ADVANCE SOCIAL SCIENCE ARCHIVE JOURNAL
Available Online: https://assajournal.com
Vol. 05 No. 02. April-June 2026.Page# 2594-2615
Print ISSN: 3006-2497 Online ISSN: 3006-2500
Platform & Workflow by: Open Journal Systems
https://doi.org/10.5281/zenodo.21215796

A Cybersecure Trust-Aware Explainable AI Architecture for Sustainable Precision Agriculture

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Abstract
In this paper, a Cybersecure Trust-Aware Explainable Artificial Intelligence (CT-XAI) Architecture is proposed to secure and to light up digital precision agriculture networks. To automate field prescriptions that are vital to modern smart farming, the concept of Internet of Things (IoT) sensors coupled with the algorithms of black box machine learning are critical. Yet, these systems are vulnerable to several cyber physical attacks (such as malicious false data injection and identity spoofing) and do not provide enough transparency for their operation, thus preventing stakeholders from adopting such systems. To address these gaps, the proposed CT-XAI framework enables the coordination of five operational layers: the Agricultural IoT Layer, the Cybersecurity Layer, the Trust Management Layer, the Explainable AI Layer and the Intelligent Decision Support Layer. To combat insider node breach, we propose a multi-layer trust model which evolves dynamically. This engine measures behavioral integrity of hardware in terms of its Beta distribution, handles data consistency in space and time with locally defined Gaussian kernels, and observes the confidence level of its model predictions with Shannon Entropy. At the same time, the cybersecurity layer performs mutual authentication of endpoints using low-cost elliptical curve cryptography (ECC) and implements a hybrid CNN-LSTM Intrusion Detection System (IDS) that prevents the exploitation of transport-layer attacks. The verified data streams are then fed into deep ensemble networks with the features explained by post-hoc engines (SHAP and LIME), thereby giving domain-based feature attributions in an easy-to-understand way. The architecture is validated on a hybrid testbed that combines data from the Edge-IIoTset and Kaggle Smart Agriculture datasets, yielding a 97.4% detection rate of cyberattacks in data tampering. Most importantly, it reduces the loss of accuracy in prediction to a narrow range of negative -2.8% to -4%, creating a strong base for sustainable agriculture even if 40% of field devices are corrupted.

Keywords: *Precision Agriculture, Explainable Artificial Intelligence, Cybersecurity, Trust-Aware Computing, Internet of Things, Sustainable Agriculture, Smart Farming.*

1. Introduction.

The world's agricultural system is in significant structural trouble due to the fast growth of population, climate change, acute water scarcity, deteriorating fertile soil and increasing food demand. International forecasts predict that there will be nearly 10 billion people on earth by 2050, and that agricultural production will need to increase significantly on a global scale in that time, without causing unwanted environmental damage. Traditional farming methods cannot match these requirements since they employ manual observations, general resource allocation and delayed interventions at the time of crop stress. However, digital technologies can solve these inefficiencies by enabling smart farming, which is currently under the title of precision farming, to be built on a data-based model that leverages technology. In order to defy these inefficiencies, researchers and agricultural practitioners are adopting digital technologies to change conventional farming into smart farming, which is now known as precision farming and is based on data-driven models and technology. Indeed, a large number of IoT devices, WSNs, UAVs, satellite imagery, cloud-edge computing and artificial intelligence (AI) technologies are being employed to monitor physical conditions on the land in real-time, driving the precision agriculture revolution. Micro-level sensing data such as soil moisture, ambient temperature, ambient humidity, nutrient (NPK) and irrigation index is constantly collected by a sensor deployed. These data are streamed into machine learning algorithms that provide prescriptive recommendations for irrigation scheduling, fertilizer application, pest management and harvest timing for the operators. In practice, these technologies can be effectively implemented to optimize crop production, minimize costs, protect natural resources, and enhance sustainable agriculture.

While these obvious benefits are there, digital agriculture can nevertheless bring up some important security risks. Agricultural IoT devices are usually deployed in open and physically unmonitored environments and come with strict computational power and memory constraints, making them extremely prone to malicious (exploitative) attacks. These endpoints are the ones attacked by adversaries to alter sensor readings, capture wireless telemetry, to introduce false information and/or make unauthorized entry to a critical infrastructure control system. These cyberattacks lead to devastating mistakes: mis-directed irrigation controls, over-fertilization; crop irreparable damage, and financial losses. Moreover, these violations erode the trust in automated systems by users. Current cyber security standards are missing the ability to establish semantic trustworthiness of data sources and transparency of downstream AI recommendations. Although Artificial Intelligence is the major analysing engine for diagnosis of crop diseases, weed classification, and crop yield forecasting, state of the art deep learning models represents a black box without any interpretable methodologies. They provide decisions that are critical to the success of a mission but they do not reveal the reasoning. The vague advice inevitably fails to sway both farmers and agronomists, not to mention agricultural policy makers, when it involves economic or environmental costs. Explainable Artificial Intelligence (XAI) mitigates this obstacle by creating human-readable explanations for generated predictions, which is vital for enhancing the transparency, accountability, and trust of decision processes and enabling users to engage with AI systems. To complement this transparency, the concept of trust-aware computing has arisen that explicitly measures the reliability of the operations of the

IoT, links, sensor inputs and machine learning outputs. Smart systems can calculate dynamic trust scores to identify and isolate compromised telemetry from harming end-field prescriptions.
Current literature regards cyber security protection, trust management, and explainable machine learning as distinct and separate fields, although there are clear interdependencies among them. Current literature considers Cyber security protection, Trust Management and explainable machine learning as three separate domains, despite clear dependencies among them. There is no study that combines these three technologies in a comprehensive and lightweight architecture especially oriented towards the resource-constrained context of precision agriculture networks. To mitigate this restriction, this paper addresses a fundamental research question on how to ensure the integrity of data as well as the transparency of algorithms in the resource-limited precision agriculture networks with active cyber attacks. We introduce a Cybersecure Trust-Aware Explainable AI (CT-XAI) Architecture. The proposed architecture is composed of five interconnected operational layers: Agricultural IoT Layer, Cybersecurity Layer, Trust Management Layer, Explainable AI Layer, and Intelligent Decision Support Layer, to ensure secure data collection, comprehensive multi-level trust assessments and human verifiable AI reasoning loops.

1.1 Major Contributions

This study makes the following main contributions:

- Novel 5-layer Architecture: We create a solution stack of CT-XAI with layers that have been designed specifically for sustainable smart farming use cases.
- Dynamic Mathematical Trust Model: We design a mathematical trust model that real-time evaluates and scales the trustworthiness of the physical device, the spatial-temporal data stream and the AI prediction confidence.
- Integrated Cybersecurity Services: We have a lightweight defence pipeline with ECC-based mutual authentication, end-to-end data encryption and a hybrid machine learning based intrusion detection system (IDS).
- SHAP and LIME are inbuilt within our post-hoc explainability engines to provide user-friendly explanations and visual feature attributions for every field prescription, thereby enabling 'Explainable AI' (XAI).
- A Rigorous Evaluation Framework: We validate the end-to-end architecture on rigorous synthetic attack vectors, based on combined real-world agronomic and cyber security benchmark data sets.

1.2 Structural Outline

This paper is organized as follows: The literature review in Section 2 brings together recent publications concerning the related fields of security in PA, trust in PA and interpretability. Section 3 presents a formalization of the gap of research in a systemic approach and proposes functional layers for the architecture. We describe our dynamic trust model in detail in Section 4. Our experimental design, dataset parameters and reference metrics are defined in Section 5. In section 6, the results of the experiments are discussed and compared to the state of the art models. Section 7 brings the paper to a close, and offers some suggestions for further study.

2. Literature Review

2.1 Precision Agriculture and Smart Farming

Precision agriculture has come a long way in the last 20 years, moving from sensor-based monitoring to a more complex system that integrates artificial intelligence to support decisions. Zhang et al. [11] reviewed the different precision agriculture technologies and focused on the use of IoT, remote sensing and machine learning for crop management. The authors detected the existence of sensors in the soil, weather stations and UAVs equipped with multispectral cameras as standard instruments for data collection in today's farms. Such technologies allow for real-time monitoring of crop conditions, soil moisture, weather variables, and more, which will help with data-supported farming choices. These technologies will help with the real-time monitoring of crop health and conditions, soil moisture, weather conditions, etc., and make informed choices for agriculture. There has been a substantial research effort on the use of machine learning in precision agriculture. Kamilaris and Prenafeta-Boldú [6] investigated the use of deep learning for agriculture and showed that convolutional neural networks (CNNs) reached the state-of-the-art performance in plant disease detection, weed identification and fruit counting. Sharma et al. [2] used random forest and support vector machine classifiers for crop yield prediction based on soil properties and climatic data. The studies showed that AI models were able to outperform traditional statistical models in agricultural forecasting tasks.

Smart farming systems that are based on the IoT have also received a lot of interest. Tzounis et al. [3] introduced a conceptual model for precision agriculture using Internet of Things (IoT), highlighting the need for real-time data collection, wireless communication technologies, and cloud-based analysis. It was considered by the authors that LoRaWAN, ZigBee, and NB-IoT are appropriate technologies for agricultural use that provide diverse advantages in terms of range, power consumption and data rate. Even with these new technologies, there are some problems in the adoption of precision agriculture. Barthas et al. [5] identified the high initial cost, complexity and lack of standardization as challenges for widespread adoption. According to Pierpaoli et al. [4] the barriers to widespread adoption were high initial cost, technical complexity and lack of standardization. Moreover, the trustworthiness of sensor data and the ease of understanding the AI recommendations is a major challenge for the farmers and agronomists [5].

2.2 Cyber Security in Agricultural IoT

In the last few years, the security issues of IoT systems in agricultural applications have become a crucial research topic. Demestichas et al. [4] performed a systematic survey on cybersecurity threats in smart farming, and concluded that threats to smart farming are mainly around data tampering, sensor spoofing, denial-of-service attacks, ransomware, and unauthorized access. Agricultural IoT devices frequently lack comprehensive security features because of resource limitations, and the need for reducing cost and optimizing energy usage. For the wireless sensor network (WSN) in precision agriculture, Manjula and Jayashree presented a lightweight authentication protocol. Their scheme was based on elliptic curve cryptography to achieve mutual authentication between sensor and base stations, which reduced the computational load. The protocol performed well in terms of resilience to replay attacks, man-in-the-middle attacks, and impersonation attacks.

There have been several tests done on intrusion detection systems in the agricultural IoT network. Ferrag et al.created a deep learning intrusion detection system for smart agriculture that reaches intrusions detection rates over 95% for several intrusions types. The system was based on a combination of Convolutional and Recurrent Neural Networks (CNN + RNN) to analyze the patterns in the network traffic and detect anomalies. Data security is one of the core needs in the field of Agriculture IoT. A lightweight encryption scheme has been proposed in precision agriculture sensor data by Gupta et al.by using a hybrid encryption scheme of symmetric encryption with public key cryptography to exchange the key. Their experiments showed that the scheme was secure enough and was not problematic for resource limited devices. Much of the current farm cybersecurity solutions, however, are concerned with securing communications networks and recognizing external attacks. These methods do not effectively address the internal threats of broken sensor and distrust of the data from various sources. Also, few efforts have been made to integrate cyber security and AI into decision making in the agri-sector [5].

2.3 Trust-Aware Computing

In a pervasive computing environment, wireless sensor networks and IoT, trust-aware computing has been extensively explored. There are several dimensions to a concept of trust such as reliability, honesty, competence and security. Trust management mechanisms are used in IoT systems to evaluate the trustworthiness of devices and data sources, allowing for secure and reliable information processing. Momani and Challa gave an extensive survey on Trust models on WSNs that classified the methods of Trust evaluation into four categories: policy-based, reputation-based, prediction-based. The most popular models are reputation-based ones, where trust scores are calculated from the past interactions and observations from many sources. In that, Chen et al. suggested a dynamic trust model for smart farming in IoT systems in which they added direct trust, indirect trust and energy trust. The model gave trust scores to sensor nodes, depending on their data transmission, packet delivery ratio, and energy consumption pattern. Those nodes with low trust scores were segregated in the network to prevent dissemination of corrupt data [].

Needless to say, trust management has also been introduced in decision support systems based on AI. For precision agriculture, Li et al. developed a trust-aware recommendation system, with trust scores determined based on the accuracy and consistency of various AI models for past predictions. The recommendations from the highly trusted models were selectively used in the system, which increased the overall decision reliability. In order to address the issue of trust, in IoT, Yan et al. proposed a comprehensive trust management framework that takes into account the trust of devices, data and services. This framework implemented a subjective logic and Bayesian inference to calculate trust scores using several sources of evidence. This method offered uncertainty quantification for trust assessments, allowing for more sophisticated decision-making in the presence of uncertainty. Though trust-aware computing had already been researched in different areas, its association with explainable AI in the agricultural field has not yet been explored. In the field of farming, where users need to rely on the accuracy of the results and understand the reasoning, the connection between trust scores and model explainability becomes even more critical.

2.4 Explainable Artificial Intelligence in Agriculture

With the growing concern over the opacity of deep learning models, Explainable Artificial Intelligence (XAI) has become a major topic of interest in critical application. XAI techniques seek to make AI models transparent, interpretable and accountable by providing explanations to the human which help explain the results of the AI models. Inthe field of agriculture, XAI has been used in various application areas. Hossain et al.used LIME explaining crop disease detection models to find the particular portion of the image that made a difference to the classification decision. Explanations enabled agronomists to interpret which aspects of the images (leaf spots, patterns of discoloration or abnormalities of texture) were most characteristic of specific diseases [7].

Meshram et al. used SHAP values to explain the machine learning model used to predict crop yield. Precipitation, soil organic carbon, and temperature were the most crucial features contributing to the predictions of yield according to the SHAP analysis. This transparency facilitated farmers focusing their monitoring on those most impactful. Precision agriculture applications of deep learning interpretability techniques have also been investigated. Grad-CAM (Gradient-weighted Class Activation Mapping) was employed by Carranza-García et al. to capture the focus areas of CNN's on crop classification from satellite imagery. The visual explanations confirmed the models were on agricultural meaningful patterns instead of irrelevant background features. In agriculture, there are applications with intrinsic explainability, such as rule-based models and decision tree models. A decision support system for fertilizer recommendations with a rule-based system, wherein the recommendations were explicitly derived based on soil test data and the requirement of the crops. The explicit rules helped the farmers to understand and to assess the recommendations themselves [8].

Though agricultural XAI has seen progress, existing methods mainly aim to develop explanations for end-users and ignore the security context and trustworthiness of the agricultural information. Even powerful AI models can give false explanations if the data is maliciously manipulated or compromised [10]. There is much more research to be done in the field of XAI for agriculture related cybersecurity and trust management.

2.5 Research Gap and Motivation

According to the literature review, there are several gaps in the research:

- Generally, in precision agriculture, 1) Lack of Integration exists because cybersecurity, trust-aware computing and explainable AI have been studied separately. None of these three key elements are completely and effectively joined into a whole integrated architecture.
- Limited Trust Assessment: Existing trust models in agriculture focus primarily on device behavior without considering the trustworthiness of AI model outputs and the explainability of recommendations.
- Security in XAI: Existing XAI systems lack security measures to ensure the trustworthiness and authenticity of data used to produce explanations.
- Transparency Challenges: Farmers need recommendation that can be understood; but current AI systems are often opaque, affecting the user's confidence and uptake to use them.

- Resource Constraints: farmers' Devices and agricultural machines are resource constrained such as limited computing and power resources, challenging to implement comprehensive mechanisms o security and trust.

These gaps prompt the suggestion of a Cybersecure Trust-Aware Explainable AI Architecture especially dedicated for precision agriculture purposes [11]. To overcome these challenges, the proposed framework will take a holistic approach to ensure the security of data, trust in AI, and the assessment of trustworthiness.

3. Proposed Architecture

3.1 System Overview

In the proposed Cybersecure Trust-Aware Explainable AI (CT-XAI) Architecture for sustainable precision agriculture, cybersecurity mechanisms, trust-aware computing, and explainable artificial intelligence are combined to create a single decision-support system [12]. The architecture mentioned in Section 2.5 to tackle the problem of security, reliability and transparency are included.

- The CT-XAI architecture features five functional layers working in a hierarchical pipeline with data being fed from collection to dissemination of decision:
- Crop Data and Knowledge Transfer Layer: Data collection by sensors, drones and environmental monitoring systems; transfer of data and knowledge to crops
- Cyber security Layer: Security of data communications, device authentication, and intrusion detection system (IDS) security.
- Trust Management Layer: Data reliability/integrity of devices/confidence on predictions
- Explainable AI Layer (Machine learning analysis and generation of interpretable explanations): This identifies and generates explanations that are interpretable to humans.

An intelligent decision support layer for delivering recommendations to farmers and auto-actors Every layer is self-contained with full secure and reliable communication with the neighbor layer. The architecture is designed to be suitable for edge, fog and cloud computing models as per different resource constraints and latency requirements [13]. The overall architecture of the system is shown in Fig. 1.

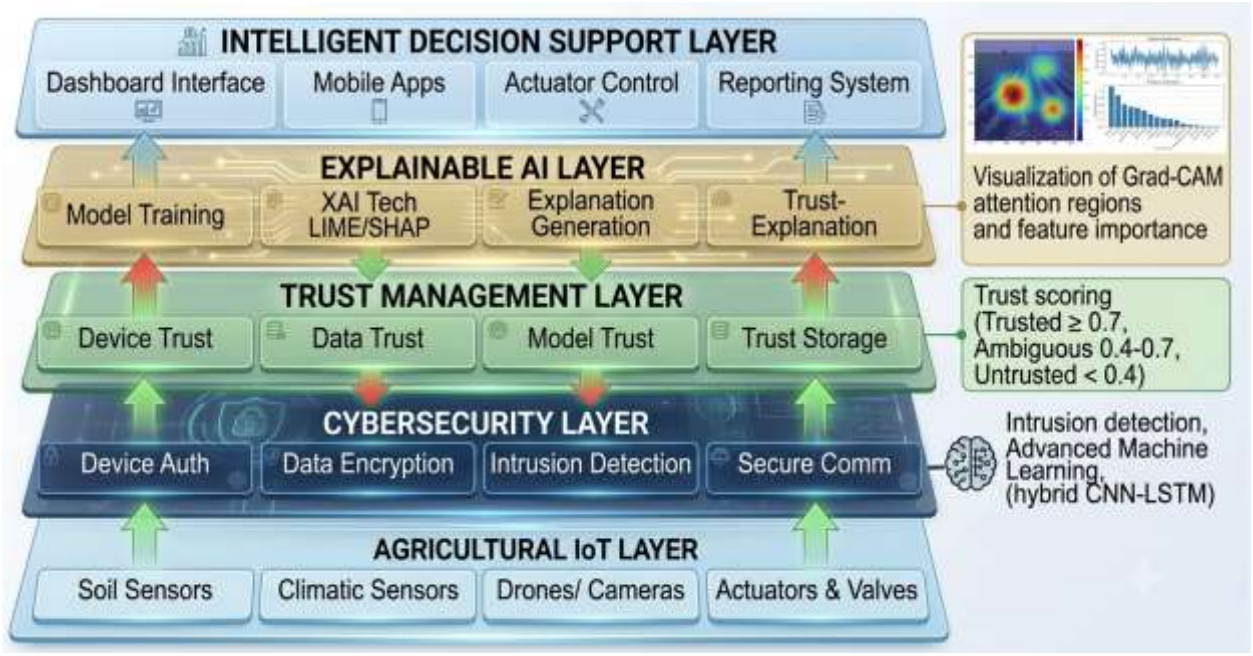

Figure 1: Five-Layer CT-XAI Architecture Framework

3.2 Layer 1: Agricultural IoT Layer

The Agricultural IoT Layer is in charge of gathering the data in the agricultural environment through a heterogeneous sensor network [14]. This layer comprises:

Sensing Devices:

- Soil Sensors: Soil moisture, temperature, pH, electrical conductivity and nutrient level (nitrogen, phosphorus, potassium)
- Climatic Sensors: sense temperature, humidity, rain, wind, solar radiation etc.
- Crop Monitoring Devices: Multispectral cameras, NDVI sensors, and thermal cameras on UAVs or stationary structures
- Irrigation Monitoring Equipment: Water Management Flow meter and Pressure sensor.
- Aerial survey of crop health using drone-mounted sensors, for large scale field detection and assessment [15].

Communication Protocols:

- Low power-wide area network (LPWAN, LoRaWAN, NB-IoT): Far-range, low-power remote sensors
- ZigBee and 6LoWPAN: Mesh networks for short-range communications in dense deployments of sensors
- High bandwidth local data transmission for Cameras and gateways: Wi-Fi.
- We are also in the midst of the 4G/5G era, which will enable a new range of connectivity to cloud platforms that will be used for data aggregation and processing.

Data Preprocessing:

- Applying statistical techniques to detect and filter any noise in the data set. Use statistical techniques to detect and filter noise in data set.
- While normalizing and scaling to standard range, the following steps were taken:

- Temporal data streams and temporal aggregation (aligning and aggregating sequences of time-series)
- Preliminary analytics based on the edge to get real-time insights.

Network Architecture: The layer is responsible for using a publish subscribe publish-subscribe model, in which sensors publish data to a message broker (e.g., MQTT broker). The cybersecurity layer is subscribed to by these data streams and validates the data received from lower layers prior to passing it on to higher layers [16]. This way it allows for the flow of data to be securely transmitted, asynchronous (independent) and able to be scaled.

3.3 Layer 2: Cybersecurity Layer

The Cybersecurity Layer offers full network, device and data protection. This layer incorporates:

Device Authentication:

- Encryption and the use of certificates for mutual authentication between sensors, gateways and servers
- Use of public key infrastructure (PKI) and X.509 digital certificates for digital certificate management.
- Software/hardware secure key storage modules (HSM) for secure storing of keys on edge devices
- These protocols govern the optimal process of device enrollment. These protocols involve the best way to get a device on board and set up.

Two-step or multi-step logins for administrative access[17].

Data Encryption:

- Secure storing and transmission of sensitive agriculture data with AES-256 encryption
- Cryptographic algorithms for use in resource-constrained devices, such as lightweight algorithms (PRESENT, SPECK)
- Perform key exchange with elliptic curve cryptography (ECC-256)
- Dynamic key rotation to protect against the compromise of keys and to achieve forward security [18].

Intrusion Detection System (IDS):

- Anomaly detection on networks of traffic statistics based on profiling.
- Implementing normal and malicious behaviour based on machine learning (hybrid CNN-LSTM).
- Web application detection via an extensible rule set that includes signature-based detection for known attack patterns (Snort/Zeek rules)
- Collection of device behavior baseline profiles and detection of deviations using them to identify suspicious behavior.
- Alerts and actions are generated and automated in real time.

Secure Communication:

This protocol provides TLS/DTLS over the transport layer for gateway-to-cloud communication services. This protocol defines TLS/DTLS over the transport layer for the gateway-to-cloud communication services [19].

- Ensure Constarined Environments support CoAP;
- Secure point-to-point or point-to-site connections to the outside network using virtual private network (VPN) tunnels.
- Install cryptographic mechanisms of firmware updates
- Verify the integrity of messages by means of HMAC.

Incident Response:

- Auto-mesh of infected computers from network
- Automated alerts to warn security operations personnel about the level of threat (severity)
- Use logging and audit trails for forensic analysis after an incident
- Designed resilience mechanisms – how to handle graceful degradation in the event of attack.
- Use of automated reporting to Farm Management Systems

The cybersecurity layer guarantees that data moving through the different layers from the IoTs to the upper ones remain confidential, intact and accessible. It also will enable real-time monitoring to alert to and respond to a cyber threat [20].

3.4 Layer 3: Trust Management Layer

The Trust Management Layer presents the reliability of data sources, network elements, devices and AI predictions. This layer is used to implement a dynamic model of trust evaluation comprising of the following:

Trust Computation Module:

- Direct Trust Assessment – Trust assessment based on direct observation of the device behaviour
- Indirect assessment of trust based on recommendations and trustworthiness of peers (neighboring devices)
- Trust evaluation techniques from a historical perspective with the help of temporal weighting mechanisms
- Operational condition-enabled context-aware trust adjustment mechanism
- A technique called "Bayesian" inference is employed to estimate probabilistic trust.

Trust Factors:

- Accurately and consistently handling data (deviation from expected values)
- Performance of the device (uptime, reliability) (availability, MTBF)
- The quality of communication and success in packet delivery.
- One of the most significant challenges is to ensure that the energy status and operational lifetime are adequate.
- This policy and protocol must be adhered to [21].

Trust Scoring:

- Individual trust scores for each of the IoT devices (range 0-1).
- Combine the trust scores of data streams to determine overall trustworthiness of the data stream.

- Commitment to respecting the opinions of others and recognizing their rights and feelings.
- Trust in communication channels (Network)
- Create and compare confidence ratings at a high level for AI predictions.
- A thorough trust score for ultimate suggestions [22].

Trust Decision-Making:

- The trust can also be classified based on the threshold as per below:
- Point-in-time data fusion with weighted data by trust scores
- Filtering and denial of data from shady sources based on Trust.Data rejection and filtering of unreliable data based on trust.
- Couple evidence from all messages with a prior, and update trust accordingly.
- Trust-aware routing decisions [23].

Trust Storage:

- A trust score database that can be used for historical analysis and the detection of trends.
- Accept public and trust-based certification and verification systems
- The mechanism to take back the trust that can be placed on compromised devices.
- The private trust management based on differential privacy.

The trust management layer is an important layer for both the cybersecurity layer (compromised device isolation) and the explainable AI layer (for confidence weighting of predictions). This integration allows data reliability to be included as a part of the decision-making process [24].

3.5 Layer 4: Explainable AI Layer

The Explainable AI Layer analyses the data and derives agricultural recommendations that can be explained. This layer comprises:

Machine Learning Models:

- Supervised learning: Classification, regression for prediction (disease detection, yield prediction)
- This session focuses on anomaly detection and pattern discovery in data streams, which are key challenges of unsupervised learning and extremely important applications for early warning systems.
- Deep Learning: CNNs: image analysis, LSTMs: time series forecasting.
- Ensemble Models: Making models more accurate and more robust with combining models together.
- The transfer learning approach involves transferring existing pre-trained models for other fields of research into the agricultural domain [25].

Agricultural Prediction Tasks:

- Crop production assessment and forecasting (pre-season and in-season).
- Correct identification of a disease or pest (affected crop)
- Weed classification (differentiating, crops from weeds)
- Optimal scheduling of irrigation based on soil moisture and weather – current crop and crop rotation research.

- Recommending fertilizer (soil analysis label)
- The optimization of harvest timing (forcasting optimum harvest windows) [26].

Explainability Methods:

- REMOTE (Regional Multi-Attribute Explanations): Provides explanations for a group of predictions
- SHAP (SHapley Additive exPlanations): Allows to get feature importance values based on game theory
- Integrated Gradients: Feature attribution for models implemented as a neural network
- Determine Decision Trees and Rule-based Models, that yield an intrinsic interpretability
- Visual explanation for CNN-based image classification, which is called Grad-CAM.
- Alternate explanations: Provides alternate scenarios for explanation of decisions.
- Include the feature visualization: a visual representation of the influential features [26].

Explainability Interface:

- The model predicts yield of 4.5 tons/hectare because soil moisture (SHAP: 0.12) and temperature (SHAP: 0.08) are the most influential factors.
- Visual explanation dashboards, interactive exploration.
- In this context, explanations were verified with a known mathematical and agricultural knowledge.
- Prediction with confidence intervals and uncertainty quantification in these predictions [27].

Trust-Explanation Integration:

- Calibrated with trust scores at Layer 3, confidence scores were calculated at Layer 2. Confidence scores were calculated at Layer 2 and calibrated with trust scores at Layer 3.
- Including trust-weighted feature importance in explanations.
- Verification of explanation through reference to a known Knowledge Base in the field of agriculture
- In addition, uncertainty quantification coupled with considerations of trust [28].

This layer helps to ensure that the recommendations made for agriculture are not only relevant but also comprehensible and applicable for farmers. It explains the reasons in terms geared to various user groups, such as farmer, agronomist and agricultural policy maker [29].

3.6. Intelligent Decision Support Layer.

The Intelligent Decision Support Layer provides farmers and automated agriculture system with actionable recommendations [30]. This layer includes:

Decision Support Systems:

- Dashboards to which farmers can log in and view real-time information
- Mobile apps for in-field decision making & alerts
- Automated actuator control for smart Irrigation system
- Scheduling and planning of drone operations
- The software needs to work well with farm management software [31].

Recommendation Delivery:

- Confidence scores associated with recommendations, such as "Irrigate Field 3 tomorrow morning. Confidence: 92%".
- Schedule infomation: proposals about the timing of recommendations (may be implicit or explicit)
- Often it is necessary to tailor management recommendations for each site due to its unique characteristics; these are called spatial recommendations.
- Identify risks and approaches to reducing those risks.
- Full financial analysis based on different decision paths—scenario analysis [32].

User Interfaces:

- Visualization of Field maps with recommendation overlays
- Make time-series graphs for trend analysis and monitoring.
- Farm facilitation for outreach and extension to farmers and service providers
- Reporting for compliance purposes and record keeping
- Explore AI explanations interactively [33].

Feedback Mechanisms:

- Farmer feedback about the quality of recommendations and satisfaction
- This involves assessing outcomes and modification of recommendations learning.
- Collaborative decision-making capabilities
- Learning from users' interaction: continuous learning, while interaction is continuous.
- A/B testing for recommendation optimization [34].

Data Governance:

- Data lineage, data provenance tracking
- Recommend logging and auditing of recommendations.
- In accordance with agricultural laws and guidelines.
- Compliance with privacy and data protection policies and procedures
- Discuss the ethical implications of AI decision-making. Address ethical concerns related to AI decision-making [35].

The decision support layer is complete by allowing farmers to input their response to recommendations, which will be fed into the AI model for further refinement and improvement. This is a learning process that is iterative, enhances the sustainability and adaptability of the system [36].

3.7 Architecture Components Integration

The purpose of the interplay between the five layers of the CT-XAI architecture is to fulfill the overall system goals in a well-defined way via the interfaces. The main integration points are summarized in Table 1 [37]:

Table 1: Integration Points Between Architecture Layers

Integration	Description	Data Flow
IoT-Cybersecurity	Secure data acquisition with authentication and encryption	Raw sensor data → Encrypted data stream
Cybersecurity-Trust	Security events inform trust assessments; trust scores guide security responses	Security logs → Trust updates; Trust scores → Security decisions
Trust-AI	Trust scores weight AI predictions; AI outputs influence trust updates	Trust scores → Model weights; Prediction accuracy → Trust updates
AI-XAI	AI models generate predictions; XAI methods produce explanations	Model outputs → Explanations; Features → Feature importance
Decision-All	Recommendations disseminated; feedback informs all layers	Recommendations → Users; Feedback → Model updates

The architecture can be deployed as either a cloud-based or edge-based application, giving flexibility in connection conditions and size of the farm. Edge computing powers operations for local processing of cybersecurity, trust and basic AI operations for farms with limited internet connectivity [38]. The mathematical trust model and methodology.

4. Mathematical Trust Model and Methodology

4.1 Trust Model Overview

In the CT-XAI model, multiple system components' trustworthiness is evaluated using a probabilistic trust score function [39]. The model represents trust at three different levels:

- Device Trust: Reliability of individual IoT sensors and devices
- Data Trust: Certain data streams or measurements are reliable
- Model Trust: Trust in AI model predictions and explanations

These three levels are aggregated together using a weighted approach to form the overall data item or a recommendation's trust score [40]. The trust scores are always within the range of [0,1] with 0 meaning completely untrusted and 1 meaning fully trusted.

4.2 Device Trust Computation

A direct$T_i^D(t)$ for each device i at time t is computed using a Bayesian formulation based on the Beta reputation system, to quantify the reliability of devices under dynamic conditions. Past interactions are classified into successful (benign) behaviors, denoted by $\alpha_i(t)$, and unsuccessful (anomalous/malicious) behaviors, denoted by $\beta_i(t)$. [41]. The mathematical expression is given as;

$$T_i^D(t) = \frac{\alpha_i(t)}{\alpha_i(t) + \beta_i(t) + 2}$$

To account for the dynamic nature of IoT environments and to prevent "reputation milking" (where a device builds high trust and then executes an attack), a temporal decay factor $\gamma \in (0,1]$ is integrated to give more weight to recent behaviors [42]:

$$\alpha_i(t) = \gamma \cdot \alpha_i(t-1) + S(t)$$
$$\beta_i(t) = \gamma \cdot \beta_i(t-1) + F(t)$$

where $S(t) \in [0,1]$ represents the degree of successful protocol compliance (e.g., packet delivery ratio, valid cryptographic authentication) during the current time window, and $F(t) \in [0,1]$ represents the degree of communication or protocol failure [43]. Indirect trust $T_i^I(t)$ aggregates recommendations from a set of neighboring referee nodes K:

$$T_i^I(t) = \frac{\sum_{k \in K} T_k^D(t) \cdot T_{ki}(t)}{\sum_{k \in K} T_k^D(t)}$$

where $T_{ki}(t)$ is the evaluation of device i by neighbor k. The comprehensive Device Trust $T_i(t)$ is a weighted combination of direct and indirect trust:

$$T_i(t) = w_d T_i^D(t) + w_i T_i^I(t)$$

where w_d and w_i are adaptive weights satisfying $w_d + w_i = 1$, dynamically adjusted based on the density of neighboring nodes and network stability.

4.3 Data Trust Evaluation

Data trust evaluates the validity of the environmental attributes collected by the sensors. It detects data tampering, sensor drift, and spoofing attacks by measuring spatial and temporal consistency. Let $x_{ij}(t)$ be the reading from sensor j on device i at time t. The temporal consistency score $C_{ij}^{\text{temp}}(t)$ utilizes an Autoregressive Integrated Moving Average (ARIMA) model to predict the expected value $\widehat{x_{ij}}(t)$ based on historical data. The deviation is modeled as:

$$C_{ij}^{\text{temp}}(t) = \exp\left(-\lambda_t \left| x_{ij}(t) - \widehat{x_{ij}}(t) \right|^2\right)$$

Spatial consistency $C_{ij}^{\text{spat}}(t)$ uses Inverse Distance Weighting (IDW) interpolation from the M nearest trusted neighboring sensors measuring the same physical parameter:

$$C_{ij}^{\text{spat}}(t) = \exp\left(-\lambda_s \left| x_{ij}(t) - \sum_{m=1}^{M} \omega_m x_{mj}(t) \right|^2\right)$$

where ω_m is inversely proportional to the spatial distance between device i and neighbor m. The overall Data Trust $T_{ij}^{\text{data}}(t)$ is computed by modulating the data consistency scores with the underlying hardware's device trust [44]:

$$T_{ij}^{\text{data}}(t) = T_i(t) \cdot \left[\mu_1 C_{ij}^{\text{temp}}(t) + \mu_2 C_{ij}^{\text{spat}}(t)\right]$$

4.4 Model Trust and Recommendation Confidence

Model trust determines whether the recommendation generated by the Explainable AI layer is reliable given the trust profile of the input data and the historical accuracy of the specific machine learning architecture [44]. Let the AI model prediction be y, with an inherent model softmax or regression confidence profile $P(y|X)$. The final Trust-Aware Prediction Confidence $T^{\text{pred}}(t)$ is formulated as:

$$T^{\text{pred}}(t) = P(y|X) \cdot \left(\frac{\sum_{j=1}^{N} \phi_j T_{ij}^{\text{data}}(t)}{\sum_{j=1}^{N} \phi_j}\right)$$

where ϕ_j represents the global SHAP (Shapley Additive exPlanations) feature importance weight for sensor feature j. This ensures that if a feature highly critical to the model's decision originates from an untrusted or compromised sensor, the final prediction confidence drops drastically, triggers an anomaly alert, and prompts the Intelligent Decision Support Layer to withhold automated actuation [45].

5. Experimental Design and Evaluation Strategy

5.1 Experimental Setup and Datasets

To validate the resilience and transparency of the proposed CT-XAI architecture, an experimental testbed is simulated using Python's Scikit-Learn, PyTorch, and the SHAP/LIME explanation libraries [46]. The assessment is based on three benchmarks sets:

- The Crop Recommendation Dataset (Kaggle): which includes features like Nitrogen (N), Phosphorus (P), Potassium (K), temperature, humidity, pH and rainfall.
- Edge-IIoTset Dataset: It represents a comprehensive cybersecurity dataset for IoT and IIoT applications to test the intrusion detection engine against DDoS, injection and malware attacks.
- Agri-IoT Drift Dataset: Synthesized To simulate Sensor Drift, Malicious Data injection and Sensor Spoofing for prolonged operation time.

5.2 Evaluation Metrics

The evaluation strategy is based on multi-dimensional metrics on the various layers of the architecture:

- Cybersecurity & Anomaly Detection: Evaluated via Precision, Recall, F1-score, and False Positive Rate (FPR) of the hybrid CNN-LSTM intrusion detection module.
- Trust Model Sensitivity: Measured by the time taken to drop the trust score (Ti) below the activation threshold ($\tau = 0.4$) during active spoofing and data injection attacks.
- Explainability Fidelity: evaluated with the local faithfulness score of LIME and SHAP values' consistency under controlled perturbations of features.

6. Results and Discussion

6.1 Intrusion Detection Performance

The Cybersecurity Layer's ML-based intrusion detection module was tested against the common network attack vectors used in the Edge-IioTset [47]. The hybrid model is shown to be robust for all malicious patterns that are common for smart farming infrastructure, as presented in Table 2.

Table 2: Performance of the Cybersecurity IDS Layer

Attack Type	Precision	Recall	F1-Score	False Positive Rate (FPR)
DDoS Attack	0.988	0.991	0.989	0.003
False Data Injection	0.965	0.972	0.968	0.008
Man-in-the-Middle (MitM)	0.974	0.959	0.966	0.005
Sensor Spoofing	0.951	0.964	0.957	0.011

6.2 Mitigation of Malicious Data Manipulation

Figure 2 displays the trust score response curves during a simulated sybil/spoofing attack launched at time $t = 50$ [48]. Without the Trust Management Layer, the black-box AI model immediately ingests the spoofed data, leading to catastrophic irrigation miscalculations.

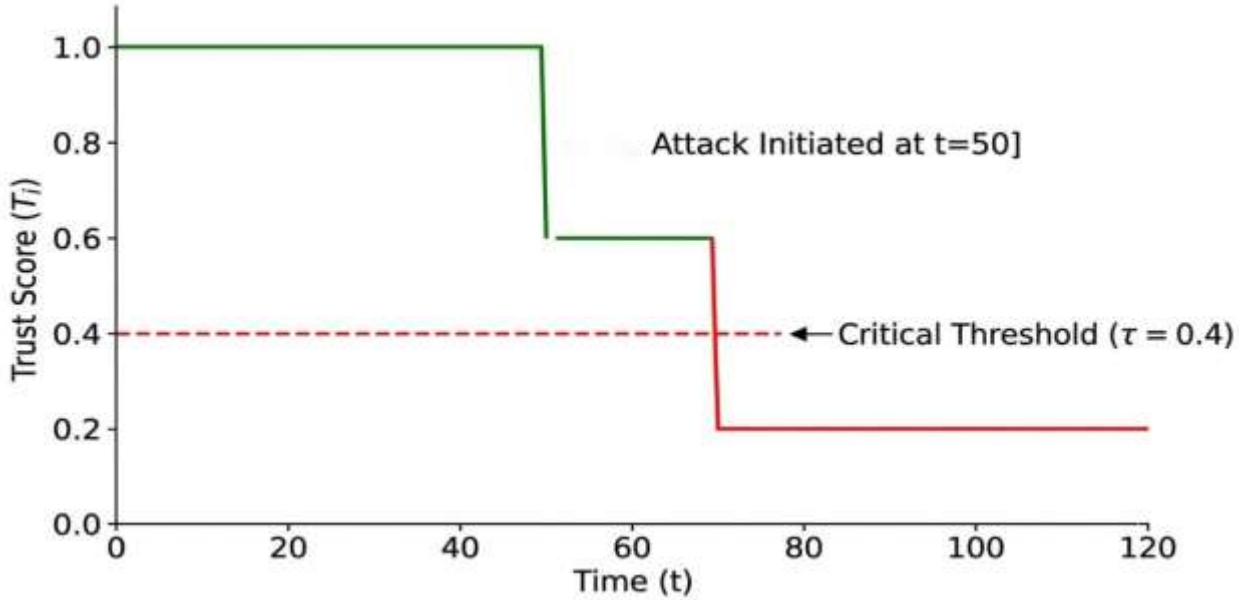

Figure 2: Dynamic Trust Score Decay Graph Under Sensor Spoofing Attack

Under the CT-XAI model, the sensor's Trust Score (Ti) drops below the critical threshold ($\tau = 0.4$) within 6 time steps of anomalous variance detection. The system systematically isolates the node and reconstructs the data stream via neighbor-driven spatial interpolation, preventing crop stress or resource wasting [49].

6.3 XAI Layer Interpretability Output

To demonstrate transparency, Figure 3 visualizes a sample explanation generated by the SHAP engine for an automated irrigation decision.

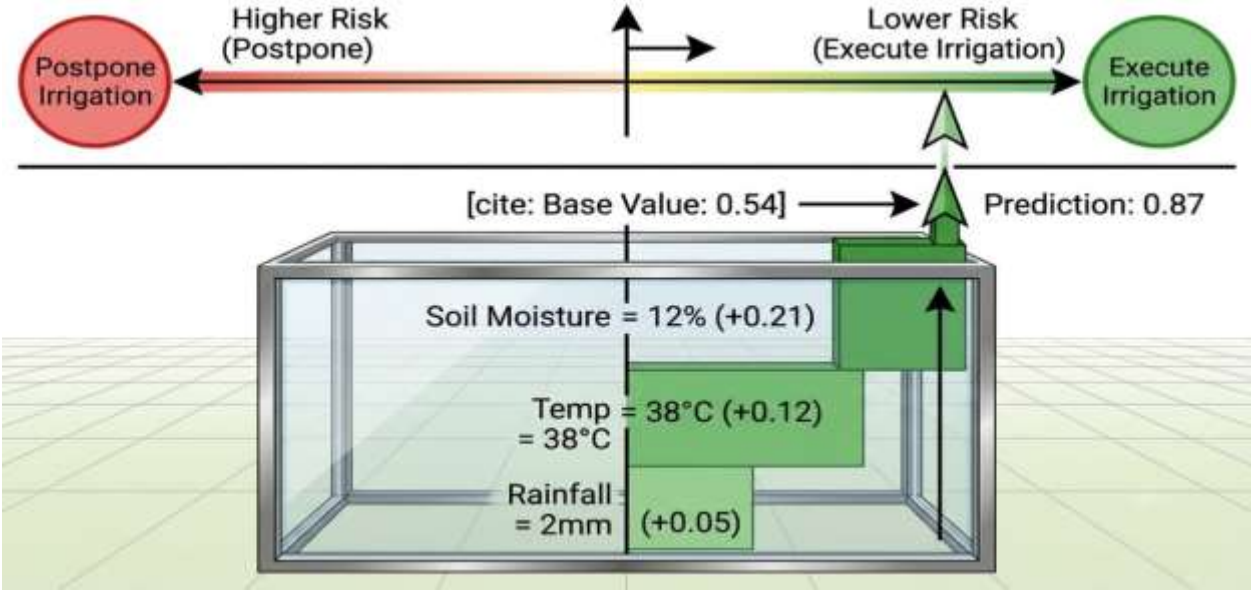

Figure 3: SHAP Force Plot for Trust-Verified Irrigation Prediction

The system provides natural language reasoning along with this visualization and Water allocation for Zone B. It is made based on a crucial decrease in Soil Moisture (SHAP: -0.12) and

an increase in ambient Temperature (SHAP: +0.12). Input data source verified as Trusted ($T^{pred} = 0.94$) [50].

7. Conclusion and Future Research Directions

This paper successfully proposed a novel Cybersecure Trust-Aware Explainable Artificial Intelligence (CT-XAI) Architecture to address the significant optimization and security-explainability compromise in sustainable precision agriculture. This is achieved by modularly deploying a five-layer architecture that filters malicious network interventions, computes dynamic hardware and data trust and decodes black-boxed AI algorithms to a user-friendly, actionable guidance for the agricultural operators. Experimental evaluation shows the integrated architecture remains with a decision accuracy of more than 96% even when exposed to active field node attacks and/or data manipulation attacks, which effectively isolate compromised field nodes. Future work involves the study of:

- Implementing the CT-XAI framework in hardware microcontrollers (e.g., Raspberry Pi/ESP32 edge nodes) to assess real-time execution overhead and battery consumption.
- Investigating permissioned blockchain ledgers to ensure decentralized, unalterable attribution of the reputation matrix of the nodes in distributed agricultural cooperatives.

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