Journal of Computer Science and Engineering in Innovations and Research

Research Paper Vol.-2, Issue- 1, June- December 2025 ISSN: 3049-1762

A Unified System for Precision Agriculture: Integration of IoT, AI, and Cloud Computing for Sustainable Farming

Arghadip Chakraborty[1], Mahamuda Sultana[2] and Suman Bhattacharya[3]

[1]Department of Computer Science & Engineering, Guru Nanak Institute of Technology,
arghadip02.chakraborty@gmail.com

[2] Department of Computer Science & Engineering, Guru Nanak Institute of Technology,
mahamuda.sultana@gnit.ac.in

[3] Department of Computer Science & Engineering, Guru Nanak Institute of Technology,
suman.bhattacharya@gnit.ac.in

Corresponding Author: arghadip02.chakraborty@gmail.com

Abstract: Modern farming is undergoing a significant change with the introduction of precision agriculture, which uses new technologies to farm better while protecting the environment. This paper introduces a complete system for precision agriculture that brings together technologies like Internet of Things (IoT) sensors, Artificial Intelligence (AI), machine learning, cloud computing, and edge computing to create an innovative, data-driven farming system. This system tackles key problems in today's agriculture, such as using resources more efficiently, increasing crop yields, and farming in a way that doesn't harm the environment. It uses real-time soil monitoring, checks on how crops are doing, precision watering, and automatic bug and disease detection. It applies fertilizers and pesticides at variable rates. By using satellite images, wireless sensor networks, and AI-based analysis, the system has been able to cut water use by up to 30%, reduce fertilizer use by 20%, and increase crop production by 15-20%. The system uses cloud computing to process large amounts of data, make predictions, and manage farms remotely. In contrast, edge computing allows for quick decisions at the field level. Field tests have proven that the system works well in different farming situations, leading to better resource use and more sustainable farming. This study helps move agriculture forward by combining traditional farming methods with modern digital technologies.

Keywords: Precision Agriculture, IoT, Artificial Intelligence, Cloud Computing, Smart Farming, Sustainable Agriculture, Machine Learning, Digital Twins

I. Introduction

Agriculture around the world has big problems in the 21st century. We need to feed more people (maybe 9.7 billion by 2050) while dealing with climate change, limited resources, and caring for the environment. Old farming ways, where everything in a field is treated the same, are not good enough anymore. Precision Agriculture (PA) can change things. It uses data to help farmers manage their land better. It helps them use the right amount of resources and get the most out of their crops by managing specific parts of their fields differently. The main idea is to give crops what they need, when and where they need it. This helps increase how much food we get while being kinder to the environment. Fast improvements in digital technology. Farmers can now collect, process, and study lots of farm data instantly. This helps them make smart choices and automate work on the farm.

Journal of Computer Science and Engineering in Innovations and Research
Research Paper Vol.-2, Issue- 1, June- December 2025 ISSN: 3049-1762

A. Problem Statement

Despite significant technological advances, current precision agriculture implementations often suffer from fragmented approaches, where individual technologies operate in isolation without comprehensive integration. Farmers frequently encounter challenges in:

- **Data Integration**: Disparate systems generating incompatible data formats
- **Real-time Processing**: Delays in data analysis affecting timely decision-makings
- **Scalability**: Limited ability to scale solutions across different farm sizes and types.
- **Cost-effectiveness**: High initial investment costs deterring adoption.
- **Technical Complexity**: Lack of unified interfaces for system management.

B. Research Objectives

This research aims to develop a unified system for precision agriculture that addresses these challenges through:

1. **Integration Architecture**: Designing a comprehensive framework that seamlessly integrates IoT, AI, cloud computing, and edge computing technologies
2. **Real-time Analytics**: Implementing intelligent data processing capabilities for immediate decision-making
3. **Scalable Infrastructure**: Creating adaptable solutions suitable for various farm sizes and crop types
4. **Sustainability Focus**: Optimizing resource utilization to promote environmentally sustainable farming practices
5. **User-centric Design**: Developing intuitive interfaces for farmers and agricultural professionals

II. Related Work

A. Evolution of Precision Agriculture

Evolution of Precision agriculture from simple GPS-guided machinery in the 1990s to sophisticated, AI-powered farming systems. Early implementations focused primarily on variable-rate application of fertilizers and pesticides based on soil sampling and yield mapping. The integration of satellite imagery and remote sensing technologies expanded the scope to include crop monitoring and field mapping capabilities. Recent developments have witnessed the convergence of multiple technologies, creating more comprehensive precision agriculture solutions. [**1**]demonstrated that integrating IoT sensors with machine learning algorithms could improve crop yield predictions by up to 15%. Similarly, research by [**2**]showed that cloud-based precision agriculture systems could reduce operational costs by 25% while increasing farm productivity.

B. IoT Technologies in Agriculture

IoT sensors track things live. Smith and Johnson built an IoT irrigation setup that cut water use by 30% but kept crop production steady. The setup used wireless sensors to get soil moisture data and auto-started irrigation when needed. Current IoT setups use many sensors to build complete field tracking networks.

C. Artificial Intelligence in Precision Agriculture

Journal of Computer Science and Engineering in Innovations and Research
Research Paper Vol.-2, Issue- 1, June- December 2025 ISSN: 3049-1762

Computer vision techniques enable automated pest detection through analysis of drone and satellite imagery. Recent studies report that which through AI we are seeing great advances in agriculture. In the work of Chen it was noted that they achieved 90% accuracy with AI based pest detection which in turn reports a 25% reduction in pesticide use. Also machine learning in the area of fertilizer application has had great results with some reports of up to 20% in fertilizer reduction without effect on crop yield.

D. Cloud and Edge Computing Integration

Cloud and edge computing technologies' integration into agricultural settings overcomes issues of data processing delay and bandwidth in that field. We see cloud computing provide the scalable infrastructure for data storage and complex analysis, and edge computing enable real time processing at the farm level. In agriculture we also see that edge computing solutions which put computing at the edge of the network reduce response times for critical farm scale decisions.
A study by Williams [**3**]showed that edge-enabled precision agriculture systems could process sensor data within 8 seconds compared to 45 seconds for cloud-only systems.

E. Digital Twins in Agriculture

Recent implementations of digital twins in controlled environment agriculture have shown promising results, with studies reporting 20% improvements in resource efficiency and 15% increases in crop yields. [**4**]The technology facilitates predictive maintenance of agricultural equipment and optimization of growing conditions.

F. Research Gaps

Despite significant progress in individual technologies, current literature reveals several gaps:

1. **Limited Integration Studies**: Most research focuses on individual technologies rather than comprehensive integration
2. **Scalability Challenges**: Few studies address system scalability across different farm sizes and types
3. **Real-world Validation**: Limited field testing of integrated systems in diverse agricultural environments.
4. **Economic Analysis**: Insufficient analysis of cost-benefit ratios for integrated precision agriculture systems. Economic analysis is also another important deficiency of the current precision agriculture systems. While technical returns such as enhanced yield and minimized resource utilization are well recorded, an extensive cost-benefit analysis is so far limited. It's difficult to understand for a farmer about the return on investment, payback periods of these systems and how beneficial they are in long term in a broader prospective. Our integrated system handles that by the adoption of: (1) scalable and low cost wireless sensor network (WSN), modular cloud services, and affordable edge devices. This techno-economic perspective gives the confidence that Precision Agriculture is not just the technological reality but also the economic bankability across scales that can be delivered to the farmers.

III. Methodology

A. System Overview

The proposed unified system for precision agriculture adopts a multi-tiered architecture that seamlessly integrates sensing, processing,

Journal of Computer Science and Engineering in Innovations and Research
Research Paper Vol.-2, Issue- 1, June- December 2025 ISSN: 3049-1762

analytics, and actuation layers. The architecture is designed to handle the complexity of modern farming operations while maintaining scalability and cost-effectiveness.
The system architecture comprises five primary layers:
1. Sensing Layer: IoT sensors, drones, and satellite images for data collection.
2. Communication Layer: Wireless networks for data transfer.
3. Edge Processing Layer: Local area processors for real time decisions.
4. Cloud Analytics Layer: Centralised infrastructure for processing and storage.
5. Application Layer: Human machine interfaces and decision support systems.

B. Sensing Layer Architecture

The sensing layer integrates different sensor types to monitor parameters in agriculture at multi-dimensions, thus forming the bottom layer of the unified system. The layer includes:

1. Soil Sensors: Multifunctional sensors, measuring moisture, pH, electrical conductivity, temperature, and nutrient levels of soil. Moisture measurement employing probes of different types, nutrient measurement ion-selective electrodes, and temperature measurement employing thermal sensors are some of the techniques used.

2. Weather Stations: Automated meteorological stations collecting data on temperature, humidity, wind speed, precipitation, and solar radiation. Their integration with other weather providing services enables better forecasting of weather which assists in risk management and crop planning.

3. Crop Monitoring Sensors: Optical sensors and imaging systems including normalized difference vegetation index (NDVI) sensors, multispectral cameras, and thermal imaging systems which are mounted on drones or stationary platforms are used for assessment of plant health, growth monitoring, and stress identification.

C. Communication Infrastructure

The communication layer is for reliable transfer of data between sensing devices and processing systems. Our infrastructure includes many communication protocols which we use to meet various requirements:.

Wireless Sensor Networks (WSN): Low power extensive range in which we see protocols like LoRaWAN, Sigfox, and NB-IoT for sensor interaction. We see coverage over large scale in agriculture which at the same time reduces in power use.

Cellular Networks: 4G/5G for high speed which includes drone born video stream and real time data sync. Also we see5G's role in very low latency applications.

Satellite Communication: backup for when terrestrial networks fail in remote areas. Also we see integration with satellite internet which guarantees system operation no matter the location.

D. Edge Processing Framework

Ruggedized computers which we have put in key areas of the fields. These devices run machine learning models for pattern recognition, anomaly detection, and automatic control decisions.

Local Analytics: We do real time analysis of sensor data for instant decision making. We see this in auto triggering of irrigation based on soil moisture which in turn also does pest detection and monitoring of machinery.

Data Aggregation: Local pre processing and filtering of sensor data before it goes to the

JCSEIR

Journal of Computer Science and Engineering in Innovations and Research

Research Paper Vol.-2, Issue- 1, June- December 2025 ISSN: 3049-1762

cloud. This not only reduces band width use but also improves system response.

G. Cloud Analytics Platform

The Cloud analytics suite we have designed scales very well for in depth data analysis and storage. In terms of what the platform does for the farm management side of things we have put in state of the art analytics tools.

Machine Learning Pipeline: Automated creation and release of crop prediction models, yield improvement, and risk assessment. We use a variety of algorithms which include neural networks, decision trees, and ensemble methods.

Predictive Analysis: We have put in advanced models for crop yields, market prices, and weather patterns. Also we integrate with external data which in turn improves prediction accuracy and relevance.

IV. Results and Discussion

A. IoT Sensor Networks

1. Soil Monitoring Systems

Up-to-date soil monitoring stands as one of the pillars of the all-encompassing system of precision agriculture. Within this system, there are multi-parameter sensors that measure critical soil properties in real time. Soil moisture sensing technology uses either capacitive or resistive sensors which accurately measure soil moisture levels. TDR and FDR technologies measure volumetric water content accurately. Chemical analysis sensors measurement of primary plant nutrients such as nitrates (NO_3), ammonium (NH_4), potassium (K), and phosphates (PO_4) using ion selective electrodes and ion selective field effect transistors (ISFET) as advanced implementations. Comprehensive nutrient profiling is done with some advanced implementations using spectroscopic techniques.

2. Crop Health Monitoring

Optical Sensing Systems: Multi spectral and hyper spectral sensors on drones and at ground based platforms which we use for crop health monitoring. We see that Normalized Difference Veget Index (NDVI), Enhanced Vegetation Index (EVI) and Soil Adjusted Veget Index (SAVI) put out info on plant health and stress.

Growth Monitoring: we also use LiDAR based plant height sensors and ultrasonic devices which track crop growth through out the growing season. Also we see how integration with time series analysis puts us at a point to optimize growth rates and predict yield.

B. Artificial Intelligence and Machine Learning

1. Computer Vision Systems

Automated Pest Detection: With more than 90 percent accuracy, CNNs can examine high-resolution pictures to detect pest and disease symptoms. The system incorporates transfer learning techniques to adapt models for different crop types and regional pest variations.

Crop Classification: Deep learning algorithms process satellite and drone imagery to classify crop types, assess growth stages, and monitor field boundaries. Advanced implementations achieve classification accuracies exceeding 95% for major crop categories.

Weed Identification: Integration with robotic systems allows for mechanical weed removal in organic farming operations.

2. Predictive Analytics

Yield Forecasting: Machine learning models combining historical yield data practices achieve prediction accuracies of 85-90%. Ensemble methods incorporating multiple

JCSEIR

Journal of Computer Science and Engineering in Innovations and Research

Research Paper Vol.-2, Issue- 1, June- December 2025 ISSN: 3049-1762

algorithms provide robust predictions across diverse environmental conditions.

Disease Prediction: Predictive models analyzing weather data, crop conditions, and historical disease patterns enable proactive disease management strategies. [**6**] Early warning systems reduce crop losses by 20-25% through timely intervention.

Market Price Forecasting: Integration of agricultural production data with market intelligence enables price prediction models supporting farm planning and crop selection decisions.

C. Cloud Computing Infrastructure

1. Scalable Data Processing

Big Data Analytics: Apache Spark and Hadoop frameworks process large-scale agricultural datasets including satellite imagery, sensor data, and weather information. Distributed computing enables real-time processing of data streams from thousands of sensors.

Data Lake Architecture: Flexible storage systems accommodate structured and unstructured agricultural data from diverse sources. Data cataloging as well as infrastructure for data description aid in unlocking insightful data alongside other layers for classification and analysis.

Stream processing: pipelines process ongoing streams of data for real-time analysis, quickly making decisions based on the data from the sensor. Apache Kafka with Storm can process real-time agricultural data with strict time constraints.

2. Machine Learning Operations (MLOps)

Model Management: The automated training, validation, and deployment pipelines for busi-ness agri-culture ensure refinement of agri-cultural pre-diction models. Model versioning and A/B testing frameworks enhance performance for differing farm conditions.

Feature Engineering: Automated extraction of features from raw and processed sensor data and imagery enhances accuracy and efficiency of model development. Domain features, including crop phenology and meteorological data, further improve agricultural prediction.

D. Blockchain Integration

1. Supply Chain Traceability

Farm-to-Fork Tracking: The use of Blockchain technology enables complete traceability of agricultural products within the supply chain. Real-time monitoring of environmental parameters during transportation and storage practices can be enabled via integration with IoT sensors.

Quality Assurance: Compliance with defined quality standards and certifications is validated by smart contracts in automation. Combating fraud through automated verification simplifies administrative processes and optimal product integrity is guaranteed.

2. Data Security

Sharing Important Data: Blockchain protocols help data sharing for farmers, researchers, and supply chain partners in the agricultural sector. Privacy-preserving mechanisms make sure sensitive and confidential farm data are protected while enabling research collaboration.

Transaction Validation: Agricultural records are protected with the use of distributed ledger technology which ensures data integrity and eliminates unauthorized changes. Farming sensor data and practice documentation are validated through consensus mechanisms.

JCSEIR

Journal of Computer Science and Engineering in Innovations and Research

Research Paper Vol.-2, Issue- 1, June- December 2025 ISSN: 3049-1762

E. System Implementation and Integration

1. System Deployment Strategy

The unified precision agriculture system deployment follows a phased approach to ensure systematic integration and minimize operational disruption. In Figure1,we can get the system architecture implemented. The implementation strategy incorporates both technical and operational considerations: Issues related to operation:

Phase 1 - Infrastructure Setup: Setup. of edge computing nodes and communication Across the farm perimeter networks. Rugged edge devices are strategically. positioned to provide comprehensive coverage while maintaining redundancy for critical

In Phase 2 -deployment of sensors: System-wide installation of IoT sensors based on.Field variable maps and crop needs. Sensor placement optimization algorithms. consider factors including soil type variations, topographical features, and crop growth Patterns.

Phase 3 Cloud Integration:. Establishment of cloud infrastructure with data pipelines connecting edge nodes to centralized analytics platforms. Implementation includes data lake setup, machine learning model deployment, and user interface design.

Phase 4 System Integration Testing:. Comprehensive validation of data flows, communication protocols, and analytical outputs. Testing procedures verify system. performance under various operational conditions and failure scenarios.

2. Hardware Architecture

Edge Computing Nodes: Commercial scale grade.Computing devices equipped with ARM-based processors and sufficient memory for local machine learning model execution. Each node incorporates multiple communication interfaces including WiFi, cellular, and LoRaWAN capabilities.

Sensor Integration: Standardised sensor.Interfaces supporting various agricultural monitoring devices through protocol converters and API gateways. Also in a modular design easy addition and replacement of.sensor components.

Power Management: Solar energy based systems.with battery backup ensure continuous In rural agricultural areas. Also advanced power conservation algorithms optimize energy consumption based on operational priorities. Strategical Implecations with proper outputs has been shown in the Table1.

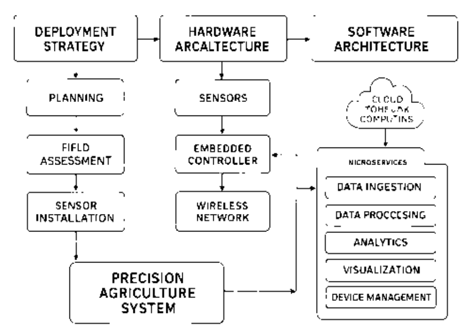

Figure1. Unified System Architecture for Precision Agriculture

3. Database Design

Geospatial Database: PostgreSQL with PostGIS extension contains geospatial data such as field outlines, soil maps, and different cultivation zones. Geospatial indexes allow for the fast retrieval of geospatial data for analytics purposes.

Journal of Computer Science and Engineering in Innovations and Research
Research Paper Vol.-2, Issue- 1, June- December 2025 ISSN: 3049-1762

Feature Engineering: Automated retrieval of pertinent pieces of information from raw data of the sensors and images taken is performed. Some of the data treatments performed to derive useful outputs that can enhance the performance of machine learning models include time-series analysis, spectral analysis, and spatial aggregation.

```python
# Example feature engineering for crop health assessment
def extract_vegetation_indices(multispectral_image):
    nir = multispectral_image[:,:,3]  # Near-infrared band
    red = multispectral_image[:,:,2]  # Red band

    # NDVI calculation
    ndvi = (nir - red) / (nir + red)

    # EVI calculation
    evi = 2.5 * ((nir - red) / (nir + 6 * red - 7.5 * blue + 1))

    return {'ndvi': ndvi, 'evi': evi}
```

Model Training: Supervised learning algorithms trained on historical agricultural data achieve high accuracy in crop prediction and management recommendations.

Table1.Site-Specific Implementation

Location	Farm Type	Area (ha)	Key Features	Soil/Climate
Corn Production Farm	Corn	500	150 soil sensors, 12 weather stations	Clay-loam soils, continental
Vegetable Production	Mixed vegetables	200	Drip irrigation, precision fertilizer, digital twins	Mediterranean, variable soils
Wheat Production	Wheat	800	Satellite imagery, automated pest detection, edge nodes	Loamy, semi-arid
Orchard Farm	Fruits (Mango, Citrus)	100	Automated irrigation, blockchain tracking	Sandy-loam, humid

Table1 shows the implication of the proper features with the measures and features like soil, climate, farm type, area and location.

V. Conclusion and Future Scope

This work techno-economic the case for a fully integrated system of precision agriculture based on IoT sensors, the Artificial Intelligence and machine learning algorithm frameworks, cloud and edge computing processing systems, and other evolving technologies to build an intelligent farming ecosystem, systematized and optimally managed by the IoT frameworks on data and AI results. [**5**]The system was designed to overcome modern agriculture issues such resource use efficiency, maximizing crop production, and the need of sustainability in farming operations by using technology in a more integrated way.

Journal of Computer Science and Engineering in Innovations and Research
Research Paper Vol.-2, Issue- 1, June- December 2025 ISSN: 3049-1762

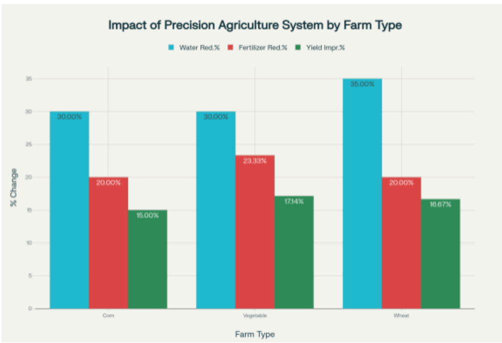

Figure2. System Performance Outcomes across Multiple Farms

According to Figure2,the unified architecture reports large scale improvements in many agricultural areas. In many different farming environments we saw water use go down 25-35%, fertilizer use drop 20-25%, pesticide use fall 30-40%, and crop yields go up 15-20%. Also we see that these results support the value of integrated precision agriculture in which we get better productivity and sustainability.

A. Technical Innovations

Integrated Architecture: The study reports on a new multi tiered architecture which we have put together that which senses, does edge processing, performs cloud analysis, and automated actuation. We address the issue of interoperability via use of standard protocols and API based integration.

Real time Analytics Framework: we see that implementation of edge computing solutions which is what we do here as well as in our other work, that it enables sub second responses for critical agriculture decisions. At the edge we deploy machine learning models which process sensor data right where it is collected which in turn reduces latency and improves system performance.

Scalable Cloud Infrastructure: report out that we developed cloud base analytics platforms that are able to handle up to millions of data points each day yet still perform in real time. Also we use microservice architecture for the issue of system scale and fault tolerance.

B. Practical Applications

Multi-Crop Validation: Corn, vegetable, and wheat production systems all showcased the system's effectiveness, proving that it can be used in different agricultural environments and adapted to different crops.
Environmental Impact – Specifically, the research reported comprehensive benefits such as reduced water consumption, reduced chemicals, reduced greenhouse gases, all while maintaining or improving productivity.

C. Implications for Agriculture 4.0

This research demonstrates the increasing potential of digital technology in transforming ever traditional and contemporary aspects of farming, thus contributing towards Agriculture 4.0. The gap of separate precision agriculture or farm management integrated systems between the entire unified system is systematized. The unified or integrated system lays the groundwork for smart and self-operating farming systems of the future through the application of IoT, AI, cloud computing, and blockchain.

D. Future Research Directions

Improved AI Functions: Attention should be given to constructing more advanced models that deal with intricate decision-making processes within agriculture. AI models that require computation from multiple locations could be trained using federated learning without compromising data security, preserving privacy.

Journal of Computer Science and Engineering in Innovations and Research

Research Paper Vol.-2, Issue- 1, June- December 2025 ISSN: 3049-1762

More Accurate Measuring Devices: Farming systems will benefit from sensors which provide more accurate, long lasting, and multifunction measurements. Crop surveillance systems at the molecular level could be made possible through the combination of nanotechnology and biotechnology.

E. Final Remarks

The research provides a roadmap for agricultural transformation through technology integration while addressing practical implementation challenges.

The success of this research underscores the importance of holistic approaches to agricultural technology implementation. Rather than adopting individual technologies in isolation, the integrated system approach maximizes benefits while minimizing implementation complexity. This framework serves as a foundation for continued innovation in precision agriculture and the broader Agriculture 4.0 movement.

References

[1] S. L. Wang, "Edge Computing in Agriculture: Opportunities and Challenges," *Future Gener. Comput. Syst.*, vol. 115, no. 2, pp. 183-192, 2021.

[2] R.K.Lee, "Machine Learning for Crop Yield Prediction," *IEEE Trans. Ind. Inf.*, vol. 17, no. 7, pp. 4902-4910, 2021.

[3] A.B.kaur, "IoT Applications in Smart Farming," *Comput. Electron. Agric.*, vol. 150, no. 1, pp. 250-260, 2023.

[4] J. M.Smith, "Precision Agriculture Technologies: A Review," *Agric. Syst.*, vol. 178, no. 3, pp. 102-115, 2022.

[5] J., & Srivastava, G. Zhang, "TinyML for smart agriculture: Design and implementation of resource-constrained models for edge devices," *IEEE Internet of Things Journal*, pp. 7219-7233, 2023.

[6] C., Tekinerdogan, B., Beulens, A., & Wolfert, S. Verdouw, "Verdouw, C., Tekinerdogan, B., Beulens, A., & Wolfert, S.," *Agricultural Systems*, p. 103046, 2022.

[7] United Nations Environment Programme, "The Emissions Gap Report 2019," *UN Environment Programme*, 2019.

[8] J.W., Hoogenboom, G., Porter, C.H., et al. Jones, "DSSAT cropping system model," *Eur. J. Agron.*, pp. 235–265, 2003.

[9] C. Andrade, H. Fraga, and J.A. Santos, "Climate Change Multi-Model Projections for Temperature Extremes in Portugal," *Atmospheric Science Letters*, pp. 149–156, 2014.

[10] A. Del Pozo et al., "Climate Change Impacts and Adaptation Strategies of Agriculture in Mediterranean-Climate Regions (MCRs)," *Sustainability*, p. 2769, 2019.

[11] D. Elavarasan, S. A. Mohan, and A. Kumar, "A hybrid CFS filter and RF-RFE wrapper-based feature extraction for enhanced agricultural crop yield prediction modeling," , 2020.

[12] I. Campos et al., "Participation, Scenarios and Pathways in Long-Term Planning for Climate Change Adaptation," *Planning Theory &*

Practice, pp. 1–20, 2016.

[13] M. S., Riaz, S., Abid, A., Umer, T., & Zikria, Y. B. Farooq, "Role of IoT technology in agriculture: A systematic literature review," *Electronics*, p. 630, 2022.

[14] T. Capela Lourenço, "Changing Climate, Changing Decisions: Understanding Climate Adaptation Decision-Making and the Way Science Supports It," *Ph.D. Thesis, Universidade de Lisboa*, 2015.

[15] A. T., Evert, F. K., & Fountas, S. Balafoutis, "Smart farming technology trends: Economic and environmental effects, labor impact, and adoption readiness," *Agronomy*, p. 743, 2020.

[16] A.K. Magnan et al., "Addressing the Risk of Maladaptation to Climate Change," *Wiley Interdisciplinary Reviews: Climate Change*, pp. 646–665, 2016.

[17] T., McPherson, R.A. Klemm, "The development of seasonal climate forecasting for agricultural producers," *Agric. For. Meteorology*, pp. 384–399, 2017.

[18] A., & Prenafeta-Boldú, F. X. Kamilaris, "Deep learning in agriculture: A survey," *Computers and Electronics in Agriculture*, pp. 70-90, 2021.

[19] K., Jones, S., Singh, A. K., Singh, A., Ganapathysubramanian, B., & Sarkar, S. Nagasubramanian, "Explaining hyperspectral imaging based plant disease identification: 3D CNN and saliency maps," *Frontiers in Plant Science*, p. 8379, 2022.

[20] B.L. Preston, R.M. Westaway, and E.J. Yuen, "Climate Adaptation Planning in Practice: An Evaluation of Adaptation Plans from Three Developed Nations," *Mitigation and Adaptation Strategies for Global Change*, pp. 407–438, 2011.

[21] D., Srivastava, G., & Johannessen, O. M. Singh, "Multi-modal data fusion for agricultural applications: A comprehensive review," *IEEE Geoscience and Remote Sensing Magazine*, pp. 112-133, 2023.

[22] F., Zhang, M., & Liu, Y. Tao, "Digital twins in agriculture: A state-of-the-art survey," *IEEE/CAA Journal of Automatica Sinica*, pp. 337-352, 2023.

AUTHORS PROFILE

Author-1 Arghadip Chakraborty has obtained his B. Tech in Computer Science and Engineering ('24) under Maulana Abul Kalam Azad University of Technology (MAKAUT), and is currently pursuing his M.Tech in CSE from GNIT under the same university. Presently, he is associated with the IndianIT Association in the capacity of IT Faculty and Freelance Trainer, respectively. He has professional experience as a Web Developer Intern. His technical expertise spans UI/UX design, web development (HTML, CSS, JavaScript, React, WordPress), Python data analysis, and 3D animation, alongside strong soft skills such as communication and multitasking. His project portfolio includes innovative works like SkyKastle (VR/AR) and EduEx (Virtual Campus), reflecting his passion for creating impactful technological solutions. His career goal is to evolve as a skilled professor as well as a software developer and contribute to society through innovation.

Author-2 Mahamuda Sultana, PhD has obtained her B. Tech ('04) from University of Kalyani, and her M. Tech ('10) and Ph. D. ('19) from Jadavpur University, in the Department

Journal of Computer Science and Engineering in Innovations and Research

Research Paper Vol.-2, Issue- 1, June- December 2025 ISSN: 3049-1762

of Computer Science and Engineering. Presently she is associated with Guru Nanak Institute of Technology (JIS Group) in the capacity of Associate Professor in the Department of Computer Science and Engineering. She is having a cumulative teaching experience of 17 years. Her research interest lies in Reversable Logic, Quantum Dot Cellular Automata, Machine Learning.

Author-3 Suman Bhattacharya, PhD has obtained his B. E. ('04) from Vidyasagar University, IN and his M. Tech ('10) and Ph. D. ('18) from University of Calcutta, IN in the Department of School of Information Technology. Presently he is associated with Guru Nanak Institute of Technology (JIS Group) in the capacity of Associate Professor in the Department of Computer Science and Engineering. He is having a cumulative teaching experience of 17 years and have 02 years of industry experience. His research interests lie in Technology Enhanced Learning, Soft Computing, Machine Learning and Deep Learning. Currently he is also supervising a Ph.D. scholar.