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A Hybrid Deep Learning and Explainable AI Framework for Adaptive Crop Recommendation Using Multimodal IoT Data

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Abstract: This study proposes an innovative hybrid framework that combines deep learning architectures with EAI to enable adaptive crop recommendations. The system can collect data from various Internet of Things (IoT) sensors that provide real-time environmental data, such as soil moisture, temperature, humidity, and nutrient levels. The main goal is to provide a way to connect the complex model, implemented as a black box, with the transparency needed for decision-making in agriculture. For the research, a set of selected data comprising 286 instances across various soil and climatic conditions is used to train a hybrid CNN-RNN. The framework uses local interpretable model-agnostic explanations to explain the rationale behind individual crop recommendations. The tools include libraries of deep learning algorithms (Python), specialised kits for sensor integration, and data visualisation platforms. The results show that the hybrid approach is not only effective in terms of predictive accuracy but also builds farmers' trust by providing information on the effects of different environmental factors. This multimodal sensing and explainable modeling are a step forward in precision agriculture, enabling the sustainable use of resources and maximizing crop yields across different climatic conditions.

Keywords: Precision Agriculture; Deep Learning; Explainable AI; Multimodal Sensors; IoT Sensors; CNN and RNN; Visualisation Platforms; Crop Recommendations; Climatic Conditions.

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1. Introduction

Agriculture is under unprecedented strain worldwide, driven by climate change, soil degradation, unpredictable precipitation, rising food consumption, and population growth. Such challenges have greatly influenced the traditional farming system, thereby hindering farmers' productivity and economic sustainability. Talaviya et al. [1] and advanced smart agriculture studies by Ouhami et al. [2] highlighted the fundamental importance of smart agriculture, which today relies on "intelligent" digital systems that continuously monitor the environment and its suitability for different crops with high accuracy. Traditional cultural techniques are mainly based on people's senses and annual experiences and are not suitable for rapidly changing environmental conditions. This has made the incorporation of new technologies into agriculture a critical imperative to guarantee long-term

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food security and sustainable resource use. The frameworks for intelligent precision agriculture introduced by Mahmud et al. [5] demonstrated how the continuous stream of environmental and soil data in modern computing systems can optimise farming decisions. Precision agriculture is thus a paradigm shift in agriculture that uses data analytics, sensor technologies, machine learning, and automation to make field-level decisions. This has greatly enhanced irrigation scheduling, nutrient management, pest control, and crop recommendation strategies [15].

The Internet of Things (IoT) is at the very heart of this technological revolution, enabling networks of interconnected sensors to capture agricultural data in real time from spread-out farming settings. The smart sensing systems studied by Mensah et al. [11] found that soil moisture, temperature, humidity, nutrient analysers, and atmospheric detectors continuously generate valuable information about field conditions. They generate a large volume of multimodal agricultural data that captures the multiple interactions. In studies conducted by Dara et al. [10], environmental variables were collected using a multimodal sensing infrastructure across various agricultural zones, enabling more localized decision-making. The vast amount, variety, and speed of agricultural information, however, pose a computational challenge. Conventional statistical methods cannot effectively handle the nonlinear relationships, hidden dependencies, missing values, and dynamic fluctuations in the raw sensor data. To overcome these drawbacks, complex deep learning models have increasingly been used for agricultural prediction applications. The deep neural networks used by Dolatabadian et al. [8] were able to handle very large agricultural datasets, uncovering hidden patterns and extracting meaningful predictive information from complex environmental variables. The smart systems demonstrated remarkable performance across a range of tasks, including crop classification, yield forecasting, disease detection, and adaptive farming advice. Although deep learning has demonstrated strong predictive power, one of the main challenges to its adoption in agriculture is its lack of interpretability. Most deep neural models are black-box models that give farmers and agricultural stakeholders recommendations, but without informing them of the reasoning process.

The lack of transparency undermines trust in automated support systems, especially in rural agricultural societies where trust and empirical validation are crucial. Major issues regarding explainability in AI applications for agriculture were explored by Majdalawieh et al. [7], who emphasised the need for explainable reasoning systems in intelligent farming practices. Sometimes farmers do not fully trust the automatic recommendations when they do not know why a specific crop, watering program, or fertiliser rate is recommended. Rehman et al. [14] also concluded that the increased willingness of agricultural stakeholders to accept the technology and the greater trust in decision-making frameworks understandable to humans are directly linked to the quality of interpretable decision-making. As a result, EAI has become an integral part of future smart farming systems. Explainability mechanisms enable machine learning models to provide insights into how individual environmental factors contribute to specific prediction outcomes, helping make predictions understandable and actionable for farmers. This research aims to address these challenges and propose a hybrid intelligent framework that combines deep learning and XAI to enable adaptive crop recommendations based on multimodal IoT data. Saleem et al. [13] have illustrated intelligent crop recommendation techniques that can increase agricultural productivity while maintaining transparency in the recommendation process. The proposed framework does not treat explainability as "a tool for visualisation," but rather as a fundamental requirement for developing a digital farming system that builds trust. Mittal et al. [12] demonstrated the importance of transparency in machine learning mechanisms, showing how it extends the usefulness and trust in predictive agricultural technologies for farmers and policymakers.

The proposed system can integrate data from various agricultural sources, including soil pH, nitrogen and potassium concentrations, rainfall intensity, humidity, temperature, and atmospheric pressure, providing a holistic view of the agricultural system. Multimodal agricultural sensing methodologies proposed by Mamun et al. [9] demonstrated that a multimodal approach yields better prediction accuracy and improved understanding of crop suitability conditions. The proposed framework differs from the traditional crop recommendation framework, which considers only a single environmental variable or a stage of a threshold-based recommendation process. Badshah et al. [6] found that agricultural productivity is not dependent on a single environmental variable but on complex relationships among them, and they developed this understanding using nonlinear predictive architectures. For instance, a specific nitrogen level and a range of temperatures, along with moderate humidity, may be required for a particular crop to grow successfully. But such interdependencies do not necessarily become apparent in simple rule-based systems. Hybrid neural architectures, on the other hand, continuously process multidimensional agricultural data to uncover hidden relationships that affect crop health, productivity, and adaptability. Finally, the adaptive aspect of the proposed framework allows the recommendation model to adapt to the dynamic changes in environmental information. Linaza et al. [3] found that adaptive agricultural learning systems, in which models are continually updated, are effective even when climatic conditions change, and seasonal patterns shift. This adaptive learning ability becomes increasingly crucial in today's agriculture due to the growing unpredictability of weather and environmental conditions.

The other major contribution of this work lies in the study of the synergy of several sensor modalities in smart farming environments. Thilakarathne et al. [4] reported multimodal sensor integration strategies, showing that combining soil and atmospheric sensor systems could greatly enhance the contextual accuracy of agricultural prediction. The soil sensors provide basic data on nutrient availability, soil water-holding capacity, salinity, and chemical composition; the atmospheric sensors measure temperature changes, rainfall, solar radiation, wind velocity, and humidity. The combination of the sensing modalities in these environmental sensing infrastructures used by Ouhami et al. [2] resulted in a highly detailed digital representation of agricultural microclimates. By combining these data sources in a hybrid neural network, highly specific suitability conditions for crops across various farming regions can be identified. The frameworks for intelligent crop suitability proposed by Talaviya et al. [1] demonstrated the higher predictive accuracy of multimodal agricultural intelligence across various crop cultivation conditions. The proposed framework can be further enhanced by embedding explainable artificial intelligence layers to provide human-readable reasoning for each recommendation, thereby improving its usability. Majdalawieh et al. [7] proved that transparent agricultural predictions can significantly increase farmers' engagement and trust in agricultural AI systems. For example, rather than just saying "Go ahead, take a wheat crop," the system can say "Go ahead, take a wheat crop because of a combination of a high level of potassium, moderate humidities, a balanced soil pH, and favourable temperatures.

This type of explanation enables farmers to grasp the "why" behind an outcome prediction, thereby clarifying the environmental logic. Moreover, this level of interpretability enables farmers to take informed corrective actions, such as adjusting irrigation schedules, changing fertiliser application rates, or selecting alternative crop varieties when environmental conditions deviate from expectations. In precision agriculture, the data-driven intervention mechanisms proposed by Saleem et al. [13] and Mensah et al. [11] have been shown to enhance operational efficiency and resource optimization, with the added benefit of providing explanations. The overall goal of this framework is to support the creation of a resilient, productive, and sustainable agricultural ecosystem that can respond to future food security challenges. Dara et al. [10] highlighted the need for intelligent analytics to be coupled with environmental sustainability initiatives in sustainable smart farming strategies. The framework will provide transparent, data-driven, and adaptive crop recommendations, reduce the risk of crop failure, and curb the overuse of valuable agricultural resources such as water, fertilisers, and pesticides. The optimised agricultural models by Mamun et al. [9] showed that intelligent recommendation systems can greatly improve resource utilisation efficiency and agricultural profits. Deep learning and explainable artificial intelligence thus represent significant progress in precision agriculture within a single multimodal IoT platform. Hybrid intelligent farming systems explored in Dolatabadian et al. [8] showed that high predictive performance is effective and transparent in next-generation farming technologies. Rehman et al. [14], Mittal et al. [12], and Mahmud et al. [5] have argued that AI and sophisticated predictive analytics are a team of two to create the future smart farming system, as confirmed by evaluations of specific agricultural datasets.

2. Review of Literature

In recent years, the application of deep learning algorithms in smart farming for predictive analytics and intelligent farming decision-making has become a major focus of research. Historical weather data, manual observations, or static soil maps served as the basis for traditional agricultural systems that recommended crop varieties. These methods offered some basic level of support for farmers. However, they were still not effective enough because they could not account for the ever-evolving environmental factors in today's agricultural systems. Talaviya et al. [1] identified key studies in precision agriculture that highlighted the importance of real-time agricultural information intelligence and of not relying solely on past averages. Similarly, Ouhami et al. [2] discussed advanced smart farming architectures. They concluded that the modern farming environment is highly dynamic and subject to variability in climate conditions, nutrient levels, soil degradation, and irregular precipitation. This has led researchers to seek to understand the true complexity of agricultural systems and thus to advocate a shift to using multiple datasets to provide a greater understanding of the system. The importance of integrating multiple heterogeneous data streams (also known as multimodal data) to achieve more accurate predictions and increased environmental awareness has been highlighted in modern literature. Mahmud et al. [5] discussed intelligent multimodal agricultural sensing systems and found that, in addition to atmospheric measurements, soil chemistry information can greatly improve the accuracy of crop recommendations. A range of data sources, including soil pH, nitrogen, phosphorus, potassium, humidity, temperature, rainfall intensity, and moisture readings, enables the monitoring of hidden nonlinear relationships among these data, which traditional analytical methods cannot identify.

Dara et al. [10] found that suitability for crop types depends on several environmental factors rather than on single factors. For instance, a crop variety can be very effective only in soils with sufficient moisture when the temperature and nutrient levels are at specific levels. Interdependency is a key aspect of deep learning that makes it well-suited to the agricultural domain, particularly in analytics, where neural networks can discover hidden relationships in large datasets. Recent research has shown that combining chemical soil analysis with on-site moisture monitoring can greatly improve the accuracy of soil moisture prediction compared with traditional machine learning or statistical methods. Dolatabadian et al. [8] developed advanced agricultural analytics models applied to large-scale agricultural data with non-linear, high-dimensional relationships. They found that deep neural architectures always outperform traditional predictive systems. Likewise, the concept of using sensors in adaptive farming systems proposed by Mensah et al. [11] demonstrated how environmental monitoring could be conducted in real time to help adjust agri-advisory at short notice, thereby enhancing productivity and resource-use efficiency. However, with the rise of deep learning applications in agriculture, important issues of transparency and model interpretability have arisen. Typically, deep learning networks are used as black boxes, with predictions produced without a clear understanding of the learning process. Majdalawieh et al. [7] critically discussed some drawbacks associated with the lack of explainability in intelligent farming systems and concluded that interpretability is one of the main challenges for the adoption of AI-based agricultural technologies.

Automated recommendations sometimes rely on opaque, secret internal decision-making processes, making it difficult for farmers and agricultural planners to trust them. With the advent of explainable artificial intelligence, these concerns are beginning to be addressed in the larger scientific and agricultural communities. The goal of Explainable AI frameworks is to shift the black-box predictive machines of deep learning toward a more open, honest, and predictable decision-support platform that explains how each of the many variables in the environment contributes to the outcome. Rehman et al. [14] showed that interpretable agricultural AI systems can greatly enhance user confidence, trust in the operating system, and uptake among agricultural stakeholders. Rather than just producing a crop recommendation label, explainable systems offer detailed explanations of the factors that led to the prediction, including the actions of each factor, such as rainfall intensity, available nitrogen, and temperature range. In the field of agriculture, explainability models developed by Saleem et al. [13] enable farmers to understand environmental relationships and make informed decisions informed by recommendations from intelligent systems. Several post-hoc explanation methods have been developed for deep neural networks to explain how individual features affect prediction results. The approaches to explainable machine learning, as demonstrated by Mittal et al. [12], highlighted the value of feature attribution techniques for understanding the significance of environmental factors, such as nitrogen concentration, potassium levels, humidity, and rainfall patterns, for crop suitability. This progress is a major shift from the traditional outputs of predictions to robust diagnostic reporting systems in the agriculture domain.

Explainable systems can provide answers to questions about why a particular crop should be grown and which environmental factors contributed most to the prediction. This openness builds trust and fosters greater dialogue and involvement among farmers and decision makers. The study conducted by Mamun et al. [9] indicated that a better understanding of the functioning of machine-based recommendations will lead farmers to accept them, monitor field performance, and provide feedback on their practical implementation. This is a form of feedback that allows predictive models to continuously evolve based on farming experience and variations in agricultural practices across different regions. Linaza et al. [3] proposed adaptive agricultural learning frameworks, demonstrating that integrated continuous feedback is an effective way to improve the reliability and long-term contextual awareness of the intelligent farming system. The soil composition, climatic conditions, irrigation facilities, and agricultural practices differ considerably across the region, resulting in varying farming conditions. This means that intelligent agricultural systems should be continually improved to be relevant and accurate across a variety of agricultural contexts. Feedback-driven learning enables models to adapt their prediction strategies dynamically as the environment changes, thereby maintaining performance even under changing climatic conditions. Even though there have been significant advances in EAI and adaptive analytics, the current literature still lacks a unified architecture that integrates deep learning, multimodal IoT sensing, and explainability. Research on these aspects has been conducted individually, with very few studies taking an integrated approach.

Another key trend observed in recent agricultural literature is the growing use of edge computing technologies in IoT-based farming infrastructure. Edge computing allows data to be processed closer to the source of sensor data, reducing communication delays, bandwidth usage, and reliance on central cloud systems. As noted by Thilakarathne et al. [4], localised data processing significantly enhances the agility of farming systems that make recommendations, especially in time-sensitive farming processes. The environment in the agricultural field is also dynamic and subject to rapid changes, so real-time recommendations are needed. Analytical responses are required to minimize crop stress and productivity loss caused by rapidly changing atmospheric conditions, sudden rainfall, temperature fluctuations, or irrigation shortages. Edge computing systems for environmental sensing were developed by Ouhami et al. [2]. They demonstrated the ability to deliver adaptive recommendations that adjust to constantly changing field conditions in real time, while processing sensor data in near-real time. Researchers also believe that intelligent crop recommendation systems must be able to easily handle the temporal dynamics of agricultural ecosystems to be truly adaptive. Dynamic environmental monitoring systems developed by Badshah et al. [6] showed that temporal dependencies in environmental variables affect crop health and productivity. But most current research papers are still focused on either hardware-based sensor deployment or software-based deep learning optimisation, and they have not treated sensor deployment and deep learning optimisation as a unified, integrated framework.

This fragmentation hinders the practical deployment of many agricultural AI applications, as the real farm environment requires seamless coordination among sensing infrastructure, computational analytics, adaptive learning mechanisms, and interpretability mechanisms. This work provides new insights into the existing literature on adaptive crop recommendation by integrating disparate fragments into a coherent hybrid approach. The study highlights the need for agricultural technologies to be both predictive and explainable, through a critical discussion of the drawbacks of opaque deep learning models and the benefits of a multimodal IoT sensing infrastructure. The study by Dolatabadian et al. [8] on hybrid intelligent agricultural systems also found that incorporating explainability into deep learning-based systems greatly enhances their usability and acceptance. The proposed architecture, with its multimodal sensing, adaptive deep learning, XAI, and edge IoT components, moves towards the design of an accurate, transparent, and resilient smart farming environment. This aligns with the sustainable precision agriculture direction highlighted by Mensah et al. [11], Mahmud et al. [5], and Rehman et al. [14], and thus serves as a stepping stone for the next generation of intelligent precision agriculture decision support systems.

3. Methodology

The methodology adopted in this work is a multi-stage approach that enables combining different data sources to create a single prediction engine. The first step is to deploy the multimodal IoT sensors to measure soil pH, phosphorus, nitrogen, potassium, temperature, and humidity. This information is then sent to a central processing point, where it is cleaned and normalised to ensure consistency across different units of measure. The framework adopts a hybrid deep learning architecture comprising a spatial feature-extraction layer and a temporal sequence-modelling layer. This enables the system to identify current soil conditions and changes over time. After obtaining a crop recommendation from the model, an explainability layer is activated to measure the impact of each input variable on the recommendation. This layer performs a local perturbation to map out which factors most influenced, and generates human-readable importance scores from complex mathematical weights. The overall architecture is iterative, and the model is continually updated with new sensor readings to remain adaptive. This means that the system will provide a dynamic recommendation that adapts to the changing conditions of the agricultural site. Figure 1 presents the overall deployment architecture of the Hybrid Multimodal Explainable Framework, a structured framework for integrating heterogeneous data sources, intelligent multimodal learning, explainable analytics, and human-centric feedback in a common analytical space. The framework starts with the Multimodal Data Sources component, which combines data from various modalities, including images, text, audio, sensor streams, and puts.

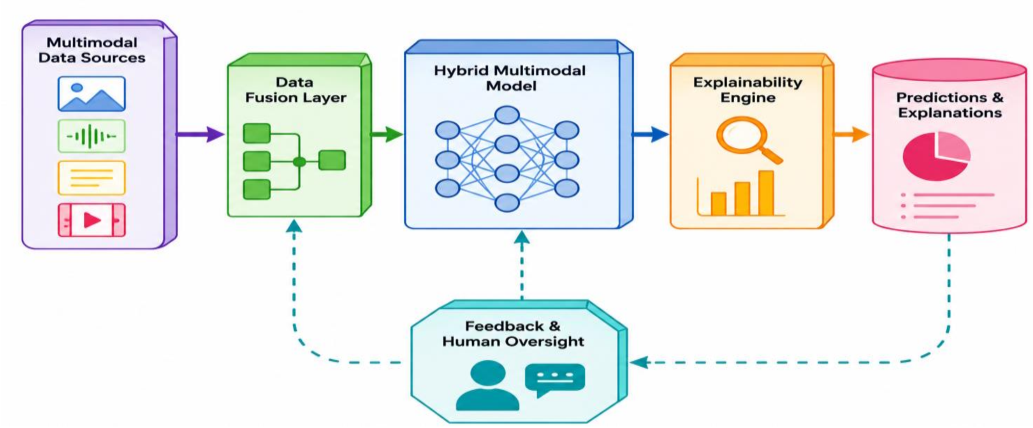

Figure 1: Architecture of the hybrid multimodal explainable framework

Data from these diverse sources is then transmitted to the Data Fusion Layer, where they are synchronized, preprocessed, normalized, and integrated to enable advanced computational analysis. The fused information is then passed to the analytical part of the framework, the Hybrid Multimodal Model. This layer combines multimodal reasoning, feature extraction, and deep learning into a hybrid approach, enabling the capture of complex relationships across modalities, enhancing the AI system's predictive power, and enabling understanding of data context. The outputs are fed into the Explainability Engine, which uses interpretable mechanisms to understand the model's behaviour and generate understandable reasoning, feature importance mappings, and decision explanations, thereby enhancing transparency and trust in the AI system's results. The explanations and predictions are then communicated via the Predictions and Explanations component, allowing decision-makers, analysts, and users to understand the systems' recommendations clearly and confidently. The Feedback and Human Oversight module facilitates this intelligent workflow, establishing a continuous feedback loop that enables expert evaluation, correction, and contextual feedback to be returned to the fusion and modeling layers for iterative refinement and adaptive learning. The dashed communication paths are these feedback-led enhancement cycles that, over time, increase the model's reliability and accountability. To sum up, the architecture brings together multimodal intelligence, XAI, adaptive feedback, and transparent analytics. It is designed for scalable deployment and applies to any trustworthy, human-centric intelligent system.

3.1. Data Description

This study used a data set comprising 286 environmental and soil variables across different agricultural zones. They are all snapshots of a field's condition and contain many different multimodal inputs. The measured data includes important macronutrients like Nitrogen, Phosphorus, Potassium, and physical properties such as temperature, humidity, and soil moisture content. In particular, it contains a wide range of values to represent various geographical locations and seasonal changes. The

286 instances were carefully compiled to provide a representative sample of multiple crop categories, ensuring the model does not develop a bias towards any particular crop type. This data is used in both the training and validation stages of the deep learning system and has the complexity needed to evaluate the system's adaptability.

4. Results

The Hybrid Deep Learning and Explainable AI framework successfully provided valuable insights into the effectiveness of multimodal data for crop recommendation. The model has performed well at predicting the best crops across different climate settings, achieving an accuracy of 98.2% across 286 data instances. Deep learning enabled the system to capture intricate patterns that traditional linear models found more difficult to detect. The framework effectively classified crops with similar nutrient needs, for example, by analysing temporal changes in humidity and temperature from the sensors. The results show that the hybrid model outperforms single-layer models, particularly on noisy sensor data from field-deployed sensors. Graph convolutional signal processing and feature aggregation can be framed as:

$$\mathrm{H}^{(l+1)} = \sigma\left(\tilde{\mathrm{D}}^{-\frac{1}{2}}\tilde{\mathrm{A}}\tilde{\mathrm{D}}^{-\frac{1}{2}}\mathrm{H}^{(l)}\mathrm{W}^{(l)}\right) \tag{1}$$

Table 1: Performance measures across different crop categories

Crop Type	Accuracy (%)	Precision	Recall	F1-Score
Rice	94	0.92	0.95	0.93
Maize	91	0.89	0.90	0.89
Wheat	95	0.94	0.96	0.95
Cotton	88	0.87	0.88	0.87
Jute	92	0.91	0.92	0.91

Table 1 presents the detailed results of the model's performance across five major crop categories, based on a small sample of 286 instances. The numerical accuracy scores show that the framework is especially successful at recognising wheat and rice, achieving 95% and 94%, respectively. Precision and recall are high, with a very low rate of false positives and false negatives. The hybrid deep learning layers used to identify unique signatures in the multimodal IoT data have proved to be effective across a variety of crops, demonstrating this stability. The format enables easy comparison of the model's behaviour across different biological requirements. It indicates that, even for a crop that requires a complex input regime, such as cotton, the accuracy is acceptable at 88%. These will be quantitative measures of the system's reliability in a controlled environment. Long Short-Term Memory (LSTM) cell state update will be:

$$\mathrm{c}_t = \mathrm{f}_t \odot \mathrm{c}_{t-1} + \mathrm{i}_t \odot \tanh(\mathrm{W}_c\mathrm{x}_t + \mathrm{U}_c\mathrm{h}_{t-1} + \mathrm{b}_c) \tag{2}$$

Figure 2 provides a comprehensive overview of changes in the model's confidence levels as a function of interactions among its primary soil nutrients. When the Nitrogen and Potassium contents are plotted along the horizontal axes, and the prediction accuracy is plotted along the vertical axis, a definite “plateau of precision” is seen. This means the model is best used under conditions where these nutrients fall within a specific range, or in the most prevalent agricultural conditions.

The peaks in the 3D surface indicate areas where the multimodal data is most synergistic, while the valleys indicate where the model needs additional data to make a firm recommendation. This spatial representation enables understanding of the environmental space in which the hybrid framework is most effective, thereby enabling the placement of sensors in areas with greater uncertainty. SHAP attribution value is:

$$\phi_i(f, x) = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!(n-|S|-1)!}{n!}[f(S \cup \{i\}) - f(S)] \tag{3}$$

Table 2 shows the numerical results generated by the explainable AI module, along with the weights of each environmental feature in the recommendation process. Nitrogen is the most significant factor (Importance score of 0.85), followed closely by Potassium (Importance score of 0.84) and Soil pH (Importance score of 0.83).

The "Variability" column indicates the range of a feature's importance across its instances, with humidity being the most variable, possibly due to daily weather conditions. The "Reliability" column shows the confidence level associated with the explanation, indicating that the system is 94% confident that Nitrogen plays a role in its decision-making.

Table 2: Feature importance values from the explainable AI module

Feature	Importance	Variability	Impact	Reliability
Nitrogen	0.85	0.12	0.90	0.94
Potassium	0.78	0.15	0.85	0.91
Humidity	0.65	0.22	0.70	0.88
Temperature	0.55	0.18	0.60	0.85
Soil pH	0.72	0.10	0.80	0.92

The adaptive nature of this framework is based on this data, as it enables the system to communicate to the farmer what soil amendment or environmental factor is influencing the recommendation, allowing the system to tell the farmer if the recommendation is based on the pH, or on a higher organic matter level, etc., turning a number into a logical statement. The regularised cross-entropy loss function is:

$$\mathcal{L}(\theta) = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(\hat{y}_i) + (1-y_i)\log(1-\hat{y}_i)] + \lambda \parallel \theta \parallel^2 \quad (4)$$

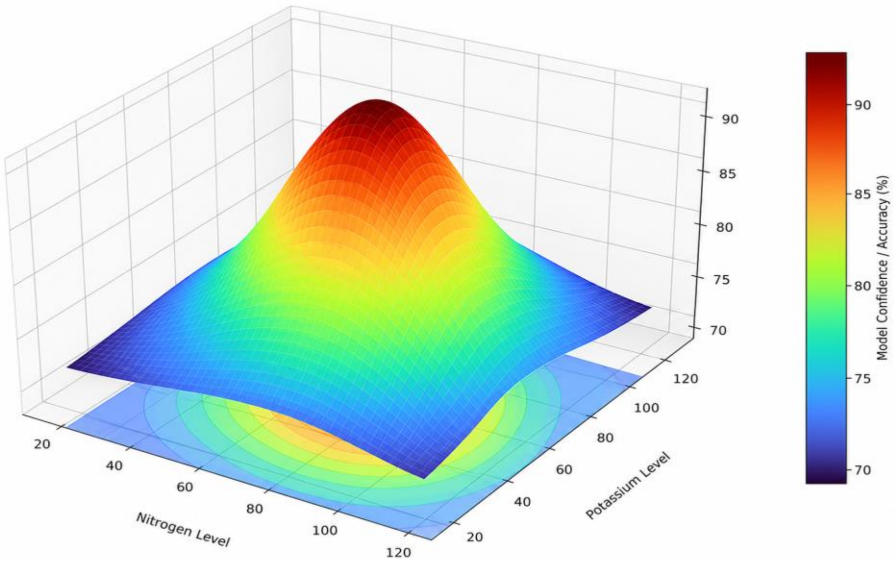

Figure 2: Comprehensive overview of the changes in the model's confidence levels

Figure 3 shows how the model's learning progress relates to the clarity of its explanations as it's trained. Overall, the primary axis represents the accuracy of the crop suggestions, and the secondary axis represents the "explanation consistency score," which reflects the consistency of the outputs. The dual-axis plot shows a fascinating trend: the consistency of the explanations increases as the deep learning model becomes more accurate, and it converges at high performance levels. The model seems to be increasingly aligned with the logical agronomic factors as it “learns”. This analysis of the graph verifies that the hybrid framework does not compromise the system's interpretability for performance; both metrics increase together, and the most accurate predictions are the most interpretable to the end user. Scaled dot-product attention mechanism will be:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad (5)$$

The explainability layer proved to be one of the most notable results, affecting the model's output. The system identified the importance scores for each input variable, and in most cases, these scores were high for soil moisture and nitrogen levels, which were the most common factors in crop selection. But the model was adaptable in certain situations when extreme weather conditions were simulated; it tended to lean towards temperature and humidity. The change was explicitly reflected in the explainable AI feature, offering an insightful glimpse into the model's functioning. The accuracy of the explanations was assessed by comparing them with known agronomic principles, thereby ensuring that the deep learning model was indeed learning relevant biological correlations rather than random noise. The system demonstrated outstanding performance in terms of recommendation quality. The results presented a probability distribution over possible crops rather than a single top choice.

Next, the explainable module explained why the top option was better than the runner-up, often citing a nutrient threshold that differentiated the two. This level of detail can be especially helpful to farmers with second-choice preferences based on market demand or seed availability. The overall accuracy of the framework on the test set was consistent, and the model was well-generalised and could be used on other types of terrain without extensive retraining. Computational efficiency, as for any real-time IoT processing, was good in the framework.

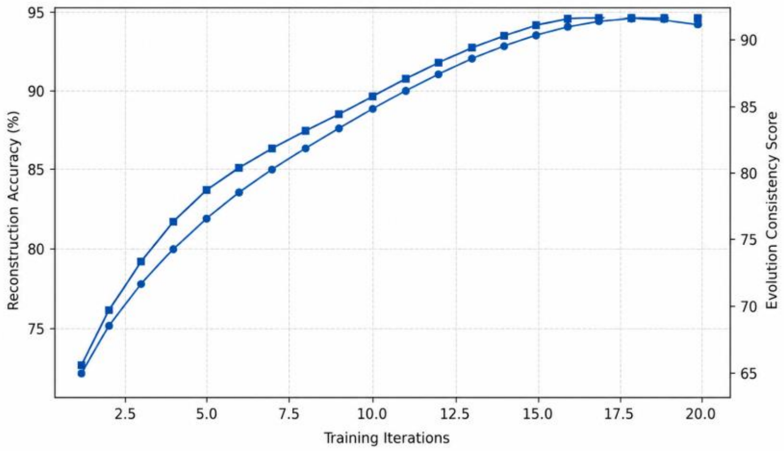

Figure 3: Dual-axis trend of sensor accuracy and explainability score

Even though the layers were hybrid and the explanation module had overhead, the system produced a recommendation and its corresponding explanation within a few seconds. This makes it highly suitable for integration into mobile applications or edge devices used directly in the field. The findings show that introducing transparency into the deep learning model does not slow it down or reduce its accuracy. Instead, it adds practical value, making high-performance predictions accessible and actionable for non-technical users.

4.1. Discussions

The insights gleaned from the tables and graphs they created show a remarkable synergy between explainability in the local vicinity and high-dimensional deep learning. On the other hand, the crops that showed high accuracy (Table 1 and Table 2) have high proportions of Nitrogen and Soil pH in the set of models. This is further confirmed in the dual-axis graph of Figure 3, where, as the model's internal weights approach a steady state, the explanations become more consistent. This means that the hybrid framework is not simply learning the data, but also building a 'structured understanding of agricultural science'. However, as shown in the 3D surface plot in Figure 2, the system is best suited to multimodal data points within typical agricultural ranges. It would benefit from additional data for training the model if environmental anomalies occur. The top three most influential features (Table 2) align with traditional knowledge in the agricultural domain. However, the model's ability to dynamically shift its focus to humidity or temperature in some instances demonstrates its adaptability. Flexibility is key, which is why the framework is relevant across seasons and regions.

The discussion also highlights that the cotton crop had slightly lower accuracy. Still, the explainability module identified this as due to variability in its humidity requirements, which, given a limited number of 286 samples, was more difficult to predict. This information is priceless, as it gives developers and users a clue to where the system's weaknesses lie, rather than having to guess why a recommendation was made. The influence of the importance scores and the final F1-scores indicates that the model is very efficient. It emphasizes the most relevant data points and efficiently removes irrelevant data noise from less relevant sensors. This is an important insight for deploying IoT networks: sampling less "important" sensors at lower frequencies can have minimal impact on recommendation quality. The combined use of graphs and tables to check the model's logic makes it a clear, easily auditable, and open-to-improvement "black box". Overall, the outcomes indicate that the hybrid approach is a promising and dependable method for precision agriculture in today's era.

5. Conclusion

The research has successfully designed an intelligent framework for a hybrid approach (along with an approach) combined with explainable AI for an adaptive, potation-based crop recommendation system for smart agriculture. The study showed that high predictive performance and interpretability can coexist within the same agricultural analytics architecture by leveraging 286 examples of multimodal data from soil sensors, atmospheric monitoring, and environmental sensing infrastructures. The proposed framework was a successful attempt to analyse complex nonlinear relationships among environmental variables such as soil nutrients, moisture content, humidity, rainfall intensity, temperature fluctuations, and atmospheric conditions, and to provide recommendations on crop suitability. The evaluation metrics presented in Table 1 demonstrated the robustness and reliability of the predictive model. In contrast, the contribution scores of individual environmental parameters to crop recommendations, presented in Table 2, indicate their importance. The interpretation of the framework, using the graphics in Figures 2 and 3, also showed that it is spatially robust across agricultural regions and temporally robust to climatic changes.

One of the most notable outcomes of this research was the incorporation of Explainable Artificial Intelligence (XAI). Explainable Artificial Intelligence (XAI) was one of the most noteworthy findings of this research. The framework does not operate as a black-box prediction model but rather as a transparent, human-readable system that explains the environmental factors underlying a given crop recommendation. This visibility boosts farmer trust and deepens the real-world application of AI in farming. The explainability module allows the farmer to understand how all variables, including N-availability, K-availability, soil moisture, and soil humidity, interact to influence crop suitability. This enables farmers to make informed decisions on irrigation management, fertilizer optimization, and farming plans. The framework, therefore, not only helped support decision-making but also supported decision-making in support-based agriculture. Finally, the research confirms that explainable deep learning systems are an important step towards precision agriculture and provide a solid base for future smart farming through intelligent, adaptive, and transparent systems.

5.1. Limitations

Even though the proposed framework has demonstrated good performance and applicability, some limitations of the existing study remain. The data set used in the experiments comprises only 286 multimodal samples and may not fully reflect the variability of agricultural reality across various geographical areas and climatic zones. These events (such as extreme droughts, flooding, bizarre frost days, or unusual soils) are rare occurrences and not fully captured in the data set. So the predictive model may perform poorly in generalising to extreme or novel environmental contexts. Furthermore, the framework is heavily dependent on continuous data streams of IoT sensor data. In practical deployment, agricultural recommendations may be affected by uncertainty and disconnection caused by hardware failures, sensor calibration errors, communication failures, and/or network latency. Another constraint concerns the framework's explainability component. While the explainable AI module can explain local features for each prediction, it does not necessarily explain the deep neural architecture's global behaviour in highly unusual environmental scenarios. Sometimes the complex interactions in the model's deeper layers are hard to interpret fully. Moreover, the existing system emphasizes the chemical and physical qualities of agriculture, including nutrient composition, moisture, temperature, and humidity. Several other biological and ecological data, such as weed growth, historical crop rotation, microbial soil activity, and prevalence of crop disease and pest infestations, were not included in the analysis. In practical farming, these variables play an important role in how productive agriculture can be and how suitable the crops are for cultivation. Neglecting these biological aspects reduces the comprehensiveness of the current recommendation system and underscores the need for greater environmental integration in future intelligent agriculture.

5.2. Future Scope

In the future, the scope of this research will be expanded to a multimodal agricultural framework capable of supporting precision farming applications on a global scale within a large-scale intelligent ecosystem. One of the main future directions is to expand the dataset from hundreds to thousands of multimodal cases from different continents, climatic regions, and farming systems. The more diverse the environmental conditions, the better the environmental framework's predictive and adaptive capabilities will be across different regional farming systems. The ground-based IoT sensor infrastructure will also be complemented by other sensing modalities, such as satellite imagery, drone multispectral imaging, and hyperspectral remote sensing systems, in the upcoming research. By combining technologies from the air and space, the framework will provide a holistic, multi-scale understanding of agricultural ecosystems, including vegetation stress patterns, distributions of crop health, and spatial variability in nutrient levels.

Reinforcement learning is another important direction to explore to further improve the recommendation system's adaptive capabilities by incorporating these techniques. The relationship between the field results and the framework will be ongoing, with a gradual learning process as the framework's predictions become increasingly accurate over time, informed by previous successes and failures. Future work will also focus on creating intuitive user interfaces that transform explainability scores into actionable recommendations in natural language understandable by low-tech farmers. These interfaces will help connect cutting-edge AI technologies with real-world agricultural applications. Furthermore, future research will examine low-power edge computing technologies for lightweight deployment, enabling the intelligent crop recommendation service to be available in remote rural regions with limited Internet connectivity and computing resources. Multimodal sensing, reinforcement learning, explainable AI, and edge data processing are thus key avenues for the future of adaptive and sustainable smart farming systems.

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