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Edge-Enabled Hybrid AI Framework for IoT-Based Crop Management and Irrigation Control

Dineshnath Gopinath[1*]

[1*]Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Guntur, Andhra Pradesh, INDIA

Corresponding Author E-mail ID: [1*]dinesh31mkl@gmail.com

Abstract

The intersection of the Internet of Things (IoT) and Artificial Intelligence (AI) technologies has ushered in a new era of modern agriculture, transforming it into a data-driven, intelligent, and sustainable system. This paper presents an IoT and AI-based Agriculture Framework (IAAF) that integrates heterogeneous sensor networks, drone-based imaging, and hybrid deep learning for real-time precision crop management. The IAAF implemented a CNN-LSTM network for time-dependent sensor data analysis, a transfer-learning-based CNN for multispectral image classification, and a multimodal attention-based fusion model that combines time-dependent and spatial information to facilitate integrative decision-making. Additionally, the framework utilized edge computing to minimize latency and reduce bandwidth consumption and cloud services to manage model retraining and facilitate long-term analysis. Experimental assessments using multi-season field datasets provide evidence that the IAAF framework achieved significantly better performance than baseline models, with a prediction accuracy of 98.78%, a precision of 98.43%, a recall of 98.51%, and an F1 score of 0.986. Accordingly, the IAAF proposes an innovative, intelligent, and resource-efficient model of real-time precision agriculture, promoting a sustainable vision of smart farming.

Keywords: *Internet of Things, AI-based Agriculture Framework, CNN, Smart Agriculture*

1. INTRODUCTION

Agriculture is undeniably vital for human survival and the global economy. Nevertheless, persistent climatic and socioeconomic changes are increasing the demand for efficiency, productivity and sustainability in agriculture Lou Y et al, (2024). Evidence suggests that conventional agricultural systems have traditionally relied on knowledge acquired through manual observation, historical experience, and tradition. These methods are often inaccurate, slow, and wasteful. As the world's population grows and demand for food increases, the global agricultural ecosystem is under pressure to produce more food with fewer resources. Due to this growth, we must cultivate more food using less land, fertiliser, and water. According to the Food and Agriculture Organization (FAO), agricultural productivity must increase by

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around 70% between 2009 and 2050 to meet the predicted global food demand Lupien J.R et al, (2025). This is because the industry is largely low-tech.

Internet of Things (IoT) and artificial intelligence (AI) technologies Jaiganesh S et al, (2017)offer significant opportunities to transform farming systems into smart, data-driven, automated practices that

protect the environment and support sustainable production De Abreu CL et al, (2022). This is due to the challenges and opportunities posed by a growing population, as well as the long-standing commitment to conductivity and sustainability. Smart farming utilizes IoT technology to transform the way farms are operated, enabling you to monitor and regulate soil conditions, crop growth, and weather or environmental factors in near real-time. This is made possible by sensor- and actuator-based systems that connect to communication networks. IoT-based sensors measure and report vital and complex elements important for farming, such as soil moisture, temperature, pH, humidity and nutrient levels Dhanalakshmi R et al, (2021). While we could previously observe these vital signs, they were only considered in terms of space. They lacked measurable standards, making it difficult to link them with the numerous critical tactics available to farmers. Simply collecting sensor data gives farmers several types of numerical data, but aggregating this data doesn't help them make decisions. However, these variables can provide a pathway to actionable insights by utilising IoT-collected data evaluated by AI algorithms to help farmers make informed decisions about agricultural management. Trends, forecasts and optimal strategy implementation guide this. Deep learning algorithms can determine what crops require, such as water, and notice when plants are becoming ill, as well as forecast when diseases will spread before they appear. Precision agriculture uses measurable intelligence from data rather than human judgment to determine the best time to act (e.g., watering, fertilising, or spraying pesticides). This can be achieved with sufficient data and cooperation Durai SK et al, (2022).

Although frameworks for reliable IoT-AI and AgTech solutions are still being developed, building these systems to work effectively in various agricultural settings remains challenging Holzinger A et al, (2024). Real-time dataset analysis and fusion are complex due to the variety of sensors and connection methods available. Although cloud analytical tools are constantly improving, they can also slow down operations in general. This poses a persistent threat to cloud infrastructures, particularly in remote or rural agricultural systems. We expect localised edge devices to use only a small amount of computing power and resources. Consequently, these models will not be able to leverage AI power in that area effectively Pal D et al, (2023). To achieve the optimal balance of computational efficiency, low latency, organisational deployment, and additional infrastructure, hybrid frameworks (model-validating frameworks) must be carefully designed, constructed, and implemented. This will enable scalable methodologies for enhancing real-time predictive inference in learning models.

Moreover, from a multimodal standpoint, several contemporary frameworks inadequately link extensive geographic and temporal (sensor-based) agricultural datasets for forecasting El Sakka M et al,

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(2025). This suggests that there are significant opportunities for improvement in the integration and application of frameworks in future smart agricultural contexts. Therefore, in the full smart farming framework, most models are not very useful for making predictions. Linking temporal data too often can cause delays and result in fragmented intelligence becoming less accurate. However, merging all the temporal IoT sensor data with spatial data from satellites or UAVs could improve our planning frameworks, making them more akin to smart agricultural ecosystems Choudhary V et al, (2025). This integration would lead to a more thorough predictive study of farming systems Shahab H et al, (2025).

This study defines the Internet of Things (IoT) and artificial intelligence (AI)-based Agriculture Framework (IAAF) as a hybrid deep learning system architecture that addresses three critical challenges in agriculture and food systems: automation, efficiency and precision. Our objective is to cultivate multilayered cognition within a neural architecture that analyses IoT sensors and time series cognitive data across all continuous dimensional boundaries using CNN-LSTM and a temporal encoder. Ultimately, this will be connected to a CNN-like UAV architecture and a transfer-learning encoder utilising multispectral sensor data to assess plant health or stress levels. Together, these two datasets would facilitate predictions based on diverse cognitive and environmental evidence. While minimising 'true false' outputs, explanations or constraints, these diverse outputs will invariably enhance reporting precision. Similar to edge functions, which are evaluated based on resilience and edges, they will yield stable and responsive outputs depending on the environment and the pursuit of equilibrium in scheduling.

The next layer of our system's decision support output suggests a series of equitable societal analyses and actions. For example, when plants are under stress or when precipitation is anticipated, the system can autonomously determine the necessary quantity of water or fertiliser to supply to the farm, or how to regulate water usage. There may be a feature for an edge-cloud collaboration layer in the decision support section. Conversely, cloud processing would enable processes and/or constraints to occur without latency or iterations. This would provide a retraining event that evaluates all previous models over time without requiring full loads. Any pertinent asset or subjective factor designated as 'latency- and time-sensitive' would be processed at the periphery. Themes were integrated annually across all farms through the use of loading streams. We expect the layers and chapters we have examined to evolve into authentic models once reactivity, size and energy economics are factored in. Furthermore, these models will facilitate more flexible communication if required and may also preserve private areas (such as lakes) amidst the array of responsive and supportive technologies. Clouds will retain previous data regarding agricultural site locations.

2. LITERATURE SURVEY

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The authors Babar AZ et al, (2024)explore the transformative potential of the Internet of Everything (IoE) in agriculture in conjunction with traditional IoT, utilising specialised sub-negotiable technologies such as molecular communication, the Internet of Fungi (IoF), the Internet of Nano Things (IoNT) and the Internet of Bio-Nano Things (IoBNT). They have also outlined an extensive evaluation of the potential benefits of other IoE technologies within the context of 6G, blockchain and machine learning frameworks, which could help to manage finite resources, predict disease outbreaks and monitor the agricultural ecosystem, moving towards precision agriculture that adds value. The study examined the progress of the Internet of Everything (IoE) and its exceptional concepts, as well as the value-added aspects of agriculture in terms of efficiency and renewed resilience. This builds on previous work that primarily focused on the Internet of Things (IoT) and its associated advancements in molecular and biological agriculture.

This study Lu J et al, (2017) demonstrated how autonomous in-field wheat disease diagnosis based on deep learning could incorporate minimally supervised learning through deep multiple instance learning, using elements of disease differentiation through classification, as well as the ability to pinpoint affected regions in an image accurately. The only annotation performed was at image level, using real-world scenarios to assess photos. To evaluate our methods, we created a new labelled dataset of in-field wheat disease photos—the Wheat Disease Database 2017 (WDD2017). We evaluated our methods using 5-fold cross-validation on the WDD2017 dataset. Methods using the VGG-FCN-VD16 system achieved an average recognition accuracy of 97.95%, while a similar method, VGG-FCN-S, achieved an average recognition accuracy of 95.12% on the WDD2017 dataset. These methods surpassed two baseline CNN models utilising VGG-CNN-VD16 and VGG-CNN-S, achieving average recognition accuracies of 93.27% and 73.00%, respectively. These results suggest that the new method achieves suitable parameter counts, comparable to a standard CNN architecture, and forms disease maps with similar accuracy while demonstrating a superior threshold in terms of average recognition accuracy.

A deep neural network (DNN) and several sophisticated approaches were used to model agricultural problems and the repeatability of tasks in prediction Khaki S et al, (2019). The DNN exhibited excellent predictive power on the validation dataset, outperforming modelling with anticipated meteorological data, with an RMSE of 50% of the standard deviation and 12% of the mean yield. Had the weather data been more accurate, the RMSE would have been less than 11% of the mean yield and 46% of the standard deviation. The DNN's feature selection method reduced the dimensionality of the input feature space more effectively than the method that maintained the anticipated accuracy. Furthermore, the simulation results demonstrated the superiority of the DNN model over simpler methods such as regression trees, Lasso, and shallow neural networks. Additionally, environmental influences were found to have a greater impact on agricultural productivity than genetic inheritance conditions.

Another alternative could be designing a deep learning model, specifically for monitoring the stress levels of plants in agricultural settings, called Retina-UNet-Ag Butte S et al, (2021). The Retina-UNet structure, which is based on a previously tuned deep-learning architecture, is effective because it is still

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part of an FFPN and provides a low-level semantic representation mapping as linkages throughout the design. A Parrot Sequoia camera was used to capture images of the field, establishing a complete dataset of manually labelled border boxes that captured both stressed and healthy plant areas. Next, the study examined the model's ability to differentiate between stressed and healthy plants in ground images from the field. The model achieved an average Dice Score Coefficient (DSC) of 0.74. This concept clearly outperforms state-of-the-art deep learning configurations. The study utilises and assesses three-dimensional aerial photography with respect to potato production in order to monitor developments and represent the new concept of detecting and measuring plant stress levels.

This work Albanese A et al, (2021) illustrates an adaptive embedded system for detecting insect infestations in fruit fields. The intended method detects insects by using common traps that are configured to capture a photograph of the insects' reaction to pheromones. Neural accelerators and low-power sensor technologies are used to process the information. Three separate classification models were combined to create machine algorithms that indicate the intended functionality of the embedded platform. For instance, it was anticipated that the system would use a long-lasting battery.

The article Talaat FM et al, (2023) presents a new precision agricultural device called the Crop Yield Prediction Algorithm (CYPA), which is based on the Internet of Things. Crop yield models are generally useful for understanding how pests, diseases, drought and a limited supply of fertiliser may each reduce yield during the cropping cycle, and for understanding crop yield as a management unit. A wealth of data on plants, weather, soils and technologies is available, and related databases provide open access to this data for research purposes. CYPA can help farmers and the government to predict the annual food production based on weather conditions, agricultural practices, pesticide use and other environmental factors.

The authors of Jiang D et al, (2025) designed a multimodal IoT agricultural data analytics application called Farm-LightSeek, combining edge computing with large language models (LLMs). The sensor technology enables the access and compilation of real-time agricultural data from various sources, such as maps, weather reports, and images. Model enhancement is performed in the cloud and illness diagnosis and cross-modal reasoning are performed at the edge nodes. Rather than providing a plan of action, it orchestrates the plan through bossy tendencies, inducing prescriptive actions. As a result of being supported by IoT and LLM technologies, Farm-LightSeek includes three features: a closed perception-decision-action loop for agriculture; cross-modal adaptive monitoring; and a novel LLM design that enhances speed, efficiency and overall performance. When provided with additional computing power, Farm-LightSeek continues to improve on mission-critical agricultural tasks; this was proven during testing using two real-world datasets. This research presents collaborative outcomes for combining IoT and LLMs in real-time, intelligent agricultural contexts.

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3. METHODOLOGY

Farmers can collect data and use it to make decisions throughout the agricultural life cycle by using the Internet of Things (IoT) and the Artificial Intelligence-based Agriculture Framework (IAAF). This is made possible through trusted data integration and predictive analytics from flexible sensors. This means that tools, data and outcomes can be obtained in real time at various levels of the system. The Perception Layer of the IoT collects real-time data on plants and the environment, such as temperature, humidity, soil moisture, nutrient concentration and crop/plant health, via sensors. Unmanned aerial vehicles (UAVs) also gather data from several wavebands for this purpose. LPWAN technologies such as LoRaWAN, NB-IoT, and ZigBee allow the Network Layer to facilitate communication between devices in a reliable, consistent, and energy-efficient way over long distances, enabling the remote connection of devices that would otherwise be inaccessible. The peripheral-AI layer enables prototype devices such as the Raspberry Pi and the Jetson Nano to perform low-latency pre-processing, accurate inference and feature extraction. This improves system performance and enables AI systems to operate without a centralised cloud framework. The Cloud Intelligence Layer collects data from a wide range of sources, fully analyses it and retrains AI models using historical data. It also allows stakeholders to communicate via an easy-to-use interface. This is intended to support farmers, agronomists and decision-makers. The multi-tier interface will provide greater efficiency in farming by automating the prediction of crop yields, counting insects, and providing smart irrigation. These innovations make farming more sustainable by using fewer resources and increasing productivity and efficiency.

3.1 Data Acquisition and Preprocessing

The proposed agri-food system could provide AI support for monitoring and collecting important soil and environmental data, such as pH levels, temperature, inventory, light intensity and nutrient levels. Some of the sites carrying out the testing will have Internet of Things sensors. UAVs could take aerial and multispectral images of the canopy for analysis. These images could then be analysed to extract photophysiological specifications (e.g. NDVI and EVI) that indicate the overall health of the crop and rates of photosynthesis. Peripheral gateways will transmit data measured by the sensors and UAVs to a central hub every five minutes. This reduces processing time and resource consumption. It takes considerable time and care to ensure that the data measured by UAVs or sensors for AI metrics is accurate and consistent. The Savitzky–Golay smoothing filter eliminates noise from time-series data while maintaining informative characteristics. K-nearest neighbour interpolation maintains temporal continuity by filling in gaps in the time series data. Min-max scaling allows every integer representation to contribute equally to model training. We also applied Contrast Limited Adaptive Histogram Equalization (CLAHE) to aerial photographs to optimise plant textures under various lighting conditions. There could be many more descriptors. Together, our analyses of these two pre-treatment techniques demonstrate that evaluating these changes could reduce bias noise and improve AI-driven analytics. These analyses can provide farmers with precise information to help them make the best decisions and farm more effectively

3.2 Hybrid Deep Learning Model

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The proposed hybrid deep learning architecture uses sensory temporal data streams and aerial photographs to develop an intelligent model for supporting decisions and making predictions in precision agriculture. This version's strength lies in its multimodality, since UAV imaging generates considerable spatiotemporal data on phenotypic markers. Each modality has its own stream of sensor data designed to provide a near-continuous, semi-fine-grained picture of micro-environmental processes over time. The proposed methodology will identify temporal variations in data collected at canopy level and below. This should enable more accurate characterisation of crop health, water use and detrimental events.

Sensor readings over time exhibit non-linear temporal dependency and cross-correlation across attributes (e.g., soil moisture and temperature are co-factors affecting evapotranspiration). Therefore, to account for such relationships, the temporal encoder uses a Convolutional LSTM architecture. Convolutional filters in CNNs are used to extract local feature patterns, while LSTM cells are used to learn long-term dependencies and temporal evolution. Let $X_{t-k:t} \in R^{k \times d}$ denote a window of d-dimensional sensor inputs over k time steps. The temporal representation h_t is computed as:

$$h_t = \mathrm{LSTM}\big(\mathrm{Conv1D}(X_{t-k:t})\big)$$

The convolutional layer improves noise tolerance and the recognition of local trends, while the recurrent cell maintains historical memory to appropriately predict soil moisture m and irrigation need(s) r. In other words, the encoder minimizes the mean-squared error between the target agronomic predictions and the actual observations.

The transfer-learning-based CNN used on multispectral drone imagery captures spatial and spectral cues related to crop health. The pretrained backbone (ResNet-50 or EfficientNet) generalizes visual features from aerial imagery data, including leaf color differences, patterns arising from pests, and stress-induced discolorations. For example, let denote the CLAHE-enhanced image at time (t); dimensionally, the feature extraction component can be described as:

$$v_t = \mathrm{GAP}\big(f_\theta(I_t)\big)$$

where f_θ denotes convolutional transformations parameterized with weights θ and GAP (global average pooling), which compress the spatial maps of features into a concise descriptor vt∈p. This

descriptor condenses various phenotypic information types that are critical for identifying disease and changes in vigor. The CNN is fine-tuned with a softmax cross-entropy objective to classify disease categories or health indices.

The fusion layer, or mechanism to merge temporal (sensor) and visual (CNN) temporal context representations, is (or consequently, could be) achieved through an attention-gating mechanism that

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conditions the more important modality depending on what the environmental context dictates. Fusing the two representations using the gated attention mechanism can also ensure robustness when sensor streams are noisy or missing.

$$z_t = \alpha_t h_t + (1 - \alpha_t) v_t$$

$$\alpha_t = \sigma(W[h_t || v_t])$$

The fused representation zt ultimately provides both temporal evolution and spatial context, which it feeds into a multilayer perceptron to produce appropriate action variables (e.g., irrigation volume, nutrient dosage, disease probability). The objective function is then a composite of regression and cross-entropy classification loss:

$$L_{total} = L_{reg} + \lambda L_{cls}$$

3.3 Decision Support and Automation

The agricultural framework, driven by the Internet of Things (IoT) and artificial intelligence (AI), aims to utilise smart, automated decision-making to convert input data from multiple sources into farming-related decisions and actions. By incorporating predictive analytics into farming processes, this technology facilitates the transition from sensor data and informatics analysis to AI modelling and real-world outcomes. The decision support system (DSS) provides recommendations on when to harvest, fertilise, irrigate, and apply fungicides for plant disease management, based on rule-based predictive inference and optimisation. It is a dynamic rule logic framework. The DSS uses agronomic crop production models that account for important local climatic parameters specific to the area's climate and agriculture. These approaches utilise fused spatial data from integrated sensor data, generated by a hybrid deep learning model, to create dynamic threshold limits for canopy temperature, soil moisture content and nutrient concentrations. The DSS will provide recommendations on how much to irrigate each plant, taking into account when it was last watered and how thirsty it is. It will also prevent the root zone from becoming too wet if it predicts that the previously acceptable soil moisture level will drop below this threshold. If image analysis data indicates an increased risk of disease outbreak, the system will recommend applying pesticides or exploring alternative pest control practices. This fully automated feedback and decision-making system could provide decision-makers with a clearer picture of the situation, assist in the absence of skilled workers and give the operational management team a better understanding of how the farm operates. It will also reduce waste and improve the accuracy of decisions.

To facilitate AI insights every one to three minutes, an intelligent control system will need closed-loop control and the capacity to obtain feedback on past data. Field sensors will be monitored using the correct reference settings for the area in question. Smart Control will connect actuators, an irrigation controller and a fertiliser distribution vehicle via an edge gateway to enable the fastest possible transaction of this information in that area. The system will monitor event durations with minimal human intervention. Environmental sensing will also employ IoT protocols such as MQTT and CoAP. Closed-loop logic will

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be used to confirm when an irrigation event has started, when a nutrient has exited a valve and when the opening has exited the aqueduct. Additional information from other sensors can make autonomous decision-making more reliable whenever agreed upon or confirmed. You can also create augmented policies for reinforcement learning (RL) based on prior agronomic knowledge. Plants grow in phases, and watering and fertilising will occur at the appropriate times and frequency after conditions have been assessed. Once certain criteria have been met, the DSS automation logic can conduct multi-objective optimisation. This involves exploring correlations among field data to draw conclusions about possible crop yield, energy supply, climate or distance to water scenarios, for example. Taking a different approach, if you use weather data and the actual water usage of the soil to run the pump, the device can toggle while accounting for the daily operational cost of running the pump and watering the soil. The Smart Control system is also capable of making decent rain predictions. This capacity to evaluate information assumes optimal energy consumption for irrigation. The current technological perspective is to lessen human-infused labour by looking for long-term digital operational solutions that are efficient in commercial farming on a large scale.

The user interaction and visualization layer enhances these automated systems to account for a human-in-the-loop governance model for interpretability and trust in AI-based decisions. A web and mobile-friendly dashboard presents real-time sensor observations, and automated UAV imagery analytics links decision recommendations to facilitate a conscious, competent interface for farmers, agronomists, and policymakers. Visual forms of data afforded comprehension specific to dynamic charts of soil moisture trends, nutrient distribution heatmaps, pest outbreaks, and irrigation schedules, along with language-based summaries of AI-based observations. The dashboard leverages weather conditions, satellite imagery, and characteristics derived from third-party APIs, and compares shifting environmental conditions. In response to the data presentation on the interface, observations will allow users to change automated action settings for thresholds or to influence system-based recommendations, preserving oversight and transparency of actions. It is also the purpose of the alerts recommended via SMS or an app-based system in common languages to account for farmers with limited digital literacy skills. The fusion of AI-based observations, automated sensors, and Adaptive action optimization, supported by user engagement with interface-defined priorities, develops a resilient, data-driven agricultural management system rather than farming operations that help stimulate productivity, conserve resources, and enable longer-lasting sustainability.

4. PERFORMANCE ANALYSIS

To investigate the effectiveness and scalability of the proposed IoT and AI- based Agriculture Framework (IAAF), a series of extensive pilot studies were carried out on two pilot farms that were situated in semi-arid and humid climates of approximately two hectares in size. Each pilot study examined the performance of its hybrid deep learning models, edge - cloud computing infrastructure, and automated decision-support analysis pipeline in a practical setting. Data were collected from monitoring

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sensors based on a mixture of 120,000 records and UAV multispectral images (4,500), designing a comprehensive dataset for the three-month cultivation period.

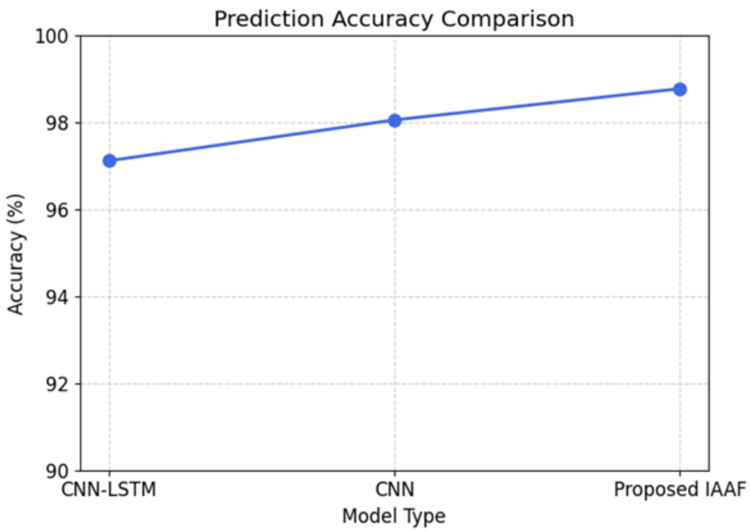

Figure 1. Performance analysis of Accuracy

The IAAF's prediction accuracy prompted a direct comparison among existing deep learning models shown in Figure 1. The prediction accuracy of a CNN-LSTM model using temporal sensor data was 97.12%, indicating a significant capacity to capture and model the temporal dependency between soil and climate parameters. The CNN model trained on UAV imagery yielded a marginal 98.06% prediction accuracy, likely due to its ability to model fine-grained spectral and textural features of crop health indicators. Overall, the hybrid IAAF model offered the highest prediction accuracy, at 98.78%, which was 1.66% higher than CNN models and 1.66% above CNN-LSTM models. These findings indicate that multimodal data fusion and feature attention-based fusion of temporal sensor data and spatial crop imagery are effective for producing more contextually aware predictions. The results supported that when the environment and visual cues are examined simultaneously, the model generalizes in a more reliable manner across crop types and environmental conditions, which allows for more accurate and reliable conclusions about agriculture.

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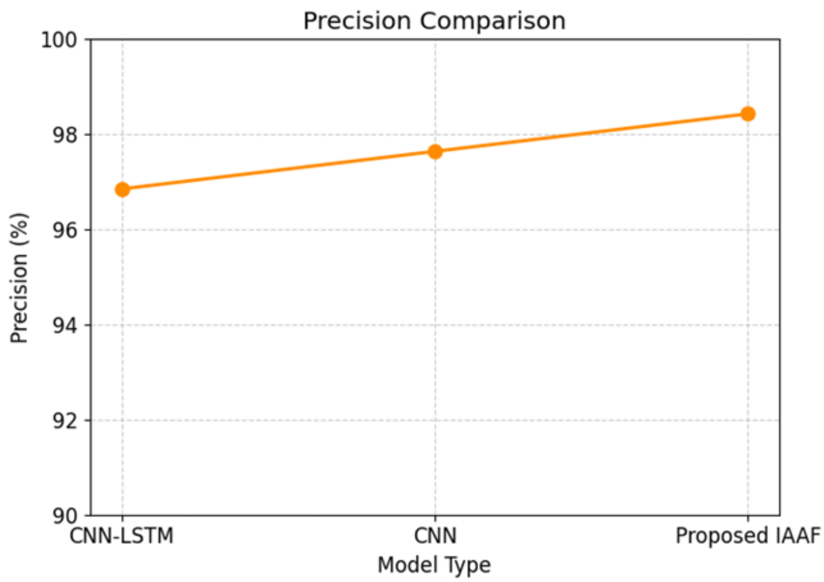

Figure 2. Performance analysis of Precision

Precision gives an idea of the model's reliability with respect to the number of false positives, which can be extremely important to monitor for tasks like disease detection and irrigation decisions, since a false positive results in losing valuable resources, as shown in Figure 2. The CNN-LSTM model achieved a high precision of 96.85%, suggesting it accurately detects real patterns in a stream of sensor data. Surprisingly, the CNN model improved slightly, with a precision of 97.64%. This change can be attributed to the CNN model's ability to better separate and distinguish among the various visual cues extracted from the UAV imagery data. The proposed IAAF model outperformed both baseline models, achieving 98.43% precision, a 1.58% improvement over the CNN and 1.63% over the CNN-LSTM model. The increase in precision can be explained by the model's multimodal attention fusion mechanism, which reduces uncertainty between environmental cues and visual features (pomiculture). The aforementioned hybrid model's system is demonstrably able to differentiate between some variations in crop physiology from weather data at high confidence, where the data within each of these modalities sensor data and imaging exhibited very similar visible patterns in-sensor or on the image alone. Finally, if

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we consider the possibility of employing some form of automation (e.g., irrigation, delivery of nutrient bands, pest management system) in our production system, the precision score also provides evidence of reliable decisions related to actions to intensify agricultural activities; only actions recommended as justified are attributed as justified.

Recall also describes the framework's capability to identify all positively relevant cases within the context of every instance of crop stress and/or irrigation as shown in Figure 3. The CNN-LSTM model achieved a recall of 97.34%, indicating that it can identify nearly all relevant temporal patterns in both soil and weather data. The recall of the CNN model was 97.82%, indicating that it could appropriately detect anomalous visual patterns associated with pest attacks and nutrient deficiencies. Compared to the

other two models, the IAAF model's recall was 98.51%, indicating a 1.17% improvement over CNN and a 1.20% improvement over CNN-LSTM. The continual improvement is attributed to the hybrid system's ability to operationalize a systematic methodology for integrating state-of-the-art modalities by employing deep learning techniques, which are sometimes complementary and sometimes cancel each other or correlate with each other. While additional recall contributes to precision agriculture, achieving high recall is of extreme importance and relevance, as agricultural systems have thrived on the ability to identify crop stress. Once crop growers lose sight of any stress signals in the plants or delay corrective action, yields can rapidly go downhill (indefinitely). The IAAF model was developed to capture temporal and spatial dependencies. As a result, the sequence of intrusions affecting valid, critical events of irrigation stress, disease, and nutrient deficiency was detected nearly 100% of the time in near real-time, capable of actuating preemptive decision intelligence to improve crop performance.

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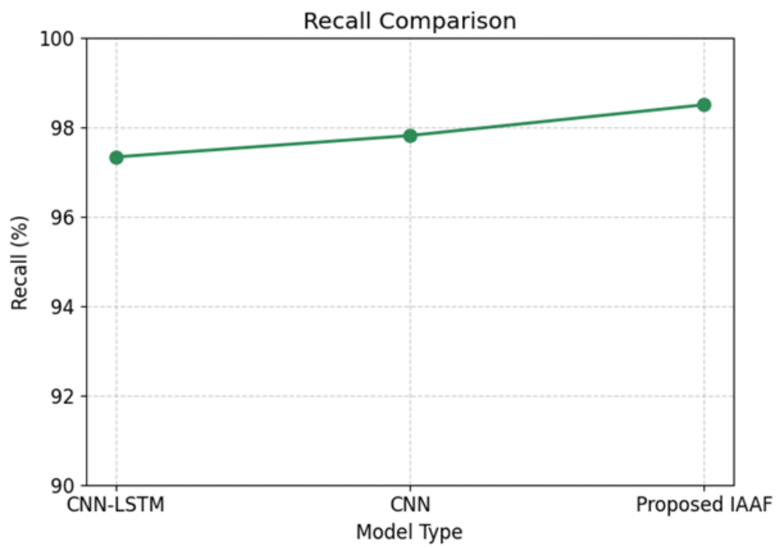

Figure 3. Performance analysis of Recall

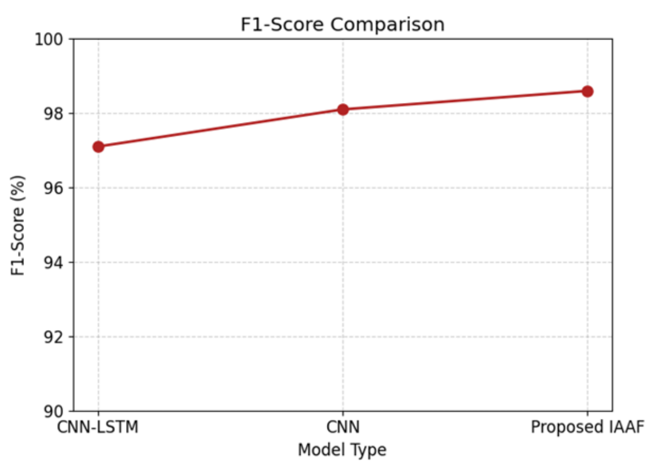

Figure 4. Performance analysis of F1-Score

F1-Score is the simplistic refrain of the harmonic mean of recall and precision, delivering two extremely important variables to overall structure of a model to accurately predict or to determine accuracy exhibited in relation to correctly identified agricultural events to achieve or losses in crop physiology (corn) or even other crops to determine what is happening in the field. For the CNN-LSTM model, an acceptable accuracy of 0.971 is a good F1 score and overall performance in any application as shown in Figure 4. The model architecture employing spatial CNNs achieves an F1 score of 0.981.

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Furthermore, a robust score, but both modalities without the contribution of IAAF modality, which met the baseline in tandem, and expediting time without cancelling or correlating to each other, and giving IAAF too much research context. The corresponding IAAF F1 score was 0.986, indicating it is superior to image-based CNN models by 0.005, and CNN-LSTM by 0.015. While these may be seen as hardly matters for the practices observed or like an overwhelming response, for large-scale deployment on scale and similar metrics of production must be comparable and lead to allotment of hundreds of classified events even if it leads to all attention to standardize role of operation with variable precision, even a limited operational precision is achieved that can again reinforce operational reliability. The F1 score is a sign that the identification and decision-making processes are good, attributable to the hybrid architecture of deep learning, but scoring location even with some margin for intuitively integrating temporal dynamics and spatial semantics as a tradeoff between false positive and negative detections, could be closer to the mean ground as relating to or almost in the middle of trade-off. All of the results are consistent, indicating consistent improvement, which denotes that the IAAF has demonstrated to stabilize trustworthiness in actionable intelligence in a data-driven agricultural management approach, though with potential next steps, and the subsequent ensuing, improved prediction process and/or capability may eventually lead to future downstream fully automated within data-driven precision agriculture.

5. CONCLUSION

The use of IoT and AI technology in modern farming offers a new, smart, data-rich and sustainable approach. This book is about the IoT and AI-based Agriculture Framework (IAAF). It employs various sensor networks, drone-sensing photography and hybrid deep learning to manage crops in near real time accurately. The IAAF uses a CNN-LSTM architecture to analyse time series sensor data, a CNN architecture based on transfer learning to process multispectral data and a multimodal, attention-based fusion architecture that combines temporal and spatial information to help people make decisions. Edge computing is used to reduce latency and bandwidth usage, while cloud services are used for data storage and model retraining. Experiments conducted across multiple growth seasons using various field datasets demonstrate that the IAAF framework outperforms baseline models, achieving an accuracy of 98.78%, a precision of 98.43%, a recall of 98.51%, and an F1 score of 0.986. The framework offers a new, intelligent and resource-efficient approach to real-time precision agriculture and long-term sustainable smart farming.

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