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Deep Learning and Optimization Approaches in IoT based soil nutrition and plant disease detection system for smart agriculture using Multi-Layer Stacked Residual Coordinate Boosted Sooty Tern Attention Network: A Review

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Abstract

The integration of Internet of Things (IoT) and Artificial Intelligence (AI) has significantly transformed modern agriculture by enabling intelligent monitoring and data-driven decision-making for soil nutrition management and plant disease detection. Traditional farming practices often face limitations such as delayed disease identification, inefficient nutrient management, and lack of real-time analysis. To overcome these issues, recent research has focused on advanced deep learning and optimization techniques for precision agriculture. This review highlights approaches centered on a novel Multi-Layer Stacked Residual Coordinate Boosted Sooty Tern Attention Network, which combines residual learning and attention mechanisms to enhance feature extraction and classification accuracy. Attention mechanisms help focus on critical regions in plant images and soil data, while residual connections support deeper and more efficient model training. The study also examines various models, including CNNs, CNN-LSTM hybrids, Vision Transformers, and Graph Neural Networks, along with optimization techniques like genetic algorithms and swarm intelligence. These methods improve detection accuracy and enable real-time monitoring through IoT systems. However, challenges such as computational complexity, scalability, and energy constraints remain, highlighting the need for efficient and deployable solutions.

Introduction

Agriculture plays a crucial role in sustaining the global population, yet traditional farming practices face numerous challenges, including inefficient resource utilization, delayed disease detection, and inadequate soil nutrient management. With the rapid growth of population and increasing demand for food, there is a pressing need for intelligent agricultural systems that can enhance productivity while ensuring sustainability. The integration of Internet of Things (IoT) and Artificial Intelligence (AI) has emerged as a transformative solution for modern agriculture, enabling real-time monitoring, automated decision-making, and data-driven optimization.

IoT-based smart agriculture systems utilize a network of sensors to collect real-time data related to soil moisture, temperature, humidity, nutrient levels, and crop health. This continuous data acquisition allows farmers to monitor field conditions remotely and make informed decisions. However, the vast amount of data generated by IoT devices requires advanced

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analytical techniques for effective processing and interpretation. This is where deep learning models play a significant role by extracting meaningful patterns and insights from complex datasets.

Among deep learning techniques, Convolutional Neural Networks (CNNs) have been widely used for plant disease detection due to their strong capability in image feature extraction. CNN-based models can automatically identify patterns in plant leaves and classify diseases with high accuracy. However, traditional CNN models have limitations in capturing long-range dependencies and contextual relationships in complex agricultural environments. To overcome these limitations, recent research has focused on integrating attention mechanisms and transformer-based architectures. Attention mechanisms enable models to focus on the most relevant features, improving detection accuracy and interpretability. Vision Transformers (ViTs) further enhance this capability by modelling global dependencies through self-attention, making them highly effective for complex image analysis tasks.

In addition to deep learning, optimization algorithms such as genetic algorithms, particle swarm optimization, and swarm intelligence techniques have been employed to improve system performance. These algorithms optimize model parameters, resource allocation, and decision-making processes, leading to enhanced efficiency and reduced computational cost. The proposed concept of a Multi-Layer Stacked Residual Coordinate Boosted Sooty Tern Attention Network represents a novel approach that combines multiple advanced techniques, including residual learning, coordinate attention, and hybrid optimization strategies. Residual connections enable deeper network architectures by mitigating vanishing gradient problems, while coordinate attention mechanisms enhance spatial awareness in feature extraction. The integration of these components results in improved model accuracy, robustness, and efficiency.

Despite these advancements, several challenges remain in the implementation of AI-based smart agriculture systems. These include high computational requirements, dependency on large labelled datasets, scalability issues, and energy constraints in IoT environments. Furthermore, real-time deployment of such models in resource-limited agricultural settings requires lightweight and efficient architectures. This paper provides a comprehensive review of recent advancements in deep learning and optimization techniques for IoT-based soil nutrition and plant disease detection systems. It analyses various methodologies, compares their performance, and identifies key research gaps. The study aims to provide valuable insights into the development of intelligent, scalable, and energy-efficient smart agriculture solutions.

Literature Review

Udutalapally et al. (2020) proposed an IoT-based smart agriculture system integrating CNN for plant disease detection. The system uses sensor nodes and image processing for real-time monitoring. It achieved high accuracy in disease prediction under field conditions. However, deployment scalability and hardware dependency remain challenges. Mohanty et al. (2020) utilized deep CNN architectures for plant disease classification using image datasets. The model demonstrated high accuracy across multiple crop types. It enabled automated disease detection without manual intervention. However, performance depends heavily on dataset quality and diversity.

Liu et al. (2020) proposed CNN-based workload prediction models for smart agriculture systems. The approach improves decision-making in irrigation and nutrient management. It enhances resource efficiency using data-driven insights. However, it requires continuous data collection for optimal performance. Verma et al. (2020) developed deep learning-based soil and crop health prediction models. The system integrates environmental and soil parameters for analysis. It improves agricultural productivity through early prediction. However, the model suffers from high data dependency.

Khan and Ali (2021) introduced deep learning-based plant disease detection using CNN models. The model provides robust classification under varying environmental conditions. It improves disease detection accuracy significantly. However, it requires high computational resources. Ibrahim et al. (2021) proposed a CNN-LSTM hybrid model for crop monitoring. The model captures spatial and temporal dependencies effectively. It improves prediction accuracy in time-series agricultural data. However, training complexity is relatively high.

Sharma and Gupta (2021) introduced AI-based cloud-assisted agriculture monitoring systems. The system integrates IoT sensors with machine learning models. It improves decision-making for soil nutrient management. However, cloud dependency increases latency. Rahman et al. (2021) proposed deep learning-based adaptive disease detection systems. The model applies neural networks for image-based classification. It enhances robustness in dynamic agricultural environments. However, it requires large labelled datasets.

Chen and Li (2021) developed neural network-based plant health monitoring systems. The system improves detection of crop diseases and stress levels. It enables real-time agricultural monitoring. However, system complexity is high. Kaur et al. (2021) proposed hybrid optimization-based deep learning models for agriculture. The model integrates genetic algorithms with neural networks. It improves prediction accuracy and optimization performance. However, convergence time is slow.

Ashawa et al. (2022) introduced LSTM-based prediction models for agricultural data analysis. The model predicts soil and crop conditions efficiently. It improves resource allocation in smart farming systems. However, memory requirements are high. Sajitha et al. (2022) reviewed ML and DL-based plant disease detection systems. The study highlights CNN, transfer learning, and hybrid approaches. It identifies key challenges such as dataset limitations. However, practical deployment issues remain.

Li et al. (2022) proposed multi-objective optimization models for smart agriculture. The system balances energy efficiency and crop productivity. It improves soil nutrient management strategies. However, optimization complexity increases computation time. Wang et al. (2022) introduced quantum-inspired CNN models for agricultural analysis. The model enhances feature extraction capability. It improves classification performance. However, computational overhead is significant.

Thakur et al. (2022) proposed a Vision Transformer-based CNN hybrid (PlantXViT). The model integrates CNN and transformer for plant disease detection. It improves accuracy and interpretability using attention mechanisms. However, implementation complexity remains high. Paul et al. (2022) analysed deep learning methods for plant stress detection. The study highlights multi-modal data integration for improved accuracy. It emphasizes the importance of environmental data. However, model generalization remains a challenge.

Muruganandam et al. (2023) proposed feed-forward deep learning models for plant disease detection. The system reduces computational complexity. It achieves efficient classification performance. However, temporal modelling capability is limited. Das et al. (2023) reviewed deep learning-based plant disease detection systems. The study highlights CNN architectures and datasets used. It demonstrates high accuracy in disease classification. However, real-world generalization remains an issue.

Li et al. (2023) introduced Graph Attention Networks for smart agriculture. The model improves spatial relationship modelling among sensor nodes. It enhances prediction accuracy. However, scalability is a concern. Zhao et al. (2023) proposed attention-based neural networks for plant disease detection. The model improves feature selection using attention mechanisms. It enhances accuracy in complex environments. However, computational cost is high.

Chen et al. (2023) developed attention-CNN hybrid models for plant monitoring. The model prioritizes important features. It improves detection accuracy. However, model complexity increases significantly. Ahmed et al. (2023) proposed optimization-based intelligent agriculture systems. The model improves energy efficiency and prediction accuracy. It enhances system performance in IoT environments. However, tuning parameters is challenging.

Zeng et al. (2023) introduced CNN + Transformer hybrid models for plant disease detection. The model improves robustness under environmental noise. It enhances real-world applicability. However, computational overhead remains high. Tong et al. (2023) proposed transformer-based prediction models for agricultural data. The model captures long-term dependencies effectively. It improves forecasting accuracy. However, large datasets are required.

Gao et al. (2023) developed transformer-based intelligent agricultural systems. The system adapts to dynamic environmental conditions. It improves decision-making. However, resource requirements are high. Chen and Li (2023) introduced lightweight CNN models for edge-based agriculture systems. The model reduces computational cost. It enables real-time deployment. However, accuracy is slightly reduced.

Wang and Liu (2023) proposed cross-layer deep learning models for agriculture. The model integrates multiple data sources. It improves prediction stability. However, design complexity increases. Gupta et al. (2023) developed hybrid AI models combining ML and optimization. The system improves scheduling and resource allocation. It enhances agricultural efficiency. However, system complexity remains high.

Singh et al. (2023) proposed attention-based deep learning models. The system improves feature extraction and prediction accuracy. It enhances smart agriculture systems. However, computational cost is high. Sharma et al. (2023) introduced hybrid AI-based agriculture systems. The model combines optimization and neural networks. It improves system efficiency and scalability. However, implementation complexity is significant.

Comparative Table

No.	Author(s) & Year	Technique / Model	Application	Key Contribution	Limitation
1	Udutalapally et al. (2020)	IoT + CNN	Disease detection	Real-time monitoring	Hardware dependency
2	Mohanty et al. (2020)	CNN	Plant disease	High accuracy	Dataset dependency
3	Liu et al. (2020)	CNN	Soil prediction	Resource optimization	Data requirement
4	Verma et al. (2020)	DL model	Soil health	Early prediction	High data need
5	Khan & Ali (2021)	CNN	Disease detection	Robust classification	High computation
6	Ibrahim et al. (2021)	CNN-LSTM	Crop monitoring	Temporal modelling	Complexity
7	Sharma & Gupta (2021)	ML + IoT	Soil monitoring	Smart decisions	Latency
8	Rahman et al. (2021)	DL	Disease detection	Adaptive system	Data heavy
9	Chen & Li (2021)	Neural Network	Crop monitoring	Real-time analysis	Complexity
10	Kaur et al. (2021)	GA + DL	Optimization	Improved accuracy	Slow convergence
11	Ashawa et al. (2022)	LSTM	Prediction	Efficient forecasting	Memory usage
12	Sajitha et al. (2022)	ML/DL review	Agriculture	Identified gaps	No implementation
13	Li et al. (2022)	Optimization	Soil management	Balanced performance	Complexity
14	Wang et al. (2022)	QCNN	Crop analysis	High feature extraction	Overhead
15	Thakur et al. (2022)	CNN + ViT	Disease detection	Hybrid accuracy	Complex model
16	Paul et al. (2022)	DL	Crop stress	Multi-modal data	Generalization issue
17	Muruganandam et al. (2023)	Feedforward DL	Disease detection	Efficient computation	Limited temporal
18	Das et al. (2023)	CNN review	Disease detection	High accuracy	Dataset issue
19	Li et al. (2023)	GNN	Smart farming	Relationship modelling	Scalability
20	Zhao et al. (2023)	Attention DL	Disease detection	Feature selection	High computation
21	Chen et al. (2023)	Attention-CNN	Monitoring	Improved detection	Complexity
22	Ahmed et al. (2023)	Optimization DL	Smart farming	Energy efficiency	Tuning required
23	Zeng et al. (2023)	CNN + Transformer	Disease detection	Robust model	Resource heavy
24	Tong et al. (2023)	Transformer	Prediction	Long dependency	Data dependency
25	Gao et al. (2023)	Transformer	Smart farming	Adaptive system	High cost
26	Chen & Li (2023)	Lightweight CNN	Edge computing	Low computation	Reduced accuracy
27	Wang & Liu (2023)	Cross-layer DL	Agriculture	Stability	Complexity
28	Gupta et al. (2023)	Hybrid AI	Optimization	Efficiency	Complex system
29	Singh et al. (2023)	Attention DL	Prediction	Improved accuracy	Computation

30	Sharma et al. (2023)	Hybrid AI	Smart agriculture	Scalability	Complexity

Comparative Analysis

The comparative analysis of the selected studies reveals a clear evolution from traditional machine learning techniques to advanced deep learning and hybrid AI-based approaches in smart agriculture systems. Early models primarily relied on CNN architectures, which demonstrated strong performance in plant disease detection due to their ability to extract spatial features effectively. However, these models were limited by their dependency on large datasets and inability to capture temporal patterns. The introduction of hybrid models such as CNN-LSTM and CNN-Transformer significantly improved performance by integrating spatial and temporal learning. These models enhanced prediction accuracy and robustness, particularly in dynamic agricultural environments. Additionally, optimization-based techniques such as genetic algorithms and swarm intelligence contributed to improved resource allocation and decision-making efficiency.

Recent advancements focus on attention mechanisms and transformer-based architectures, which enable models to capture global dependencies and improve feature selection. These approaches provide higher accuracy and adaptability but come with increased computational complexity and resource requirements. Lightweight models have been proposed to address these challenges, although they often involve trade-offs between accuracy and efficiency. Overall, hybrid deep learning models integrating attention mechanisms and optimization techniques provide the best performance, offering a balance between accuracy, efficiency, and scalability. However, challenges such as computational overhead, data dependency, and real-time deployment remain significant.

Conclusion

The integration of IoT and Artificial Intelligence has revolutionized modern agriculture by enabling intelligent systems for soil nutrition management and plant disease detection. This study presented a comprehensive review of deep learning and optimization approaches, focusing on advanced architectures such as CNNs, hybrid models, and attention-based transformer networks. Traditional agricultural methods are often inefficient due to lack of real-time monitoring and delayed decision-making. The adoption of IoT-based systems allows continuous data collection, enabling timely and accurate analysis of environmental conditions. Deep learning models, particularly CNNs, have significantly improved plant disease detection by automating image-based classification tasks.

Hybrid models combining CNN with LSTM and transformer architectures have further enhanced performance by capturing both spatial and temporal dependencies. Attention mechanisms improve feature selection, allowing models to focus on relevant information and achieve higher accuracy. Optimization algorithms contribute to efficient resource management and decision-making, improving overall system performance. Despite these advancements, several challenges remain. High computational complexity, data dependency, and scalability issues limit the deployment of these models in real-world agricultural environments. Additionally, energy constraints in IoT systems require the development of lightweight and efficient models. Future research should focus on developing scalable, energy-efficient, and real-time AI models for smart agriculture. The integration of edge computing and federated learning can further enhance system performance by reducing latency and improving data privacy. Advanced architectures such as the proposed Multi-Layer Stacked Residual Coordinate Boosted Sooty Tern Attention Network offer promising solutions for next-generation agricultural systems. In conclusion, deep learning and optimization techniques provide a powerful foundation for intelligent agriculture, enabling improved productivity, sustainability, and resource efficiency. Continued research in this domain will play a critical role in addressing global agricultural challenges.

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