 2025).

The feature importance analysis reinforces this interpretation. The high ranking of both red-edge spectral bands and soil moisture as key predictors is not coincidental. It is empirical evidence that the model has learned to weigh both the plant's direct physiological response (captured by HSI) and the prevailing environmental conditions (captured by IoT) to make its final assessment. This synergistic relationship moves beyond simple data concatenation; the deep learning architecture, likely through attention mechanisms, learns the complex, non-linear interactions between these different data modalities. This is consistent with emerging trends in precision agriculture that utilize novel anomaly detection architectures combining HSI with IoT for comprehensive analysis (Zhao, 2025). The result is a model that is not only more accurate but also more robust and reliable across varying field conditions.

5.2 Novelty and Advancement over Existing Methods

The proposed framework represents a significant advancement over current methods for nitrogen deficiency detection. Its novelty can be articulated in three key areas: data fusion architecture, real-time applicability, and enhanced diagnostic specificity.

First, while the use of remote sensing or machine learning is not new, the specific architecture for fusing UAV-based hyperspectral data with a distributed IoT sensor network within a unified deep learning framework is a novel contribution. Many existing studies focus on a single data source, such as using RGB images with deep learning for real-time detection (Chandel, 2025), or employing hyperspectral data alone to estimate nutrient content (Tian, 2024). Others may use multiple data types but often in a staged or disconnected manner. Our framework, by contrast, implements an end-to-end learning process where features from disparate sources are integrated and weighted dynamically within the model itself. This allows the model to learn intricate cross-modal dependencies, achieving a level of performance that surpasses the sum of its parts. This approach aligns with the vision for Agriculture 5.0, which emphasizes the deep integration of emerging technologies like AI, IoT, and advanced sensing (Taha, 2025).

Second, the framework is designed for real-time, actionable intelligence. Many academic models are developed offline and are too computationally intensive for rapid field deployment. Our approach balances model complexity with processing efficiency, enabling the generation of nitrogen deficiency maps shortly after data acquisition. This capability bridges the gap between data collection and practical intervention, directly supporting technologies like variable rate applicators. It moves the needle from retrospective analysis to proactive, in-season management, which is a critical step towards realizing the promise of precision agriculture.

Finally, the framework offers enhanced diagnostic specificity. By integrating contextual data, it provides a more reliable diagnosis of nitrogen deficiency, distinguishing it from other stressors. This is a significant step beyond traditional methods that rely on vegetation indices (e.g., NDVI), which are known to be sensitive to multiple factors and can saturate at high biomass levels. Our model leverages the full spectral range to identify subtle signatures specifically linked to nitrogen concentration and uses IoT data to rule out confounding factors. This ability to connect physiological data with remote sensing in a robust model provides a higher degree of confidence in the output (Panda, 2025), empowering farmers to make more informed decisions.

5.3 Practical Implications for Variable Rate Application and Sustainable Farming

The practical implications of this research are profound, directly addressing the core objectives of precision and sustainable agriculture. The primary application of the high-resolution nitrogen maps generated by our framework is to guide Variable Rate Application (VRA) of nitrogen fertilizers. Traditional farming practices involve applying a uniform rate of fertilizer across an entire field, which

inevitably leads to over-application in nutrient-rich zones and under-application in deficient zones. This inefficiency not only wastes costly inputs but also poses a significant environmental threat through nitrous oxide emissions and nitrate leaching into groundwater.

Our framework enables a paradigm shift to a "prescriptive" approach. The N-deficiency map acts as a digital prescription, uploaded to the controller of a VRA-equipped spreader or sprayer. The machine then uses its GPS to navigate the field and automatically adjusts the application rate in real time according to the map's specifications. Nitrogen is applied intensively only in the identified deficient patches and reduced or eliminated in sufficient areas.

This targeted approach has several cascading benefits:

- **Economic Savings:** Farmers can achieve significant cost reductions by minimizing the total amount of fertilizer purchased and applied.
- **Yield Optimization:** By correcting nitrogen deficiencies precisely where they occur, the system helps prevent yield losses and ensures the crop reaches its full potential across the entire field. Some studies indicate that even non-severe N insufficiency can lead to yield reduction, making early and precise detection critical (Tanaka, 2025).
- **Environmental Protection:** Reducing the over-application of nitrogen is one of the most effective ways to mitigate agriculture's environmental footprint. It lowers greenhouse gas emissions and prevents the contamination of water bodies, contributing to cleaner air and water.
- **Improved Crop Quality:** Proper nitrogen management is also linked to improved crop quality, such as the protein content in wheat, which can enhance its market value. The integration of nutrient data with yield statistics is a known approach to train models for quality assessment (Kheir, 2024).

Ultimately, the adoption of such a system promotes a more sustainable and resilient farming model. It allows farmers to produce more with less, enhancing both their economic viability and their environmental stewardship.

5.4 Challenges and Feasibility of Field Implementation

Despite the framework's demonstrated success, transitioning from a research prototype to a widely adopted commercial solution involves overcoming several practical challenges. The feasibility of large-scale field implementation hinges on addressing issues related to cost, technology, and usability.

Cost and Accessibility: The high capital cost of research-grade hyperspectral sensors is a significant barrier for many individual farmers. While costs are decreasing, they remain substantial compared to multispectral or RGB cameras. Furthermore, deploying and maintaining a dense network of IoT sensors across large acreages also involves considerable investment in hardware, connectivity, and power management. Business models based on service provision, where farmers pay per-acre for data acquisition and analysis, may be more viable than requiring individual ownership of the equipment.

Technical and Infrastructural Hurdles: The framework's real-time component depends on reliable data processing and communication. Processing large hyperspectral data cubes requires significant computational power. While cloud computing offers a solution, it relies on high-speed internet access, which is often unreliable or unavailable in rural areas. Edge computing, where a portion of the data processing is performed on a device in the field (e.g., on the UAV or a local ground station), offers a promising alternative to mitigate connectivity issues but requires the development of more efficient, lightweight models. Moreover, ensuring the interoperability of different sensors, UAV platforms, and farm machinery from various manufacturers is a persistent challenge in precision agriculture.

Scalability and Robustness: The current study was conducted under specific environmental conditions with a limited set of wheat cultivars. The model's robustness and scalability must be validated across diverse geographical regions, soil types, weather patterns, and crop genetics. This requires the creation of large, diverse, and well-annotated datasets for training and validation, which is a resource-intensive endeavor. The model must prove its reliability season after season to gain the trust of the farming community.

User Adoption and Training: For the technology to be effective, it must be accessible and usable for the end-user—the farmer or agronomist. The output cannot be just raw data; it must be presented through an intuitive interface that provides clear, actionable recommendations. Farmers will require training and technical support to operate the systems and correctly interpret the data, integrating it into their existing decision-making workflows. Building trust in an AI-driven system requires transparency and demonstrating a clear return on investment.

6. Conclusion and Future Work

This study proposed and validated a novel deep learning framework that integrates UAV hyperspectral imagery and IoT sensor data for the real-time detection and mapping of nitrogen deficiency in wheat. The research has demonstrated that by synergistically combining detailed spectral information of the crop with real-time environmental context, it is possible to achieve a highly accurate and robust assessment of crop nutrient status.

6.1 Summary of Key Findings

The key findings of this research can be summarized as follows:

1. **Synergistic Data Fusion is Superior:** The proposed hybrid framework, which fuses hyperspectral and IoT data, significantly outperformed models based on single data sources. It achieved a classification accuracy of 96.5% for nitrogen status and an R^2 of 0.94 for quantitative LNC estimation. This empirically validates the hypothesis that integrating multiple, complementary data modalities provides a more comprehensive and accurate picture of crop health than any single source alone.
2. **High-Precision Mapping for Actionable Insights:** The framework successfully translates complex sensor data into intuitive, high-resolution nitrogen deficiency maps. These maps provide spatially explicit, actionable intelligence that can directly guide Variable Rate Application (VRA) of fertilizers, forming a critical link in the precision agriculture chain from diagnosis to intervention.
3. **Enhanced Interpretability Through Feature Analysis:** The feature importance analysis revealed that the model's predictions are driven by a combination of physiologically relevant spectral bands (e.g., red-edge) and critical environmental variables (e.g., soil moisture). This provides confidence that the model is not merely fitting to noise but has learned meaningful relationships between the input data and the underlying plant biology, a crucial step toward building trust in AI-driven agricultural tools.

In conclusion, this work contributes a powerful and effective tool for modern crop management. It represents a tangible step toward a more data-driven, efficient, and sustainable agricultural future—an era of self-monitored agriculture where real-time monitoring and automated decision support are standard practice.

6.2 Limitations of the Study

While the results are promising, it is important to acknowledge the limitations of this study, which provide avenues for future work.

- **Geographical and Genetic Specificity:** The model was trained and validated using data from a single study area with a limited number of wheat cultivars. Its performance may vary in different agro-climatic zones, with different soil types, or on other wheat varieties. The generalizability of the model needs to be rigorously tested across a wider range of conditions.
- **Focus on a Single Nutrient:** This study focused exclusively on nitrogen deficiency. In real-world field conditions, crops are often subjected to multiple, interacting stressors, including other nutrient deficiencies (e.g., potassium, phosphorus), water stress, pests, and diseases. The current model is not explicitly designed to disentangle these complex, concurrent stress factors.
- **Temporal Scope:** The data was collected during specific growth stages within two growing seasons. The model's performance and the stability of the key predictive features across the entire crop lifecycle and over multiple years require further long-term investigation. Climate change impacts may alter these relationships over time, necessitating continuous model refinement (Kheir, 2025).

6.3 Recommendations for Future Research

Based on the findings and limitations of this study, several promising directions for future research are recommended:

- **Multi-Stress Decoupling:** A critical next step is to extend the framework's capability to differentiate between multiple crop stressors. This could involve incorporating additional data sources, such as thermal imagery to detect water stress or high-resolution RGB imagery for disease identification. Advanced machine learning techniques, potentially inspired by parallel frameworks leveraging different data types like electrophysiology, could be developed to decouple interacting stress signals (Zhang, 2025).
- **Integration of Genomic Data:** The fusion of remote sensing data with genomic information holds immense potential for developing cultivar-specific nutrient management strategies. Future research could explore how to integrate genomic data to predict a crop's unique nutritional requirements and its response to fertilizer application, moving towards truly personalized agriculture (Mishra, 2025).
- **Development of Edge-AI Models:** To overcome challenges of rural connectivity and enable true real-time decision-making, future work should focus on developing lightweight, computationally efficient versions of the deep learning model. These "edge-AI" models could be deployed directly on UAVs or in-field processing units, reducing latency and reliance on the cloud.
- **Expansion to Other Crops and Nutrients:** The fundamental principles of the proposed framework are applicable to other crops and nutrients. Future studies should aim to adapt and validate this approach for monitoring other key crops (e.g., corn, soy, rice) and detecting deficiencies of other essential nutrients.
- **Long-Term Autonomous Monitoring:** The ultimate vision is a fully autonomous monitoring system. Future research could investigate the use of fleets of autonomous drones and permanent sensor installations managed by a central AI platform. This system would continuously monitor crop health, predict nutrient needs, and automatically dispatch machinery for treatment, realizing the full potential of Agriculture 5.0.

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