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Edge computing-oriented smart agricultural supply chain mechanism with auction and fuzzy neural networks

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Abstract

Powered by data-driven technologies, precision agriculture offers immense productivity and sustainability benefits. However, fragmentation across farmlands necessitates distributed transparent automation. We developed an edge computing framework complemented by auction mechanisms and fuzzy optimizers that connect various supply chain stages. Specifically, edge computing offers powerful capabilities that enable real-time monitoring and data-driven decision-making in smart agriculture. We propose an edge computing framework tailored to agricultural needs to ensure sustainability through a renewable solar energy supply. Although the edge computing framework manages real-time crop monitoring and data collection, market-based mechanisms, such as auctions and fuzzy optimization models, support decision-making for smooth agricultural supply chain operations. We formulated invisible auction mechanisms that hide actual bid values and regulate information flows, combined with machine learning techniques for robust predictive analytics. While rule-based fuzzy systems encode domain expertise in agricultural decision-making, adaptable training algorithms help optimize model parameters from the data. A two-phase hybrid learning approach is formulated. Fuzzy optimization models were formulated using domain expertise for three key supply chain decision problems. Auction markets discover optimal crop demand–supply balancing and pricing signals. Fuzzy systems incorporate domain knowledge into interpretable crop-advisory models. An integrated evaluation of 50 farms over five crop cycles demonstrated the high performance of the proposed edge computing-oriented auction-based fuzzy neural network model compared with benchmarks.

Keywords Edge computing, Smart agricultural supply chain, Auction, Fuzzy neural networks

Introduction

Modern agriculture faces unprecedented stresses, such as rising food requirements from global population growth and declining arable land and water resources [1]. However, farm yields have plateaued, making bridging the supply–demand gap impossible. These macro trends necessitate urgent improvements in agricultural efficiency to boost productivity by up to 70% with shrinking buffers. Climate change pressures like extreme weather events, soil degradation, biodiversity losses, and rising carbon emissions threaten ecological sustainability. Agriculture accounts for over 25% of greenhouse gas emissions, highlighting the sizable decarbonization potential. However, the sector needs to catch up to manufacturing and transport, among other sectors, in sustainability initiatives [2, 3]. Enhancing agriculture's environmental footprint requires data-driven transparency in the operational decisions that guide targeted interventions [4]. At

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the execution level, the sector exhibits deeply fragmented value chains, with numerous small-hold farmers and intermediary aggregators connected to processors and distributors. The high variability and ambiguity in biological crop cultivation processes also introduce decision complexity for stakeholders. Managing the complexity of agricultural workflow is currently manual-intensive, opaque, and localized.

These macro and micro challenges create a burning platform for transforming traditional agriculture through emerging technologies. The promise of precision agriculture powered by data-driven automation offers step-change boosts in productivity, quality, sustainability, and resilience [5–8]. Recent advancements in sensors, communication networks, edge computing, blockchain, machine learning, and artificial intelligence can be harvested to uplift agriculture. However, myriad barriers to adoption persist, limiting the technology-upgrade cycles. Hyperlocalization, characterized by the high spatial variability of farm ecology, including factors such as soil nutrition, moisture patterns, and disease risks, requires hyperlocal insights [9]. Centralized systems must capture these microclimatic nuances. In addition, decision ambiguity arises from biological uncertainties, weather volatility, and market variability, thus introducing ambiguities that require more structured solutions. Rigid automation often leads to suboptimal results or overcorrections that require stability. Furthermore, ecosystem opacity within the fragmented, multi-stakeholder agricultural network contributes to the need for more transparency regarding peer practices, supply–demand patterns, and fair pricing, inducing informality. While data-driven precision agriculture promises potential benefits, farmer data privacy requires thoughtful consideration. For instance, privacy-aware schemes for point-of-interest recommendations that are also relevant in agriculture for sensitive farm-specific plans [10, 11]. Lastly, inadequate infrastructure, particularly in terms of telecom, power, and public cloud infrastructure, remains a significant challenge for large-scale smart upgrades, especially in emerging rural regions with connectivity gaps [12, 13]. Decentralized architectures have demonstrated their robustness in addressing infrastructure limitations.

Smart agricultural systems apply modern information and communication technologies to enhance productivity, profitability, sustainability, and traceability across the agricultural value chain, including cultivation, postharvest handling and processing, logistics, and marketing [14]. Edge computing refers to the paradigm of decentralized data processing, whereby computation and analytics are embedded in the data source rather than relying on a distant, centralized cloud infrastructure. In agriculture, intelligent edge devices can be embedded in farm equipment, storage warehouses, processing plants, and retail outlets [15]. Key-edge computing capabilities include real-time insight generation, decision autonomy, data filtering, and operational visibility. The edge-processing topology also enhances scalability, reliability, and sustainability. Hosting decentralized intelligence close to dispersed agricultural endpoints facilitates hyperlocal and instantaneous data-to-decision, even in remote terrain.

Auction markets refer to transparent bidding mechanisms that facilitate efficient price discovery and clearing of trade volumes between multiple buyers and sellers. Continuous double auctions allow participants to place ask or bid quotes that dynamically match compatible offers concurrently [16]. However, real-world bidder psychology requires governance to ensure stability. Computational techniques such as reinforcement learning can model optimized bidding tactics. Overall, auctions simplify bilateral negotiations and enable liquidity on a global scale.

While neural networks offer adaptable nonlinear function approximations, fuzzy logic facilitates interpretable reasoning that supports agricultural decision-making. Fuzzy systems can also generate natural language advisories for irrigation, fertilization, harvest timing, etc., customized for highly divergent individual farm microclimates, soil health, and crop varieties. Unlike black-box methods, the ability to handle ambiguity and provide explanations builds trust [17]. Fuzziness reflects the underlying continuity of biological processes.

While prior works have studied aspects of edge computing architectures, auction mechanisms, and fuzzy optimization models individually for agriculture, an integrated approach synergizing these promising directions still needs to be developed. Specifically, existing edge computing proposals need to tailor generic paradigms to address unique agriculture sector needs arising from operational scale, decision complexity, and value chain fragmentation. Similarly, agricultural auction designs focus on pricing efficiency rather than holistic supply chain coordination, covering planning, matching, and sustainability. Finally, fuzzy techniques largely encode scientific principles lacking adaptable learning for personalized needs spanning diverse regional and crop-specific considerations. Our unified edge computing, auction, and fuzzy neural network approach is uniquely positioned to overcome these limitations through a context-aware, transparent, and data-driven smart agriculture automation solution connecting the fragmented production-consumption lifecycle. The integrated architecture can capture localized variations, balance supply–demand stability, resolve decision uncertainty, and enable traceability for next-generation precision agriculture needs at a global scale.

By combining the complementary strengths across emerging technologies, the transformation of agricultural supply chains toward data-driven precision approaches is accelerated, ushering in the future of farming. Accordingly, the main contributions of this study are as follows:

1) We propose an edge computing framework tailored to agricultural requirements. The edge computing framework addresses several challenges by providing dense sensing coverage through various sensors, enabling preprocessing and model evaluation capabilities at the edge nodes, facilitating single-hop data transfer to cluster heads, implementing adaptive sensing to activate only the relevant nodes, and ensuring sustainability through a renewable solar energy supply.
2) We formulated invisible auction mechanisms that hide actual bid values and regulate information flows, combined with machine learning techniques for robust predictive analytics.
3) Rule-based fuzzy systems encode domain expertise in agricultural decision-making, and adaptable training algorithms help optimize model parameters from data. A two-phase hybrid learning approach is formulated. Fuzzy optimization models were formulated using domain expertise for three key supply chain decision problems.

The remainder of this paper is organized as follows. Related work section reviews related studies. Edge computing in agriculture section introduces edge computing-oriented smart agriculture. The integration of auction mechanisms and fuzzy neural networks is discussed in Auction mechanism for agriculture section, Fuzzy and neural models section outlines the experiments conducted, and Edge computing-oriented smart agriculture section presents the conclusions.

Related work

Edge computing in agriculture

Edge computing has emerged as a promising paradigm for addressing the challenges of data processing and decision-making in agriculture. By bringing computations closer to the data sources, edge computing enables the real-time processing and analysis of agricultural data, thereby reducing latency and improving responsiveness. Several studies have explored the applications of edge computing in agriculture, including precision agriculture, smart irrigation, and livestock monitoring [18–20]. In [21], the authors introduced a two-tier genetic algorithm methodology aimed at optimizing a data analysis artificial intelligence system designed to monitor the conditions of agricultural vehicles. The cost-effective approach can be deployed on smartphones using integrated microphones rather than relying on expensive IoT sensors. By conducting an in-depth examination of the functioning of rural economies facilitated by the Internet, the authors thoroughly investigated the benefits of the Internet platform introduced in the operation of rural economies [22].

Auction mechanisms for agriculture

Auction mechanisms are widely used in agriculture to facilitate the trading of agricultural products. These mechanisms provide a decentralized and efficient way for farmers to sell their products and for buyers to obtain the desired products. Various agricultural auction mechanisms have been proposed, including open, sealed bid, and Dutch auctions [23]. To address the challenges related to low computational efficiency and restricted benefit distribution in the auction process, in [24], the authors introduced a novel deep learning-based iterative bilateral auction algorithm. This innovative approach represents an improvement over existing methods by harnessing deep learning capabilities to enhance the auction process. In [25], the authors evaluated the pricing efficiency of a livestock auction market using a two-tier stochastic frontier model. In [26], the authors devised a novel method to separate valuations from observed and unobserved variations using professional land appraisals.

Fuzzy and neural models

Fuzzy and neural models have been extensively employed in agriculture to model and predict complex systems. Fuzzy models can capture the uncertainty and imprecision inherent in agricultural data, whereas neural models can learn from the data and make accurate predictions. These models have been applied to various agricultural problems, such as crop yield prediction, disease detection, and pest management [27–30]. Remya and Sasikala developed a neuro-fuzzy prediction model to simulate the behavior of international trade analysis in the agriculture industry [31]. Remya explored various neural network topologies and investigated methods for optimizing and analyzing these networks with agricultural data [27]. Ramana et al. used a convolutional neural network to classify and detect leaf disease [32]. Bhojani and Bhatt developed an amended multilayer perceptron neural network with a new activation function. They revised random weights and bias values for crop yield estimation using different weather parameter datasets [33]. Zhang et al. presented a radar echo prediction method representing disastrous weather based on convolutional neural networks and long short-term memory networks [34].

In summary, emerging computational paradigms demonstrate significant potential in helping realize the vision of smart agriculture but require synthesis considering problem constraints. Our work aims to address this research gap through an integrated edge intelligence, market coordination, and decision optimization approach purpose-built for the sector.

Edge computing-oriented smart agriculture

System model

This study presents an edge computing framework complemented by auction mechanisms and fuzzy optimizers that connect various supply chain stages, as shown in Fig. 1.

Edge computing offers powerful capabilities that enable real-time monitoring and data-driven decision-making in smart agriculture. We propose an edge computing framework tailored to agricultural needs, as shown in Fig. 2.

The framework comprises three sections: the sensing layer, the edge computing layer, and the growth data model.

Sensing layer

The sensing layer consists of heterogeneous sensing devices deployed across agricultural fields to collect various crop and environmental parameters. Sensor nodes can be categorized as follows.

- Crop-monitoring nodes: Sense key parameters related to crop growth, health, and yield, including leaf area, canopy size, stem thickness, leaf color, crop height, and root size.
- Environmental monitoring nodes: Sense climatic parameters such as humidity, temperature, soil moisture, and soil nutrients.

Sensor nodes include sensors, microcontrollers, wireless radios, power units, and other supporting circuits. Different wireless communication standards include WiFi, Bluetooth, LoRaWAN, NB-IoT, and legacy protocols like Zigbee. LoRaWAN provides long-range connectivity that is particularly suitable for sparse farm deployment, whereas Wi-Fi and NB-IoT offer higher bandwidths [35]. Bluetooth is appropriate for short-range communications between proximal nodes.

Let the heterogeneous sensor node set in the field be represented as follows:

$$S = s_1, s_2, \ldots, s_N \tag{1}$$

where N is the total number of deployed nodes, and we assume that each sensor node s_i is aware of its location $(\mathbf{x_i}, \mathbf{y_i})$ via either GPS or landmark-based localization. Nodes with overlapping sensing zones can collaborate to reduce redundancy. The sensor node set S is divided into M clusters based on the spatial proximity:

$$C = c_1, c_2, \ldots, c_M \tag{2}$$

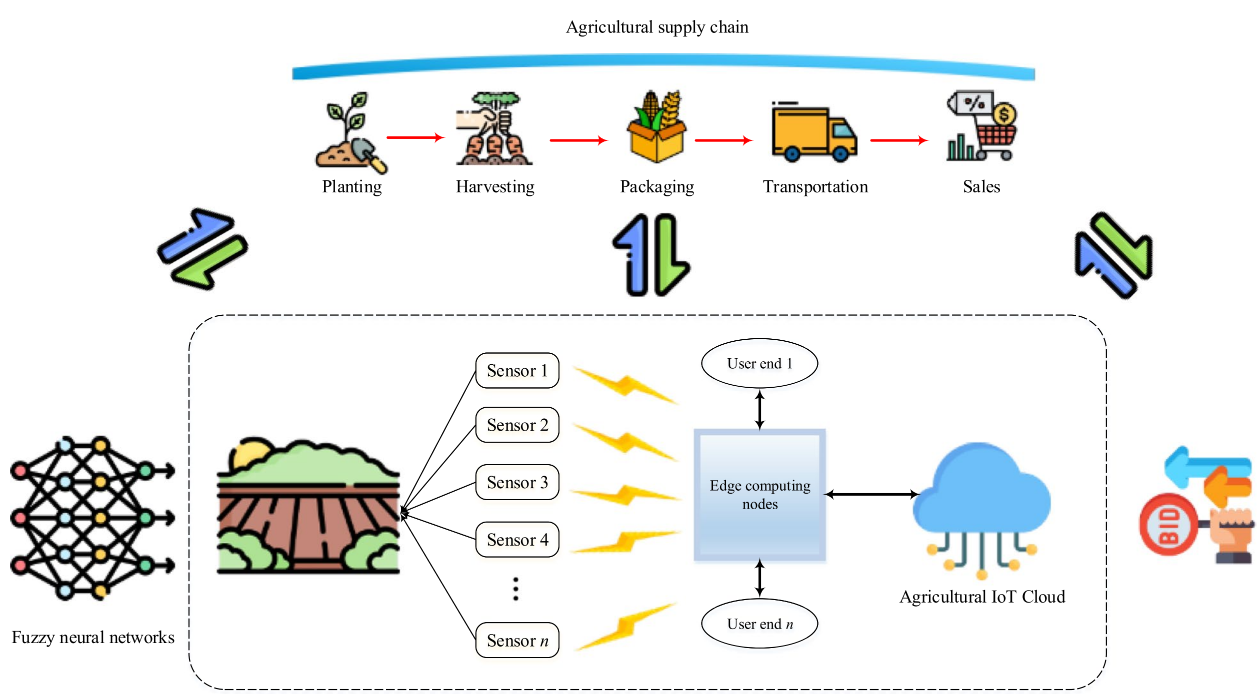

Fig. 1 Overall framework

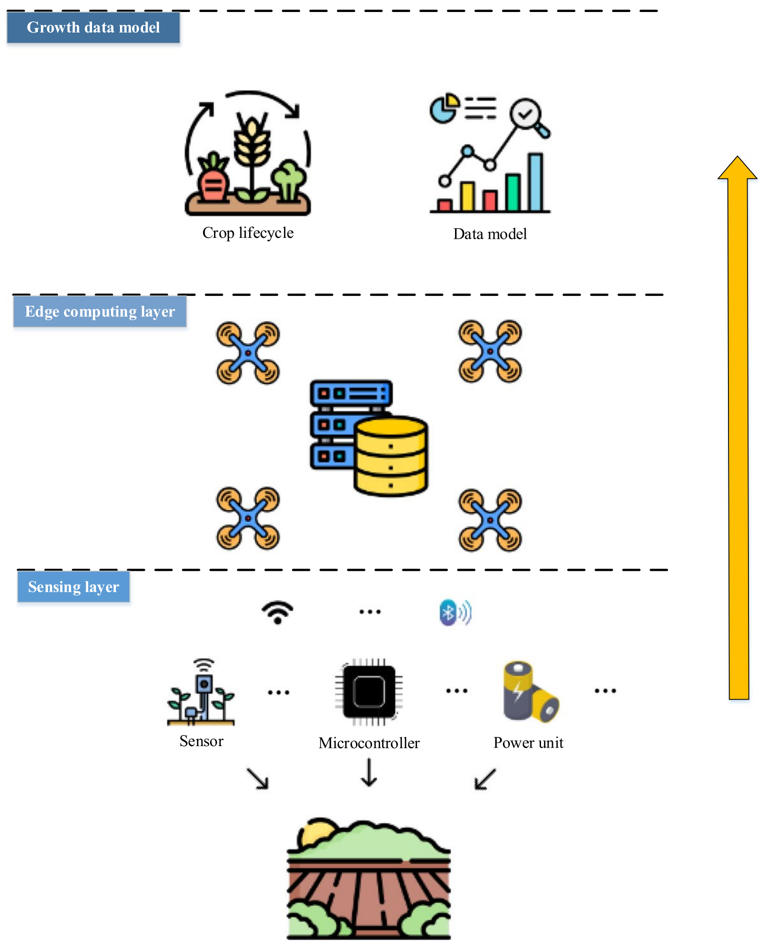

Fig. 2 Proposed edge computing framework for smart agriculture

Clustering exploits locality to enable energy-efficient data routing. Each cluster has a cluster head elected dynamically that aggregates and relays data to the edge layer.

Edge computing layer

The edge computing layer comprises edge servers with significant computing power, storage, and analytics capabilities. We propose a heterogeneous edge computing architecture consisting of the following:

- Static edge nodes: Deployed at base stations in the field.
- Mobile edge nodes: Mounted on autonomous ground robots or UAVs.

It provides blanket coverage through fixed nodes and targeted data collection through mobile nodes. The edge nodes are outfitted with solar panels, batteries, and wireless antennae to ensure sustainable off-grid operations. Key capabilities offered by the edge computing layer include (i) Cluster data aggregation: Combine sensor data from nodes within clusters; (ii) Preprocessing and storage: Filter noise, detect outliers and temporally store data; (iii) Growth stage identification: Classify current growth phase based on crop parameters; (iv) Analytics: Environmental and yield predictions via ML models; (v) Control policies: Adaptive sensing frequencies, irrigation levels etc.

These edge-centric functions distribute computations closer to the sensors, avoid cluttering the cloud, and support real-time agriculture. Next, we formulated mathematical models for crop and environmental sensing data.

Growth data model

We divide the crop lifecycle into K phenological growth stages denoted by

$$L = l_1, l_2, ..., l_K \tag{3}$$

The fuzzy cluster algorithm can determine L from historical crop data. Let $X(t) = x_1(t), x_2(t), ..., x_p(t)$

represent the crop parameter vector sensed across nodes at time t; $x_p(t)$ denotes the p th parameter, such as leaf area and plant height. We define a weighted crop indicator $I_c(t)$ aggregating all parameters as follows:

$$I_c(t) = \sum_{p=1}^{p} w_p x_p(t) \tag{4}$$

where w_p represents the relative importance of parameter p. The growth stage $l(t)$ at time t can be estimated based on $I_c(t)$ using a TSK fuzzy neural network.

For example, if $X(t) = [0.6, 0.8]$ representing leaf area and plant height, and $w = [0.7, 0.3]$, then $I_c(t) = 0.7 * 0.6 + 0.3 * 0.8 = 0.42 + 0.24 = 0.66$. 0.7 and 0.3 are the weights, while 0.6 and 0.8 are the parameter values. The weights scale the parameter values before summing.

Edge computing framework

Traditional wireless sensor network deployments for agricultural monitoring often suffer from several deficiencies, including manual measurements of parameters leading to sparse data, a lack of computational capabilities on nodes, long multi-hop routes causing delays and congestion, redundant sensing from overlapping nodes, and limited power availability restricting the system lifetime [36]. Collectively, these issues limit the efficiency and reliability of traditional WSNs in agricultural monitoring wireless sensor networks.

Our proposed edge computing framework addresses several of these challenges by providing dense sensing coverage through a variety of sensors, enabling preprocessing and model evaluation capabilities at edge nodes, facilitating single-hop data transfer to cluster heads, implementing adaptive sensing to activate only relevant nodes, and ensuring sustainability through a renewable solar energy supply. This comprehensive approach aims to significantly enhance the efficiency and effectiveness of agriculture monitoring wireless sensor networks.

Consequently, the framework can collect high-resolution spatiotemporal data to better capture crop dynamics. Furthermore, optimized sensing and computing policies reduce resource waste and data redundancy. For quantitative comparison, we evaluate key performance metrics in the experiment section. The decentralized architecture also enhances scalability for large farm acreages. Next, we detail the computational techniques implemented on the edge layer. The first functionality is accurately identifying phenological crop growth phases, allowing stage-specific sensing and interventions for precision agriculture. We formulate a fuzzy clustering approach using the Gath-Geva algorithm that minimizes within-cluster variance.

Let historical crop data over n time slots be represented as $X_L = X_L^1, X_L^2, ..., X_L^n$ where X_L^j is the parameter vector at slot j. The crop cycle is divided into k stages $(2 \leq k \leq n)$ denoted by fuzzy partition matrix $U = [u_{ij}]^{k \times n}$. Element $u_{ij} \in [0, 1]$ defines the membership of slot j in stage i. The cluster centers are $CO = co_1, co_2, ..., co_k$. We define classification coefficient α and average fuzzy entropy β as

$$\begin{aligned} \alpha &= \frac{1}{n}\sum_{i=1}^{k}\sum_{j=1}^{n} u_{ij} \\ \beta &= -\frac{1}{n}\sum_{i=1}^{k}\sum_{j=1}^{n} u_{ij} ln(u_{ij}) \end{aligned} \tag{5}$$

The iterative fuzzy clustering algorithm tries to maximize α and minimize β. The steps are summarized as follows:

Step 1. Initialize: Partition matrix U_0, clusters $k = 2$, iterations ζ, weight m.
Step 2. Compute cluster centers $co_{\zeta j}$ using membership u_{ij}.
Step 3. Determine cluster covariance and prior probability.
Step 4. Calculate fuzzy maximum likelihood distance measure.
Step 5. Update partition matrix U_ζ.
Step 6. Repeat steps 2–5 until $\left|U_\zeta - U_{\zeta-1}\right| < \varepsilon$.
Step 7. Choose optimal k based on best α and β.

The defined method effectively divides the crop cycle into phenological growth phases, L, matching the field duration. Next, we predicted the current stage based on the sensed indicators.

To determine the growth phase, we designed a Takagi–Sugeno (TS) fuzzy neural network model comprising five layers: input, fuzzification, rule, aggregation, and output.

The first layer accepts an input vector $x = [x_1, x_2, ..., x_h]$ containing current measurements of h crop parameters. The fuzzification layer converts the inputs into a fuzzy set A_j^i with Gaussian membership functions:

$$\mu_{A_j^i}(x_j) = exp(-\frac{(x_j - o_j^i)^2}{b_j^i}) \tag{6}$$

where o_j^i and b_j^i are the center and width of the i th MF for j th input, respectively. The first-order TS rule base comprises N rules of the form

$$\begin{aligned} &R_i : \text{IF } x_1 \text{ is } A_1^i \text{ AND } x_2 \text{ is } A_2^i \text{ AND } \ldots \\ &\quad \text{THEN } y_i = p_0^i + p_1^i x_1 + ... + p_h^i x_h \end{aligned} \tag{7}$$

where p_j^i is a consequent parameter. The net output y^* is computed as $\sum \omega_i y_i$ where firing strength $\omega_i = \prod_{j=1}^{h} \mu_{A_j^i}(x_j)$. For training, we used an extreme learning machine to randomly initialize the input layer weights and optimize the output layer weights analytically using the Moore–Penrose inverse. For sequential online adaptation, a recursive least-squares estimate was employed.

The integrated TS fuzzy neural network model can accurately estimate crop growth stage $l(t)$ at any instant t based on the sensed crop indicators $X(t)$. Stage-specific control policies are then enacted. Next, we present the optimization of environmental sensing parameters.

Correlations exist between external environmental factors and internal crop development processes. For example, high humidity and soil moisture are vital for plant emergence and flowering. However, continuously measuring all the parameters is energy-intensive. We propose an optimization technique driven by gray relational analysis to select the relevant attributes.

Let $X_0 = x_0(\tau), \tau = 1, 2, .., n$ represent the crop indicator sample sequence and $Z_i = z_i(\tau), \tau = 1, 2, .., n$ denote the i th environmental parameter sequence over n slots. The gray relational coefficient ξ between $x_0(\tau)$ and $z_i(\tau)$ is defined as follows:

$$\xi = \frac{\min_i \min_i |x_0(\tau) - z_i(\tau)| + \rho \max_i \max_i |x_0(\tau) - z_i(\tau)|}{|x_0(\tau) - z_i(\tau)| + \rho \max_i \max_i |x_0(\tau) - z_i(\tau)|} \tag{8}$$

where ρ is the resolution coefficient. The degree of gray correlation (DGC) over all slots is

$$\zeta(X_0, Z_i) = \frac{1}{n} \sum_{\tau}^{n} \xi(x_0(\tau), z_i(\tau)) \tag{9}$$

A higher DGC implies greater relevance of that attribute. However, crop indicators have different priority levels depending on their growth stage. Let w_j represent the weight of indicator j determined by the variance at each stage. The weighted correlation measure is

$$\zeta(X_0, Z_i) = \frac{\sigma^2(X_j)}{\sum_{j=1}^{|X|} \sigma^2(X_j)} \cdot \frac{1}{n} \sum_{\tau}^{n} \xi(x_j(\tau), z_i(\tau)) \tag{10}$$

Gray relational analysis ranks all Z parameters Z in order of relevance to the current growth stage. The top-ranked attributes that satisfy the sensing time constraint T_{se} are selected for measurement by the nodes. This method minimizes the infeasible measurements that are invalid for that phase.

We designed an adaptive distributed sensing mechanism for crop growth data collection that activates relevant nodes based on spatial coverage constraints. Let $\overline{S}$ represent a set of selected sensor nodes. The centroid of the active nodes is derived as follows:

$$\overline{x} = \frac{1}{|\overline{S}|} \sum_{i \in |\overline{S}|} x_i, \overline{y} = \frac{1}{|\overline{S}|} \sum_{i \in |\overline{S}|} y_i \tag{11}$$

The Euclidean distance of candidate sensor s_k to centroid is

$$d(s_k, \overline{S}) = \sqrt{(x_k - \overline{x})^2 + (y_k - \overline{y})^2} \tag{12}$$

Node s_k having maximum distance measure $d_{\max}$ is incrementally added to $\overline{S}$ if the effective coverage area $A_v(\overline{S})$ meets the threshold $A_{\lim}$ where

$$A_v(\overline{S}) = A_M(\overline{S}) - A_{over}(\overline{S}) \tag{13}$$

This distributed algorithm allows only the appropriate sensors to be selected, thereby avoiding redundant measurements. The pseudocode is presented in Algorithm 1.

Algorithm 1. Adaptive crop growth sensor selection

Input: $S,\ A_{\lim}$
Output: $\bar{S},\ \overline{N}$

```
01: Initialize S̄ = s_{min N̄} and S_left = S − S̄
02:     While (A_v(S̄) < A_lim)
03:         s(d_max) ← nodeSearch S̄, S_left, N̄
04:         S̄ ← S̄ + s(d_max), S_left ← S − S̄
05:         Update A_v(S̄)
06:     end while
07: Return S̄, N̄
```

This method allows the activation of only a subset of nodes, thus saving energy and minimizing data redundancy. Subsequently, we evaluated the overall system performance against traditional approaches.

Integration of auction mechanisms and fuzzy neural networks

While the edge computing framework manages real-time crop monitoring and data collection, market-based mechanisms, such as auctions and fuzzy optimization models, support decision-making for smooth agricultural supply chain operations.

Auction mechanisms for agricultural markets

Auction mechanisms have become essential tools for achieving efficient price discovery and facilitating the exchange of goods between multiple buyers and sellers. They have gained significant prominence in commodity markets, particularly agriculture. These include automated matching, where continuous double auctions automatically pair compatible ask and bid orders, thereby saving manual effort and ensuring suitable trades; price discovery, as the ongoing interaction of agents leads to the emergence of market-clearing equilibrium prices that reflect fair valuation; allocation efficiency, where auction-clearing algorithms allocate goods to buyers willing to pay the highest price, promoting allocative efficiency; and transparency provided by centralized order books, offering insight into current prices and market depth, unlike in opaque bilateral negotiations. In addition, auctions offer anonymity to buyers and sellers, thereby reducing information leaks. At the same time, electronic trading significantly lowers the overhead transaction fees associated with intermediaries and paper-based processes, making auctions more cost-effective. Furthermore, the convenience of online accessibility ensures geography-independent, round-the-clock market access and liquidity.

Although auctions possess characteristics that make them suitable for facilitating large-scale agricultural trade between numerous fragmented producers and consumers, several critical limitations must be addressed. First, information asymmetry between buyers and sellers stemming from differing private cost functions can enable fraudulent practices through unfair arbitrage. Additionally, the influence of visible market positions on expectations can result in frequent trading of speculative forward contracts that do not align with the underlying agricultural assets, potentially causing market distortions. Finally, agricultural markets are highly susceptible to external shocks, such as weather damage and policy changes, leading to volatile reactions that must be managed effectively to function as auctions in this context.

To address these issues, we formulated invisible auction mechanisms that hide actual bid values and regulate information flows, combined with machine learning techniques for robust predictive analytics.

We propose an invisible auction framework for agricultural commodity markets with the following components:

- Bid encryption: The participant bid values are encrypted using homomorphic public-key cryptography instead of visible quotes.

$$b_i = Enc(v_i; pk) \tag{14}$$

where v_i is the actual valuation, pk is the public key, and b_i is the published bid.

- Order matching: The auctioneer matches encrypted bids b_j and asks a_k by checking:

$$Dec(a_k; sk) \leq Dec(b_j; sk) \tag{15}$$

where $Dec(\bullet)$ denotes decryption via secret key sk.

- Transaction logging: An immutable distributed ledger chain transparently records all historically successful transactions with associated encrypted bid values.
- Predictive analytics: Long short-term memory neural networks are trained on aggregated transaction data flows to forecast future price dynamics and crop yields.

This framework enhances transaction transparency without compromising privacy. Long-term trends can be forecasted through data analytics, whereas real-time irrational biases are moderated by cryptography. Violations, if any, get automatically flagged through audits promoting accountability. Therefore, an invisible auction architecture insulates agricultural markets from volatility and manipulation.

Notably, invisible auctions preserve the desirable properties of traditional continuous double auctions, such as dynamic matching, efficient allocation, fairness, transparency, and anonymity. Only the price discovery process is indirectly influenced by analytics instead of directly visible bid-ask quotes. Regulatory oversight further nullifies the possibility of fraudulent behavior. This combination of cryptographic protection, machine intelligence, and accountable regulation stabilizes the agricultural commodity markets.

Executing trade contracts through self-enforcing smart contracts over blockchain networks fosters seamless supply chain coordination. Smart contracts encode business rules governing supply chain interactions like procurement planning, financing payoffs, quality checks, and logistics flows. Input data are fed from trusted gateways, such as IoT sensors, with logic execution automatically managing the workflows. Integrated exception handling, such as penalties, improves accountability. Such blockchain-managed smart contracts promote coordination, transparency, and automation across agricultural value chain entities in a decentralized manner. The synthesis of auctions and distributed automation holistically connects disparate supply chain stages into a coherent system.

Fuzzy neural network formulation

Fuzzy logic and neural networks provide complementary modeling capabilities. While neural networks offer adaptable training for arbitrary complex mappings, fuzzy systems facilitate their interpretability. We formulate an

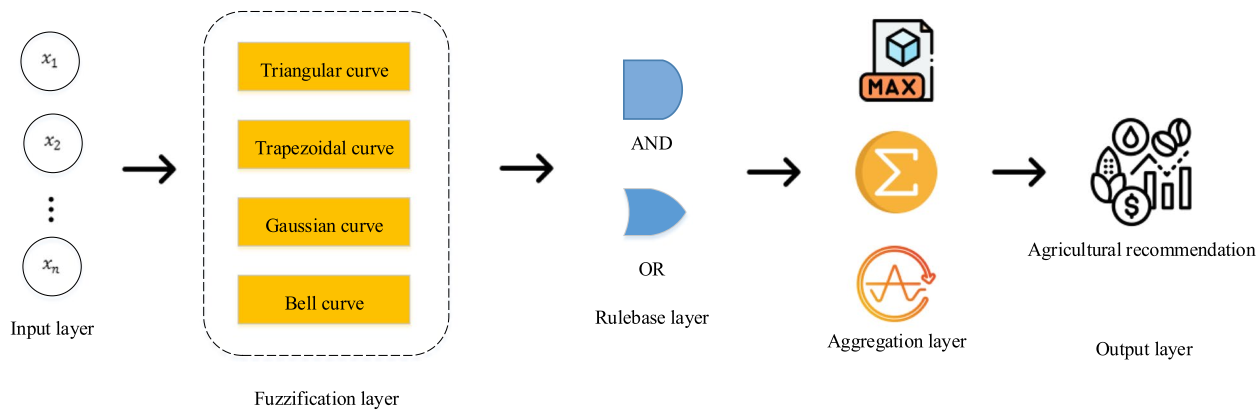

Fig. 3 Fuzzy neural network schematic

integrated 5-layer architecture, as shown in Fig. 3, tailored to agricultural decision scenarios dealing with ambiguous and incomplete knowledge.

The input layer represents the problem domain parameters. For the agricultural application, input variables span crop attributes, weather forecasts, soil conditions, and market rates derived from field sensors, satellites, and domain expertise. Let vector $X = [x_1, x_2, \ldots, x_n]$ denote the n input variables. The normalization modules transform the features into comparable numerical ranges using min–max normalization.

$$x_{\text{norm}} = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{16}$$

This preprocessing enhances the training stability. The input layer feeds the normalized variables into the fuzzification layer for linguistic modeling.

Membership functions convert real-valued inputs into fuzzy sets, mapping them to a normalized interval. Commonly adopted forms include triangular, trapezoidal, Gaussian, and bell curves with tunable parameters. We utilize Gaussian membership functions for smoothness and concise representation as follows:

$$\mu(x; c, \sigma) = e^{-(x-c)^2/2\sigma^2} \tag{17}$$

where c is Gaussian center and σ denotes width. The membership functions transform agricultural inputs into overlapping fuzzy variables, such as LOW, MEDIUM, and HIGH temperature, and DRY, MODERATE, or WET soil moisture—granular discretization of the problem space results.

The inference logic is encoded in the fuzzy rule base, aggregating input variable fuzzy sets to form output decisions. Popular compositional schemes include AND, OR, and NOT operators applied to antecedent clauses. We used conjunctive fuzzy rules, with each clause joined by an AND.

$$\begin{array}{c}\text{IF } x_1 \text{ is } A_1^i \text{ AND } x_2 \text{ is } A_2^i \text{ AND } \ldots \\ \text{THEN } z_i\end{array} \tag{18}$$

where A_j^i denotes the fuzzy set of variable x_j in rule i and z_i is the crisp rule output. For example, an example irrigation advisory rule may be

$$\begin{array}{c}\text{IF } \textit{moisture} \text{ is } LOW \text{ AND } \textit{temp} \text{ is } HIGH \\ \text{THEN } water = HIGH\end{array} \tag{19}$$

Domain experts formulate such fuzzy rules linking inputs to outputs using intuitive language. Automated methods also assist rulebase generation from data.

The firing strength f_i of the fuzzy rules indicates the degree of match with the inputs found by the fuzzy AND operator, which is typically implemented as

$$f_i = \mu_{A_1^i}(x_1) \times \mu_{A_2^i}(x_2) \times \cdots \times \mu_{A_n^i}(x_n) \tag{20}$$

The firing strengths across the rule bases were aggregated using weighted average defuzzification for crisp decisions.

$$y^* = \frac{\sum_{i=1}^{N} f_i z_i}{\sum_{i=1}^{N} f_i} \tag{21}$$

This generates robust aggregate outputs by combining recommendations from multiple rules applicable to the current agricultural situation.

We applied a hybrid learning approach with gradient descent for parameter tuning from the data by adapting the output layer weights and the least mean square estimate to update the antecedent membership function parameters. Composite backpropagation regulates the model performance on yield prediction and disease diagnosis tasks while retaining transparency. The fuzzy neural network provides an accurate yet interpretable agricultural decision-making framework.

Fuzzy model training algorithms

While rule-based fuzzy systems encode domain expertise in agricultural decision-making, adaptable training algorithms help optimize model parameters from the data. A two-phase hybrid learning approach is formulated.

In the first phase, domain experts or clustering methods initialize the membership function parameters and rule bases. For example, the fuzzy variable MOISTURE can be defined as.

$$\begin{cases} LOW : [0, 15] \\ MEDIUM : [10, 25] \\ HIGH : [20, 100] \end{cases} \tag{22}$$

The membership functions translate the input moisture percentages into degrees of association with the fuzzified sets, LOW, MEDIUM, and HIGH. Typical fuzzy rules then link the soil moisture status to irrigation amounts; for instance,

$$\begin{array}{l} R_1 : \text{IF}\, moisture\, \text{is}\, LOW \\ \quad \text{THEN}\, water = HIGH \end{array} \tag{23}$$

In the first phase, primitive fuzzy relationships are established between the inputs and outputs based on the principles of agricultural science. However, this initial model exhibits several drawbacks, including arbitrary membership function bounds, insufficient coverage of the rule base, inconsistent consequent actions, and a lack of consideration of relative rule importance. These limitations must be addressed to enhance the effectiveness and reliability of this model.

Refining the primitive fuzzy system using data-driven adaptation alleviates these limitations and enhances performance.

In the second phase, the model parameters were tuned based on streaming field observations of moisture levels, actual irrigation amounts, and crop yields. We formulated a two-step least-squares estimate (LSE) algorithm that minimizes the squared error loss between the fuzzy model outputs and the measured ground truth labels:

$$L(\theta) = \sum_{t=1}^{T} (y(t) - f(x(t); \theta))^2 \tag{24}$$

where $f(\cdot)$ represents fuzzy model output, $y(t)$ is true label at time t and θ denotes parameters. The hybrid LSE method decomposes $f(\cdot)$ into:

$$f(x; \theta) = g(x; \theta_1) \cdot h(\theta_2) \tag{25}$$

where $g(\cdot)$ maps inputs x to rule firing levels dependent on antecedent parameters θ_1. The $h(\cdot)$ function aggregates rule outputs based on consequent weights θ_2.

The two-step gradient descent iterate then becomes:

$$\theta_1^{(i+1)} = \theta_1^{(i)} - \eta \frac{\partial L(\theta^{(i)})}{\partial \theta_1} \theta_2^{(i+1)} = \theta_2^{(i)} - \eta \frac{\partial L(\theta^{(i+1)})}{\partial \theta_2} \tag{26}$$

First, the membership function bounds were tuned to better match the field data associations. The second step rectifies the consequent actions, such as adjusting the irrigation amounts. Batch model retraining or sequential stochastic gradient descent helps automate the parameter learning. Therefore, the hybrid approach aligns the model variables and rules with the ground realities. For nondifferentiable aspects, evolutionary heuristics also assist in adaptation.

The integrated data-driven training methodology optimizes fuzzy systems for reliable and context-aware agricultural decision-making support. Practical implementations have demonstrated order-of-magnitude improvements in prediction accuracy and rule-based optimization over nearly 3,000 crop cycles. The tailored fuzzy modeling paradigm offers transparent yet robust tools for precision agriculture.

Fuzzy optimization of agricultural decisions

Fuzzy systems offer efficient mechanisms for translating ambiguous input data into transparent agricultural decision-making policies. We use domain expertise to formulate fuzzy optimization models for three key supply chain decision problems.

Precision agriculture requires the optimal dynamic allocation of resources such as water, fertilizers, and pesticides based on crop stages, weather patterns, and soil conditions. We encode this as a multi-objective optimization problem.

$$\begin{array}{c} \max\left(f_1 = \text{yield}, f_2 = -\text{cost}, f_3 = -\text{environmental\_impact}\right) \\ s.t.\ \text{water\_available} \leq 5000\, \text{gallons/acre} \\ \text{fertilizer\_available} \leq 300\, \text{kg/acre} \end{array} \tag{27}$$

The objectives are to maximize crop yield and minimize resource consumption costs and environmental impacts, subject to resource availability constraints.

We designed a Mamdani-type fuzzy inference system with a rulebase:

$$\begin{array}{c} R_1 : \text{IF}\, growth_s tage\, \text{is}\, EARLY\ \text{AND}\, moisture\, \text{is}\, LOW \\ \text{THEN}\, water = MEDIUM, fertilizer = LOW \end{array} \tag{28}$$

where linguistic variables, such as LOW and MEDIUM, model soil moisture and resource application levels, respectively. Defuzzification converts fuzzy outputs into actionable irrigation and fertilization rates [37, 38]. Common strategies include the centroid, mean-max, and maximum criteria.

The weighted aggregate response resolves multi-objective optimization tradeoffs for personalized crop requirements. Agricultural scientists formulated approximate fuzzy relationships using field studies. Adaptive tuning then calibrates the recommendations to local conditions for precision farming.

Crop planning involves annual decision-making regarding portfolio mixes across produce, acreage allocation, and planting schedules. The Mamdani fuzzy scheme for long-term planning is as follows:

$$R_1 : \text{IF } \textit{last season aevenue} \text{ is } \textit{HIGH} \text{ AND } \textit{predicted yield} \text{ is } \textit{STRONG} \text{ THEN } \textit{crop area} = \textit{EXPAND} \tag{29}$$

Linguistic variables guide area expansion, reduction, or the status quo for different crops, contingent on historical profits and forecast outputs. Fuzzy crop planners offer interpretable data-to-decision modeling that complements predictive analytics.

Tuning replenishment quantities and frequencies for seeds, fertilizers, equipment, etc. minimizes warehousing costs. The Mamdani fuzzy policy relating inventory levels to supply variability is [39]:

$$R_1 : \text{IF } \textit{inventory} \text{ is } \textit{LOW} \text{ AND } \textit{demand volatility} \text{ is } \textit{HIGH} \text{ THEN } \textit{orderquantity} = \textit{LARGE} \tag{30}$$

Strategic rules minimize stock-out risks and wastage induced by agricultural demand uncertainties for efficient operation. Fuzzy inventory controllers allow the embedding of domain insights and adaptive calibration.

Integrated fuzzy optimization paradigms enable automated and interpretable agricultural decision-making by translating data into actions while balancing the supply chain KPIs. Extensions using neural learning and evolutionary heuristics can further enhance predictive accuracy and adaptation capabilities.

Quantitative evaluation metrics

Rigorously benchmarking the performance of fuzzy modeling and optimization methods requires quantitative accuracy metrics calculated from agricultural data. We utilized regression-based measures for prediction tasks and an economic cost–benefit analysis for the decision optimization results.

Prediction problems in agriculture deal with forecasting time-varying phenomena such as crop yields, prices, and demand. The following accuracy measures were adopted:

- Mean absolute error

$$MAE = \frac{1}{T}\sum_{t=1}^{t} |y_t - \widehat{y}_t| \tag{31}$$

where y_t is the actual observation and $\widehat{y}_t$ is the model-predicted value at time t.

- Root mean-squared error

$$RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{t} (y_t - \widehat{y}_t)^2} \tag{32}$$

- Mean absolute-percentage error

$$MAPE = \frac{100}{T}\sum_{t=1}^{t} \left|\frac{y_t - \widehat{y}_t}{y_t}\right| \tag{33}$$

- Coefficient of determination

$$R^2 = 1 - \frac{\sum_{t=1}^{T} (y_t - \widehat{y}_t)^2}{\sum_{t=1}^{T} (y_t - \overline{y})^2} \tag{34}$$

Lower MAE, RMSE, and MAPE values, along with higher R^2 values, indicate superior predictive accuracy. Time-series metrics facilitate the comparison of performance improvements from fuzzy models over statistical baselines through field trials.

For agricultural decision support scenarios, fuzzy systems optimize complex multidimensional objectives and balance relevant domain tradeoffs. Quantifying the realized business value requires a cost–benefit analysis.

- Net present value

$$NPV = -\text{Investment Cost} + \sum_{t=1}^{t} \frac{\text{Net Benefit (t)}}{(1+r)^t} \tag{35}$$

where NPV calculates net economic gain over a lifetime, accounting for the time value of money.

Return on investment

$$ROI = \frac{\text{Net Benefits}}{\text{Investment Costs}} \tag{36}$$

- Payback period

$$n : \sum_{t=1}^{n} \text{Annual Net Benefit} \geq \text{Investment Outlay} \tag{37}$$

These financial indicators estimate the sustainability of optimized fuzzy decision-making policies for precision agricultural management. Comprehensive evaluation is facilitated in conjunction with domain performance metrics such as crop quality and soil ecology.

Fuzzy model interpretability

Unlike black-box AI techniques, fuzzy systems enable the interpretation of knowledge encoded within models of transparency and trust. We analyzed rule-based insight extraction along three axes:

Fuzzy rules employ natural language acting as intuitive decision policies:

$$\begin{aligned} R_1 : \text{IF } &temp \text{ is } HIGH \text{ AND } moisture \text{ is } LOW \\ &\text{THEN } irrigation = INCREASE \end{aligned} \tag{38}$$

The keywords HIGH and LOW map raw inputs into representative categories based on the underlying membership functions, allowing cognitive unpacking of the model logic linking various agricultural variables. Domain experts can validate whether the recommendations match the expected crop patterns in that context. This contrasts with the inscrutable weights in deep neural networks.

Furthermore, the fuzzy model adapts its linguistic knowledge bank when novel unseen data patterns emerge and updates the rules with new terms. Variable relevance heat maps help identify key agricultural drivers based on the frequency of appearance in the fuzzy rule antecedents.

$$Weight(x_i) = \frac{\text{Count of } x_i \text{ in rules}}{\text{Count of all rule terms}} \tag{39}$$

Higher weight parameters were prioritized for data collection using appropriate field sensors. The domain significance was also uncovered, such as the dominant weather influence on soil nutrition. Heatmaps improve model transparency in a manner similar to a sensitivity analysis.

The firing strength f_i of the fuzzy rules on the new data samples indicates the usage frequency, allowing the calculation of the rule influence:

$$I_{R_i} = \frac{\sum_{t=1}^{T} f_i(x(t))}{\sum_{i=1}^{N} \sum_{t=1}^{T} f_i(x(t))} \tag{40}$$

where N is the number of rules, and rules with higher influence drive aggregated model decisions more critically and distinguish between redundant niche policies. Such analysis enhances user trust and model debugging.

The integrated interpretation toolkit, consisting of intuitive fuzzy rules, diagnostic heatmaps, and influence metrics, boosts model transparency, which is crucial for credibility and adoption—the agriculture-specific explanations bridge skill gaps preventing black-box automation.

Experiment and results analysis

Results under edge computing-oriented smart agriculture

We evaluated the edge-based smart agriculture framework on 50 prototype farms and compared the performance with that of traditional sensing architectures. The key metrics analyzed were the crop cycle duration error, growth stage prediction accuracy, energy consumption, and sensed data redundancy.

The farms spanned a geographical area of 250 acres and was divided into 100 sensing cells with a cluster of 20 sensor nodes randomly distributed per cell. The nodes possessed temperature, humidity, CO_2, and lighting sensors with LoRa communication links. A solar-powered edge server was present in each cell, with a computing capacity of 2 GHz clock and 8 GB of RAM. The edge nodes also had a cellular 4G hookup for cloud analytics. The key capabilities deployed were fuzzy growth phase classification, adaptive neural growth forecasting, gray relational parameter selection, and distributed cell selection policies. Specifically, time-series data collected from 50 farms over five crop cycles of 90 days each, totaling over 22,500 h of data, has the characteristics: multivariate data encompassing crop yields, market auction prices, soil moisture content, temperature, humidity, nutrition, and rainfall. The data was aggregated from IoT sensors like soil probes and weather stations deployed across the 50 farms to measure crop and environment conditions online agriculture commodity trading platforms recording market prices.

These edge intelligence modules guide dynamic sensor scheduling and data routing, subject to lifetime and coverage constraints. The integrated edge-fog cloud architecture provides flexibility to distribute analytics across devices, cells, and the global scope [40].

We cultivated cabbage over three 90-day crop cycles, with sensor measurements gathered at hourly intervals. Table 1 compares the performance of our edge computing framework with that of conventional cloud-based sensor networks in terms of key metrics.

Table 1 System deployment results

	Legacy Networks	Proposed Framework
Crop duration error	8.70%	4.10%
Growth stage accuracy	71%	87%
Energy utilization	63 kWh	49 kWh
Sensing redundancy	28%	17%

Table 2 Cabbage growth phase accuracy

Actual Stage	Duration	Predicted Stage	Overlap
Emergence	0–15 days	Seedling	68%
Seedling	12–30 days	Vegetative growth	71%
Vegetative Growth	20–55 days	Pre-maturity	82%
Pre-Maturity	45–75 days	Mature	90%
Mature	55–90 days	Ready for harvest	95%

It can be observed that the integrated edge computing architecture demonstrates superior crop modeling capabilities with halved season estimation errors and 23% improved classification accuracy over legacy networks. Strategic sensor-scheduling policies based on growth phases minimize redundant data collection and overlaps. Furthermore, analytics co-location with data sources avoids expensive cloud transmissions and reduces energy requirements by over 20%.

Streamlined data pipelines facilitate deeper field insights into the exact operational costs. Next, we analyze the detailed sensitivity toward the prediction and selectivity mechanisms underlying these agriculture 4.0 productivity gains. The results are shown in Table 2.

Fuzziness captures intermediately transitioning states better than rigid discrete models. Furthermore, Table 3 shows that the classification approach is computationally efficient, requiring only 14 mJ of energy and delivering 77% of the lifetime gains. Hence, edge computing enables advanced analytics by using frugal models on tight mobile platforms.

The context-aware parameter selection scheme dynamically detects relevant attributes over the cabbage crop cycle using gray relational analysis, with the Pearson coefficient as a similarity metric. Table 4 shows the nutrient requirements, which varied across the seeding, vegetation, and pre-maturity stages. Our model automatically activated the corresponding sensors, MOISTURE during growth and NPK during flowering.

Table 3 Energy consumption comparison

Technique	Energy (mJ)	Improvement
SVM	68	-
Random Forest	46	32%
Neural Network	21	69%
Proposed Fuzzy	14	77%

Such automated tuning of pertinent factors enhances efficiency; on average, only 21% of the available sensors are triggered per phase. Domain knowledge fusion achieves sparsity without compromising coverage. Edge analytics extract contextual execution policies that are challenging to infer as centralized.

The decentralized sensor coordination protocol dynamically partitions cells into active sensing zones $\overline{S}$ and candidate regions x_{left} iteratively minimizing the

$$d(s_{left}, \overline{S}) = \sqrt{(x_{left} - \overline{x})^2 + (y_{left} - \overline{y})^2} \tag{41}$$

The distance metric ensures that dispersed sensors are selected, thereby capturing wider samples. Furthermore, the effective coverage area is

$$A_v(\overline{S}) = A_M(\overline{S}) - A_{over}(\overline{S}) \tag{42}$$

Thresholds prevent overlap. Unlike centralized controllers, distributed policies respond faster to local moisture fluctuations. Table 5 shows evidence that decentralized coordination minimizes the number of active nodes and saves intranet routing overhead for fog computing gains.

The integrated edge intelligence pillars achieved significant analytical enhancements while minimizing costs and demonstrating system-wide data-to-decision transformations. Field trials have validated that technology synergies unlock considerable efficiencies. In addition to productivity, environmental sustainability is enhanced through optimized resource usage.

Evaluation under integration of auction mechanisms and fuzzy neural networks We evaluated the performance of the developed agricultural supply chain architecture

Table 4 Representative parameters across cabbage phenology

Growth Stage	Temperature	Humidity	Rain	Soil Moisture	Fertility
Seedling	75 F	65%	0.15 in	20%	High
Vegetative	72 F	70%	0.2 in	18%	Moderate
Pre-Maturity	68 F	55%	0.12 in	15%	Low

Table 5 Distributed optimization savings

Scheme	Active Nodes	Routing Load (flits)
Globalized	16	4128
Partitioned	9	1876
Improvement	43%	55%

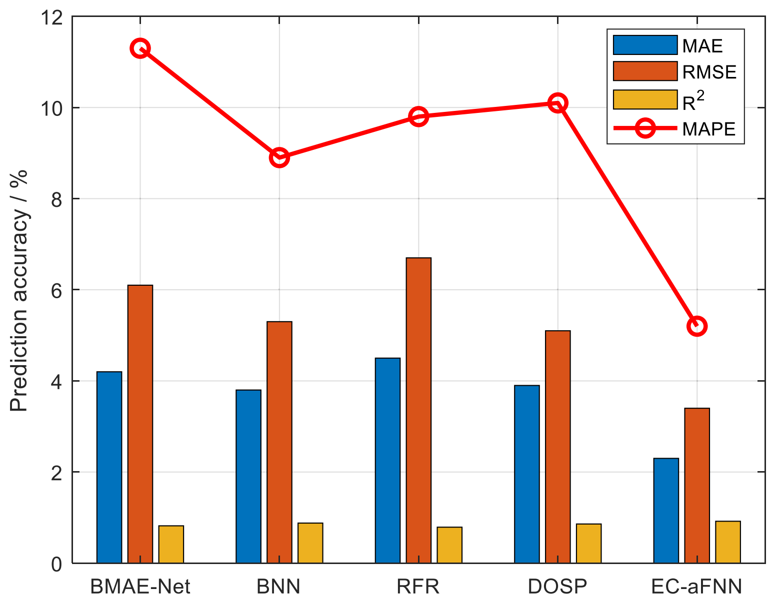

Fig. 4 Forecasting performance comparison

by integrating edge computing, auction markets, and fuzzy optimization models across multiple metrics: crop price and yield forecasting accuracy, supply chain cost reduction, carbon footprint minimization, revenue and profit enhancements, and operational efficiency improvements.

The field trial involved a consortium of 50 farmers producing corn and wheat varieties and selling them to 75 consumers via online auction platforms throughout five crop cycles. Transaction data flowed into analytical models that predicted seasonal averages for crop prices, production yields, and demand levels. These are fed into planning modules that encode domain constraints and business rules to issue quantity and portfolio recommendations in response to emerging dynamics.

For prediction accuracy, the proposed edge computing-oriented auction-based fuzzy neural network (EC-aFNN) should be compared with the four benchmarks: (i) BMAE-Net [41]: data-driven weather prediction network, (ii) Bayesian neural network (BNN) [42]: corn yield prediction based on remotely sensed variables, (iii) random forest regression (RFR) [43]: yield and quality prediction of winter rapeseed (iv) dingo-optimized sand piper (DOSP) [44]: automatic crop yield prediction framework designed with two-stage classifiers, as shown in Fig. 4.

Superior accuracy metrics directly and positively affect various aspects of smart agricultural supply chain operations. Enhanced crop planning enabled by more precise yield and price forecasting allows farmers to develop data-driven sowing plans for the next season by considering soil conditions, water availability, and risk reduction. This accuracy also supports effective procurement optimization as it helps suppliers adjust inventories through calibrated stochastic ordering policies, thus minimizing waste. Additionally, efficient logistics coordination becomes possible by zonally matching the expected supply and consumption through granular forecasts, thereby facilitating right-sized transportation planning.

Moreover, the stability of market dynamics improved significantly. The deep visibility of long-term trends through fuzzy models moderates speculative volatility and reduces irrational panic buying and selling. Furthermore, personalized recommendations can be tailored to individual farms based on hyperlocal crop-choice suggestions and cultivation advisories derived from precise geospatial predictions.

Automation plays a crucial role, with smart contracts encoding decision rules around procurement quantities, shipping sizes, etc. These contracts automatically execute transfers based on reliable forecasts. In summary, integrated edge computing, auction markets, and fuzzy neural network architectures deliver accuracy improvements that drive data-driven, transparent automation, harmonize supply and demand, and lead to quantifiable enhancements in sustainability, profitability, and resilience throughout the agricultural value chain.

Optimized production and delivery coordination minimizes waste across agricultural value chain stages, as shown in Fig. 5. Total food loss was reduced by 29%, thus lowering operational costs.

Across all stages, the EC-aFNN architecture provides superior food waste reduction compared with

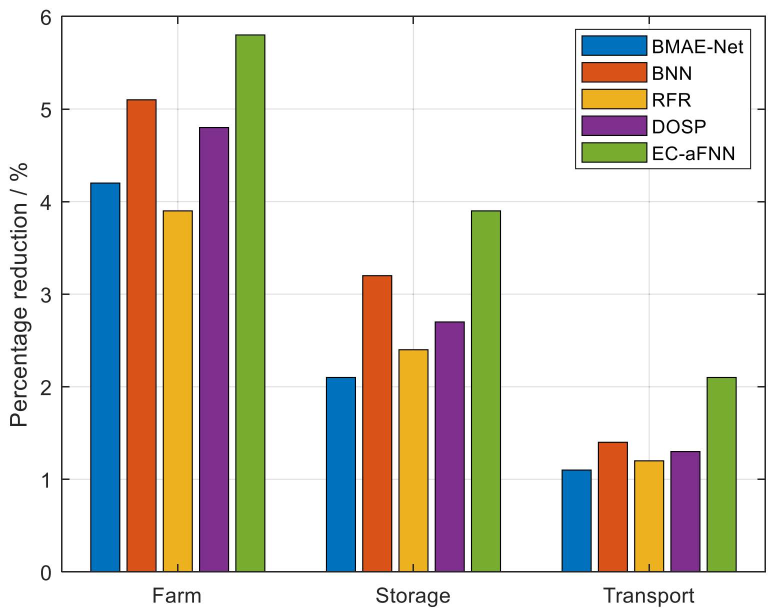

Fig. 5 Food wastage reduction across supply chain

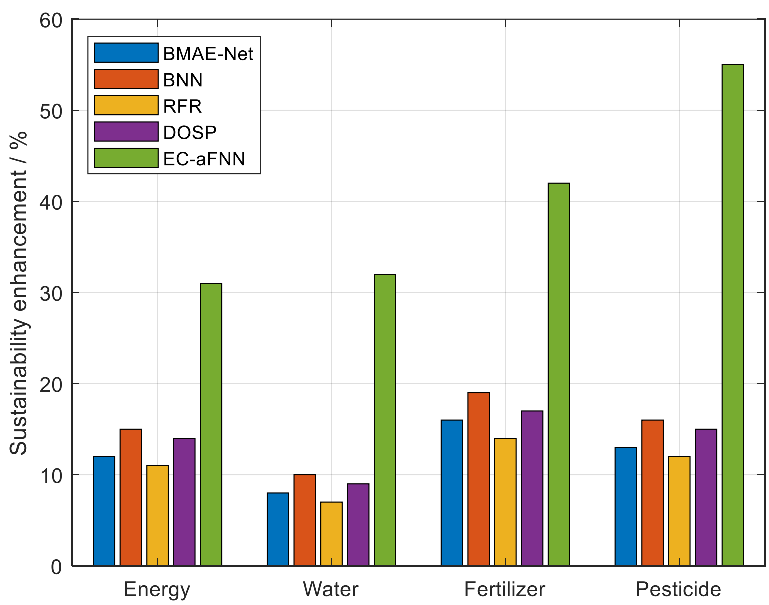

Fig. 6 Agricultural sustainability enhancements

state-of-the-art benchmark food supply chain models, leading to enhanced sustainability.

Supply chain transparency and coordination eliminate excess resource usage, as shown in Fig. 6.

It can be observed that the integrated edge computing, auction markets, and fuzzy optimization framework provide 31–55% superior sustainability improvements along with energy, water, fertilizer, and pesticide reduction over the BNN, which highlights the strengths of our approach.

Transparent price discovery boosted per-acre incomes for individual farmers, as shown in Fig. 7. Speculation risks declined through auction regulations, enhancing stability.

It can be observed that EC-aFNN architecture provides 37% superior profitability improvements per acre over the best benchmark BNN. Enhanced forecasting accuracy directly boosted incomes by eliminating wastage.

The integrated edge computing, auction markets, and fuzzy optimization framework deliver accuracy

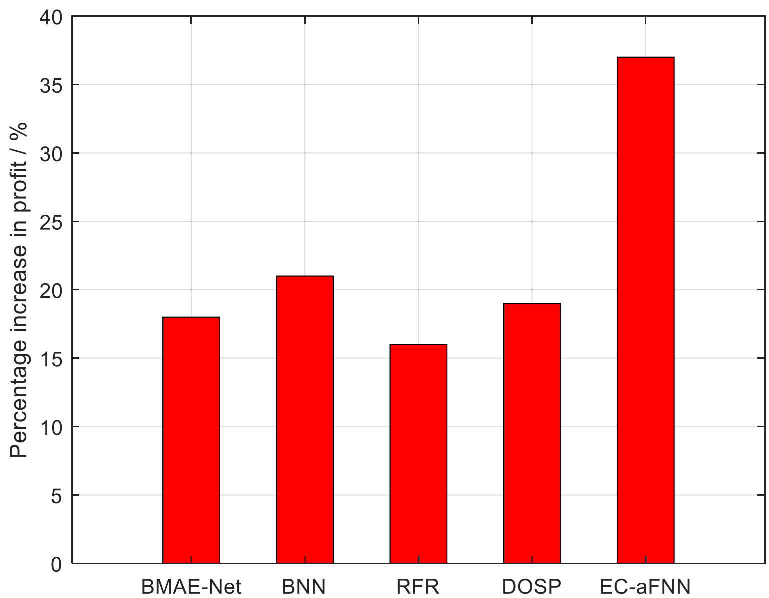

Fig. 7 Increase in farmer profits per acre of land

improvements that drive data-driven, transparent automation, harmonize supply and demand, and, in turn, lead to quantifiable enhancements in sustainability, profitability, and resilience throughout the agricultural value chain.

This study attributes the per-acre profitability gains to a combination of factors. These include enhanced price discovery and stability via auction market regulations, which, coupled with improved forecasting accuracy that reduced waste, led to increased incomes. Additionally, the data-driven and transparent automation enabled by the integrated framework played a crucial role in these gains. Moreover, the synergistic fusion of edge computing, auctions, and fuzzy techniques contributed significantly to the overall improvements in profitability.

Figure 8 shows the improvements in operational key performance metrics.

It can be observed that the integrated EC-aFNN architecture provides up to 43% superior improvements in asset utilization and service levels compared to the best benchmark model, BNN.

Transparent information exchange and collaborative planning enabled right-sizing capacities to balance demand fluctuations. Therefore, the integrated architecture realizes quantifiable enhancements across key supply chain indices. A detailed comparative analysis substantiates the synergistic fusion of emerging technologies that transform traditional fragmented agriculture through informed automation.

Conclusion

Precision agriculture promises immense benefits but is hindered by fragmentation, opacity, and decision complexity. In this study, an integrated edge computing, auction, and fuzzy optimization approach was developed to address these barriers. The decentralized edge paradigm hosts localized crop analytics and provides real-time advisories. Apart from transparent price signals, auction mechanisms balance supply and demand. Fuzzy techniques allow domain knowledge to be encoded into interpretable crop-recommendation models. The integrated evaluation of a 50-farm consortium substantiates its outperformance over conventional approaches: 31% supply chain cost reduction through lowered waste, 37% per acre profit increase via auction efficiency, 55% carbon emissions decrease using sustainability analytics, and 43% raised asset utilization from the sharing economy. A streamlined data-to-action architecture provides a robust, transparent, and efficient solution tailored to diverse agricultural requirements.

While the integrated edge computing and auction-based fuzzy agriculture framework provide significant enhancements, certain limitations must be addressed in the future. Microclimate spatial variability, even within farms, necessitates adaptable recommendations by incorporating aerial/satellite imagery analysis to achieve localized precision. Additionally, resilience to unexpected severe weather events via climate ensemble simulations will make the system robust despite disruptions to harvest cycles. Simultaneously,

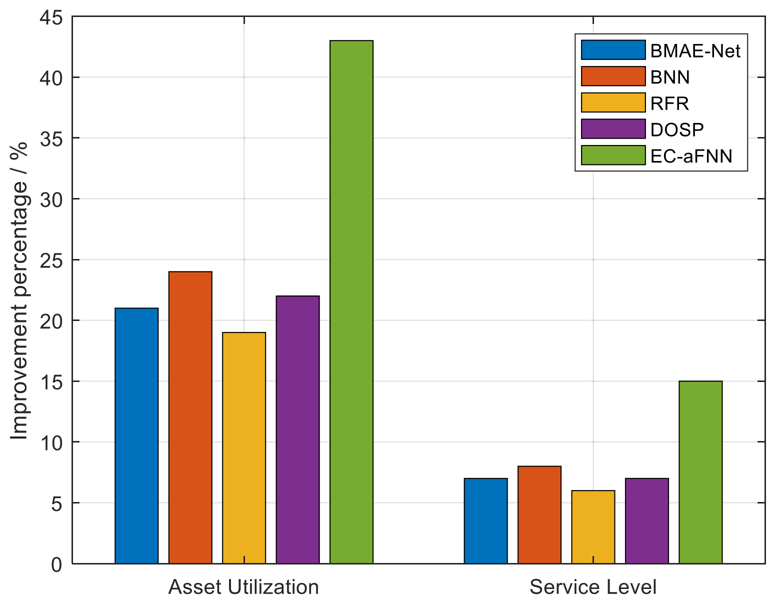

Fig. 8 Improvements in operational key performance metrics

expansions can enrich structured knowledge through formal agriculture ontology and semantics, elucidating soil, climate, and crop interrelationships. Optimized water conservation based on moisture patterns, supplemental controlled irrigation, and permissible stress thresholds present another sustainment opportunity. Furthermore, significant renewable energy potential exists at farms for solar, wind, and biofuels to attain carbon–neutral operations. Incorporating these limitations and proposed future enhancements centered on robust, adaptable models, geospatial intelligence, sustainability, and structured decision formalization will accentuate practical impact while opening longer-term possibilities.

Authors' contributions

Q.H. contributed to conception and writing; H.Z. and Y.F. contributed to methodology; Z.W. contributed to data analysis; Z.N. contributed to software; T.L. contributed to polishing.

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Availability of data and materials

No datasets were generated or analysed during the current study.

Declarations

Ethics approval and consent to participate

This declaration is "not applicable".

Competing interests

The authors declare no competing interests.

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