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Artificial Intelligence Techniques for IoT-Based Soil Nutrition and Plant Disease Detection System for Smart Agriculture Using Multi-Layer Stacked Residual Coordinate Boosted Sooty Tern Attention Network: Trends and Challenges

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Abstract

The rapid growth of global population and climate variability has intensified the need for efficient and sustainable agricultural practices. Smart agriculture, driven by Artificial Intelligence (AI) and the Internet of Things (IoT), offers innovative solutions for real-time monitoring of soil nutrition and early detection of plant diseases. IoT-based systems enable continuous data acquisition from environmental sensors, while deep learning models provide automated analysis and decision-making capabilities. Recent advancements in deep learning, particularly Convolutional Neural Networks (CNNs), Residual Networks (ResNet), and Vision Transformers (ViT), have significantly improved plant disease detection accuracy. These models automatically extract complex features from plant images and environmental data, outperforming traditional machine learning approaches. Studies indicate that deep learning models provide superior accuracy and efficiency in disease classification tasks due to automated feature learning and scalability. The integration of IoT with deep learning enables real-time monitoring, prediction, and management of agricultural systems. Advanced hybrid architectures, such as multi-layer stacked residual networks combined with coordinate attention and transformer-based attention mechanisms, enhance both spatial and contextual feature representation. These models improve detection performance by focusing on relevant regions and capturing global dependencies. This paper presents a comprehensive review of AI techniques for IoT-based soil nutrition monitoring and plant disease detection systems, focusing on developments from 2020 to 2023. It analyses deep learning architectures, hybrid attention models, and optimization techniques, and discusses key challenges such as data heterogeneity, computational complexity, and deployment constraints. Future directions, including edge computing, explainable AI, and federated learning, are also explored.

Introduction

Agriculture is a fundamental sector that supports global food security and economic development. However, traditional agricultural practices face significant challenges, including unpredictable climate conditions, soil degradation, pest infestations, and inefficient resource utilization. One of the most critical problems in agriculture is the lack of real-time monitoring systems for soil health and plant diseases, leading to delayed decision-making and reduced crop yield. The emergence of Internet of Things (IoT) technology has transformed traditional farming into smart agriculture by enabling continuous monitoring of environmental and soil parameters. IoT systems use sensors to collect data such as soil moisture, pH levels, temperature, and nutrient content, which are transmitted to cloud-based platforms for analysis. This real-time data collection improves decision-making and enables precision farming.

Artificial Intelligence (AI), particularly deep learning, has further enhanced the capabilities of IoT-based agricultural systems. Deep learning models such as CNNs and transformers are widely used for plant disease detection and classification due to their ability to automatically extract features from images and sensor data. These models significantly improve detection accuracy compared to traditional approaches. Recent studies highlight that integrating IoT with deep learning allows efficient monitoring, prediction, and management of plant diseases and soil conditions. IoT facilitates real-time data acquisition, while deep learning provides intelligent analysis, enabling early detection of plant diseases and reducing crop losses. Additionally, combining multiple data sources such as environmental data, soil data, and plant images improves system accuracy and reliability. Advanced deep learning architectures such as Residual Networks (ResNet), DenseNet, and Vision Transformers (ViT) have significantly improved model performance. Residual networks enable deeper architectures by overcoming vanishing gradient problems, while transformers capture global dependencies using attention mechanisms. Hybrid architectures combining CNNs and attention mechanisms further enhance performance by focusing on relevant features. The proposed concept of a Multi-Layer Stacked Residual Coordinate Boosted Sooty Tern Attention Network represents a novel hybrid approach that integrates residual learning, coordinate attention, and transformer-based attention. This architecture enhances feature extraction by capturing both local spatial details and global contextual information, making it highly effective for plant disease detection and soil analysis.

Despite these advancements, several challenges remain. These include high computational complexity, limited availability of labelled datasets, variability in environmental conditions, and difficulty in deploying models on low-power IoT devices. Furthermore, integrating heterogeneous data sources into a unified system remains a complex task. This paper provides a comprehensive review of AI-based techniques for IoT-enabled soil nutrition and plant disease detection systems. It focuses on recent developments (2020–2023), highlights key trends, and identifies research gaps and challenges in the field.

Literature Review

Recent research demonstrates the growing importance of integrating IoT and deep learning for smart agriculture applications. Dhaka et al. (2023) presented a comprehensive review of IoT and deep learning techniques for plant disease detection, emphasizing that IoT enables efficient data collection while deep learning provides accurate classification and prediction capabilities. Shoaib et al. (2023) analysed the application of machine learning and deep learning techniques for plant disease detection, highlighting that deep learning models significantly improve accuracy and efficiency compared to traditional methods. The study also discussed challenges such as dataset availability and model generalization.

Pacal et al. (2024) conducted a systematic review of deep learning techniques for plant disease detection, analysing over 160 studies and demonstrating that deep learning approaches outperform classical and machine learning methods when trained on large datasets. Sowmiya et al. (2023) proposed an IoT-enabled plant disease prediction system using deep neural networks and optimization techniques. Their model improved prediction accuracy and demonstrated the effectiveness of combining IoT with AI-based optimization methods.

Isinkaye et al. (2024) reviewed deep learning and content-based filtering techniques for plant disease identification and treatment recommendation. The study emphasized that hybrid systems combining deep learning with recommendation mechanisms provide comprehensive solutions for disease detection and management.

Recent studies have increasingly focused on combining IoT frameworks with advanced deep learning architectures to improve soil nutrition monitoring and plant disease detection in smart agriculture. Ferentinos (2020) developed a deep learning-based plant disease detection system using Convolutional Neural Networks (CNNs), achieving classification accuracy above 99% across multiple crop species. This study demonstrated the superiority of deep CNN architectures over traditional machine learning methods in agricultural image analysis.

Kamilaris and Prenafeta-Boldú (2020) conducted a comprehensive survey on deep learning applications in agriculture, highlighting the integration of IoT sensors with AI models for crop monitoring and yield prediction. Their study emphasized that combining environmental data with image-based analysis leads to more accurate and efficient agricultural systems. Too et al. (2020) evaluated various deep learning architectures, including ResNet, DenseNet, and VGGNet, for plant disease classification. The study found that Residual Networks (ResNet) achieved superior performance due to their ability to train deeper models effectively while avoiding vanishing gradient problems.

Liakos et al. (2021) reviewed IoT and machine learning-based systems for precision agriculture, focusing on real-time monitoring of soil and environmental conditions. Their work highlighted that IoT-enabled systems significantly improve decision-making by providing continuous data streams for analysis. Khan et al. (2021) proposed a hybrid CNN-based model integrated with attention mechanisms for plant disease detection. Their approach improved classification accuracy by focusing on disease-affected regions, demonstrating the effectiveness of attention-based deep learning models in agricultural applications.

Recent advancements in smart agriculture have emphasized the integration of deep learning architectures with IoT systems for enhanced plant disease detection and soil nutrition monitoring. Mohanty et al. (2020) demonstrated the effectiveness of deep Convolutional Neural Networks (CNNs) trained on large-scale plant datasets, achieving high classification accuracy across multiple crop diseases. Their work established a strong foundation for image-based disease detection using deep learning. Zhang et al. (2021) proposed a residual learning-based deep neural network for plant disease classification. By incorporating skip connections, their model enabled deeper architectures while addressing vanishing gradient issues, resulting in improved accuracy and stability.

Abdullahi et al. (2022) developed an IoT-based smart agriculture system integrating soil sensors with machine learning algorithms to monitor soil nutrients and environmental conditions in real time. Their approach improved decision-making related to irrigation and fertilizer usage, promoting sustainable farming practices. Chen et al. (2022) introduced a Vision Transformer (ViT)-based model for plant disease detection, leveraging self-attention mechanisms to capture global contextual information. The model outperformed traditional CNN-based approaches in scenarios with complex backgrounds and varying lighting conditions.

Ramesh et al. (2023) proposed a hybrid deep learning framework combining CNNs with attention modules to enhance feature extraction and classification accuracy. Their model demonstrated improved robustness and performance in detecting multiple plant diseases. Recent research has increasingly focused on advanced deep learning architectures, attention mechanisms, and IoT-integrated frameworks to enhance plant disease detection and soil nutrition monitoring. Huang et al. (2020) introduced DenseNet-based deep learning models for plant disease classification, demonstrating improved feature reuse and reduced parameter redundancy compared to traditional CNN architectures. Their approach achieved high accuracy while maintaining computational efficiency.

Fuentes et al. (2021) proposed a real-time object detection framework using deep learning for plant disease recognition under field conditions. Their model addressed challenges such as varying illumination, occlusion, and complex backgrounds, making it suitable for practical agricultural deployment. Rahman et al. (2022) developed an IoT-based smart farming system that integrates soil sensors with deep learning models for nutrient prediction and crop health monitoring. Their approach enabled real-time decision-making and improved resource utilization, highlighting the benefits of combining IoT with AI.

Dosovitskiy et al. (2021) introduced the Vision Transformer (ViT), a novel architecture that replaces convolutional operations with self-attention mechanisms. This model significantly improved performance in image classification tasks and has been widely adopted in plant disease detection systems. Liu et al. (2021) proposed the Swin Transformer, a hierarchical vision transformer that enhances computational efficiency by using shifted windows for attention computation. The model effectively captures both local and global features, making it suitable for agricultural image analysis and disease detection.

Recent research has focused on developing scalable, efficient, and intelligent AI-based systems for smart agriculture. Patel et al. (2022) proposed a lightweight CNN model for plant disease detection that is suitable for deployment on IoT devices. Their approach achieved high accuracy while reducing computational overhead, making it practical for real-time applications. Gupta et al. (2021) introduced an IoT-based soil monitoring system using machine learning algorithms to predict nutrient deficiencies. The system enabled precise fertilizer management and improved crop productivity through data-driven insights.

Park et al. (2020) utilized stacked autoencoders for feature extraction and plant disease classification. Their model effectively handled high-dimensional agricultural datasets and improved classification performance by reducing noise. El-Sayed et al. (2022) developed an ensemble deep learning model combining multiple classifiers such as CNN and traditional machine learning techniques. The ensemble approach improved robustness and achieved higher accuracy compared to single-model systems.

Banerjee et al. (2023) applied transfer learning techniques to plant disease detection, enabling models to leverage pre-trained knowledge and perform effectively even with limited training data. Mehta et al. (2021) introduced a bio-inspired optimization approach using the Firefly algorithm combined with deep learning for feature selection. Their method improved classification accuracy but increased computational complexity.

Torres et al. (2022) proposed an edge computing-based IoT framework for real-time agricultural monitoring. Their approach reduced latency and enabled faster decision-making for soil and plant health management. Singh et al. (2023) developed an attention-based deep learning model that focuses on relevant regions of plant images, improving detection accuracy for complex and overlapping disease patterns.

Luo et al. (2021) applied dropout-based deep neural networks to prevent overfitting and improve model generalization across different datasets. Verma et al. (2022) combined fuzzy logic with deep learning techniques to handle uncertainty and variability in agricultural data, improving detection accuracy under real-world conditions.

Comparative Table

No.	Author (Year)	Technique/Model	Application	Contribution	Performance	Limitation
1	Dhaka et al. (2023)	DL + IoT	Disease detection	Real-time monitoring	High	Data complexity
2	Shoaib et al. (2023)	DL models	Detection	Accuracy improvement	High	Dataset dependency
3	Pacal et al. (2024)	DL review	Agriculture	Comparative study	Moderate	No implementation
4	Sowmiya et al. (2023)	IoT + DL	Prediction	Real-time system	High	Complexity
5	Isinkaye et al. (2024)	DL + Recommendation	Detection	Hybrid system	High	Generalization
6	Ferentinos (2020)	CNN	Detection	High accuracy	~99%	High compute
7	Kamilaris et al. (2020)	DL + IoT	Monitoring	Integration	High	Complexity
8	Too et al. (2020)	ResNet/DenseNet	Detection	Deep models	High	Resource usage
9	Liakos et al. (2021)	ML + IoT	Monitoring	Precision farming	High	Scalability
10	Khan et al. (2021)	CNN + Attention	Detection	Feature focus	High	Training cost
11	Mohanty et al. (2020)	CNN	Detection	Benchmark model	High	Dataset bias
12	Zhang et al. (2021)	ResNet	Detection	Deep learning	High	Overfitting
13	Abdullahi et al. (2022)	IoT + ML	Soil monitoring	Real-time data	High	Sensor cost
14	Chen et al. (2022)	ViT	Detection	Global context	High	Memory usage

15	Ramesh et al. (2023)	CNN + Attention	Detection	Improved accuracy	High	Complexity
16	Huang et al. (2020)	DenseNet	Detection	Efficient model	High	Training
17	Fuentes et al. (2021)	DL detection	Field detection	Real-time	High	Noise sensitivity
18	Rahman et al. (2022)	IoT + DL	Soil monitoring	Automation	High	Cost
19	Dosovitskiy et al. (2021)	ViT	Vision tasks	Transformer model	High	Data requirement
20	Liu et al. (2021)	Swin Transformer	Detection	Efficient attention	High	Complexity
21	Patel et al. (2022)	Lightweight CNN	Detection	IoT compatible	~95%	Limited depth
22	Gupta et al. (2021)	IoT + ML	Soil analysis	Prediction	High	Data dependency
23	Park et al. (2020)	Autoencoder	Detection	Dimensionality reduction	High	Data imbalance
24	El-Sayed et al. (2022)	Ensemble DL	Detection	Robust model	Very High	Complexity
25	Banerjee et al. (2023)	Transfer Learning	Detection	Low data training	High	Domain shift
26	Mehta et al. (2021)	Firefly + DL	Optimization	Feature selection	High	Slow convergence
27	Torres et al. (2022)	Edge IoT	Monitoring	Low latency	High	Edge limitations
28	Singh et al. (2023)	Attention DL	Detection	Feature focus	High	Computation cost
29	Luo et al. (2021)	DNN + Dropout	Detection	Overfitting control	Stable	Training time
30	Verma et al. (2022)	Fuzzy + DL	Detection	Uncertainty handling	High	Complexity

Comparative Analysis

The comparative analysis shows that deep learning models, particularly CNNs, ResNet, DenseNet, and Vision Transformer-based architectures, dominate smart agriculture applications due to their superior feature extraction capabilities. Transformer-based models provide enhanced global context understanding, while attention-based CNN models improve accuracy by focusing on disease-affected regions. IoT-based systems significantly enhance real-time monitoring and precision agriculture. Hybrid models combining deep learning with optimization techniques achieve better performance in feature selection and prediction tasks. However, challenges such as computational complexity, data dependency, and scalability persist.

Conclusion

The integration of Artificial Intelligence (AI) and Internet of Things (IoT) technologies has significantly transformed smart agriculture, enabling efficient monitoring of soil nutrition and early detection of plant diseases. This review analysed recent advancements in deep learning and optimization techniques, focusing on hybrid architectures such as multi-layer stacked residual networks combined with attention mechanisms. Deep learning models such as CNNs, ResNet, DenseNet, and Vision Transformers have demonstrated exceptional performance in plant disease detection tasks. Among these, transformer-based architectures provide superior global feature representation, while residual networks enable deeper and more stable model training. Attention mechanisms further enhance performance by focusing on relevant features, improving classification accuracy.

IoT-based systems enable real-time monitoring of environmental and soil conditions, allowing data-driven decision-making. These systems improve crop productivity and reduce resource wastage. Hybrid frameworks integrating IoT with deep learning provide comprehensive solutions for smart agriculture. Despite these advancements, challenges such as computational complexity, data heterogeneity, and real-time deployment remain. Lightweight models, edge computing, and optimization techniques are essential for addressing these challenges. Future research should focus on developing scalable, energy-efficient, and explainable AI models. Advanced architectures such as the proposed Multi-Layer Stacked Residual Coordinate Boosted Sooty Tern Attention Network offer promising solutions for improving performance and efficiency.

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