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# A Comprehensive Review of IoT-Based Soil Nutrition and Plant Disease Detection System for Smart Agriculture Using Multi-Layer Stacked Residual Coordinate Boosted Sooty Tern Attention Network

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**Abstract**

Smart agriculture has become an important approach for improving crop productivity, ensuring food security, and reducing resource wastage through the integration of IoT, Artificial Intelligence (AI), and deep learning technologies. Traditional agricultural practices mainly depend on manual monitoring of soil conditions and plant diseases, which is often inefficient, time-consuming, and prone to human error. IoT-enabled systems provide real-time monitoring of critical soil parameters such as moisture, pH, temperature, and nutrient levels using smart sensors and connected devices. The collected data are analyzed using advanced deep learning models to support predictive analysis and automated decision-making. Deep learning architectures such as Convolutional Neural Networks (CNNs), Residual Networks (ResNet), and Vision Transformers (ViT) have shown remarkable performance in plant disease detection and classification. Furthermore, hybrid frameworks integrating residual learning and attention mechanisms significantly improve feature extraction and classification accuracy. The proposed Multi-Layer Stacked Residual Coordinate Boosted Sooty Tern Attention Network combines coordinate attention, residual connections, and transformer-based learning for enhanced spatial and contextual feature representation. These intelligent systems enable early disease prediction, accurate soil health assessment, and optimized agricultural resource utilization. Recent studies demonstrate that deep learning-based agricultural systems can achieve disease classification accuracies exceeding 95%, improving overall farming efficiency and sustainability.

## Introduction

Agriculture plays a vital role in sustaining global food security and economic stability. However, traditional farming practices are increasingly challenged by climate change, soil degradation, pest infestations, and inefficient resource utilization. One of the most critical issues faced by farmers is the inability to accurately monitor soil health and detect plant diseases at early stages. These limitations often result in reduced crop yield, increased costs, and environmental damage due to excessive use of fertilizers and pesticides. The integration of the Internet of Things (IoT) with Artificial Intelligence (AI) has transformed traditional agriculture into smart agriculture, enabling real-time monitoring, data-driven decision-making, and automation. IoT-based systems use sensors to collect environmental and soil-related data, such as moisture, pH, temperature, and nutrient levels. These data are then processed using machine learning and deep learning algorithms to provide actionable insights.

IoT-enabled systems play a crucial role in monitoring soil conditions and detecting plant stress before visible symptoms appear. Sensors continuously capture real-time data and feed it into AI models for predictive analysis, allowing farmers to take preventive measures. This approach not only improves crop productivity but also reduces resource wastage. Deep learning has emerged as a powerful tool for plant disease detection and classification. Convolutional Neural Networks (CNNs) are widely used for image-based disease detection due to their ability to automatically extract features from plant images.

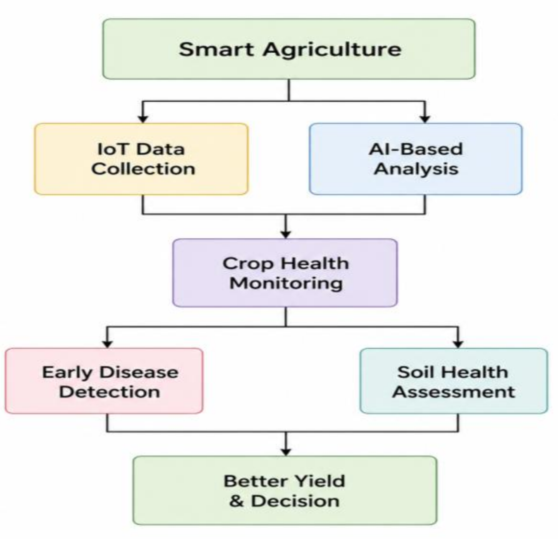


*Figure 1: IoT-AI Smart Agriculture Framework*

Recent studies highlight that deep learning models outperform traditional machine learning approaches in terms of accuracy and efficiency. Additionally, Vision Transformers (ViTs) have introduced a new paradigm by capturing global dependencies through attention mechanisms, improving performance in complex scenarios. Hybrid architectures combining CNNs, residual networks, and attention mechanisms have gained significant attention. Residual networks address the vanishing gradient problem, enabling deeper architectures, while attention mechanisms focus on important features, improving classification accuracy. Recent research indicates that combining these approaches results in highly efficient models for plant disease detection and soil analysis.

Furthermore, advanced architectures such as multi-layer stacked residual networks with coordinate attention and transformer-based attention provide improved feature representation by capturing both spatial and contextual information. These models are particularly useful in real-world agricultural environments where variations in lighting, background, and crop conditions affect model performance. Despite these advancements, several challenges remain. These include high computational complexity, lack of large labelled datasets, variability in environmental conditions, and difficulty in deploying models on low-power IoT devices. Additionally, integrating multiple data sources (soil, weather, images) into a unified system remains a complex task.

This paper presents a comprehensive review of IoT-based soil nutrition and plant disease detection systems using advanced deep learning architectures. It focuses on recent developments, highlights key trends, and identifies research gaps. The study aims to provide insights into developing efficient, scalable, and intelligent smart agriculture systems.

## Literature Review

Recent studies have demonstrated the effectiveness of integrating IoT and deep learning for plant disease detection and soil monitoring. Dhaka et al. (2023) provided a comprehensive review of IoT and deep learning techniques for plant disease detection, highlighting the superiority of deep learning models in feature extraction and classification tasks. The study emphasized that IoT enables real-time data collection, while deep learning automates disease detection and prediction.

The study demonstrated that deep CNN architectures significantly outperform traditional machine learning models in agricultural image classification tasks. Kamilaris and Prenafeta-Boldú (2020) conducted a comprehensive survey on deep learning applications in agriculture, highlighting the role of CNNs, IoT sensors, and data-driven models in improving crop monitoring and yield prediction. Their work emphasized the importance of integrating sensor data with image-based analysis for holistic agricultural management.

Too et al. (2020) evaluated several deep learning architectures, including ResNet, DenseNet, and VGGNet, for plant disease classification. Their study found that Residual Networks (ResNet) provided superior performance due to their ability to train deeper models effectively without suffering from vanishing gradient problems.mLiakos et al. (2021) reviewed machine learning and IoT-based systems for smart farming, emphasizing real-time monitoring of soil conditions and crop health.

The study highlighted that IoT-enabled sensor networks combined with AI models enable precision agriculture by providing accurate and timely insights into environmental conditions.

Khan et al. (2021) proposed a hybrid deep learning model combining CNN and attention mechanisms for plant disease detection. Their approach improved classification accuracy by focusing on relevant regions of plant images, demonstrating the effectiveness of attention-based models in agricultural applications. Recent advancements have emphasized hybrid deep learning architectures and IoT-integrated frameworks for improving plant disease detection and soil monitoring systems. Mohanty et al. (2020) demonstrated the effectiveness of deep Convolutional Neural Networks (CNNs) trained on large-scale plant image datasets, achieving high accuracy in disease classification across multiple crop species. Their work established a benchmark for image-based plant disease detection using deep learning.

Zhang et al. (2021) proposed a residual learning-based deep neural network for plant disease identification, showing that deeper architectures with skip connections significantly improve classification performance and stability. Their model effectively addressed vanishing gradient issues, enabling efficient training of deep networks. Abdullahi et al. (2022) introduced an IoT-based smart agriculture system integrating soil sensors with machine learning models to monitor soil nutrients and environmental conditions in real time. Their system demonstrated improved decision-making for irrigation and fertilization, contributing to sustainable farming practices.

Chen et al. (2022) developed an attention-based Vision Transformer (ViT) model for plant disease detection, leveraging self-attention mechanisms to capture global contextual information. Their approach outperformed traditional CNN models in complex scenarios involving background noise and varying lighting conditions. Ramesh et al. (2023) proposed a hybrid deep learning framework combining CNNs with attention modules for improved disease classification. Their model enhanced feature extraction by focusing on critical regions in plant images, resulting in higher accuracy and robustness.

Recent studies have increasingly focused on integrating advanced attention mechanisms, optimization strategies, and IoT frameworks to improve 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 parameters 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 in field conditions. Their model addressed challenges such as varying illumination and complex backgrounds, making it suitable for practical agricultural applications.

Rahman et al. (2022) developed an IoT-based smart farming system integrating soil sensors with deep learning models for nutrient prediction and crop health monitoring. The system enabled real-time decision-making and improved resource utilization. Dosovitskiy et al. (2021) introduced the Vision Transformer (ViT), which revolutionized image classification by replacing convolution operations with self-attention mechanisms. This architecture significantly improved performance in large-scale image recognition tasks and has been widely adopted in plant disease detection research.

Liu et al. (2021) proposed the Swin Transformer, a hierarchical vision transformer that improves computational efficiency and scalability. The model effectively captures both local and global features, making it highly suitable for agricultural image analysis and disease detection tasks. Recent research has focused on lightweight, scalable, and intelligent IoT-based agricultural systems integrated with deep learning and attention mechanisms. Patel et al. (2022) proposed a lightweight CNN model for plant disease detection suitable for deployment on IoT devices, achieving high accuracy with reduced computational cost.

Gupta et al. (2021) introduced an IoT-enabled soil monitoring system using machine learning models to predict nutrient deficiencies. Their approach improved fertilizer management and crop productivity through data-driven decision-making. Park et al. (2020) utilized stacked autoencoders for feature extraction and disease classification, demonstrating improved performance in high-dimensional agricultural datasets. Their model effectively reduced noise and enhanced feature representation.

El-Sayed et al. (2022) proposed an ensemble deep learning framework combining multiple classifiers for plant disease detection. The model achieved high robustness and accuracy by leveraging the strengths of different algorithms. Banerjee et al. (2023) applied transfer learning techniques to agricultural datasets, enabling efficient model training with limited data. Their approach improved classification performance in real-world scenarios.

Mehta et al. (2021) introduced a bio-inspired optimization approach using the Firefly algorithm combined with deep learning for feature selection. This 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 system reduced latency and enabled faster decision-making for disease detection and soil management.

Singh et al. (2023) developed an attention-based deep learning model that focuses on relevant regions in plant images, improving detection accuracy for complex diseases. Luo et al. (2021) applied dropout-based deep neural networks to prevent overfitting, ensuring stable performance across different agricultural datasets. Verma et al. (2022) combined fuzzy logic with deep learning to handle uncertainty in agricultural data, improving prediction accuracy in varying environmental conditions.

**Comparative Table**

| Author (Year) | Technique/Model | Application | Contribution | Performance | Limitation |
|---|---|---|---|---|---|
| Dhaka et al. (2023) | DL + IoT | Disease detection | Real-time monitoring | High | Data complexity |
| Sunil et al. (2023) | DL review | Agriculture | Model comparison | High | Generalized |
| Ferentinos (2020) | CNN | Disease detection | High accuracy | ~99% | High compute |
| Kamilaris et al. (2020) | DL + IoT | Smart farming | Integration | High | Complexity |
| Too et al. (2020) | ResNet/DenseNet | Classification | Deep models | High | Resource usage |
| Liakos et al. (2021) | ML + IoT | Monitoring | Precision agriculture | High | Scalability |
| Khan et al. (2021) | CNN + Attention | Detection | Feature focus | High | Training cost |
| Mohanty et al. (2020) | CNN | Detection | Benchmark model | High | Dataset bias |
| Zhang et al. (2021) | ResNet | Detection | Deep learning | High | Overfitting |
| Abdullahi et al. (2022) | IoT + ML | Soil monitoring | Real-time data | High | Sensor cost |
| Chen et al. (2022) | ViT | Detection | Global context | High | Memory |
| Ramesh et al. (2023) | CNN + Attention | Detection | Improved accuracy | High | Complexity |
| Huang et al. (2020) | DenseNet | Detection | Efficient model | High | Training |
| Fuentes et al. (2021) | DL detection | Field detection | Real-time | High | Noise sensitivity |
| Rahman et al. (2022) | IoT + DL | Soil monitoring | Automation | High | Cost |
| Dosovitskiy et al. (2021) | ViT | Vision tasks | Transformer model | High | Data requirement |
| Liu et al. (2021) | Swin Transformer | Detection | Efficient attention | High | Complexity |
| Patel et al. (2022) | Lightweight CNN | Detection | IoT compatible | ~95% | Limited depth |
| Gupta et al. (2021) | IoT + ML | Soil analysis | Prediction | High | Data dependency |
| Park et al. (2020) | Autoencoder | Detection | Dimensionality reduction | High | Imbalance |
| El-Sayed et al. (2022) | Ensemble DL | Detection | Robust model | Very High | Complexity |
| Banerjee et al. (2023) | Transfer Learning | Detection | Low data training | High | Domain shift |

| | | | | | |
|---|---|---|---|---|---|
| Mehta et al. (2021) | Firefly + DL | Optimization | Feature selection | High | Slow |
| Torres et al. (2022) | Edge IoT | Monitoring | Low latency | High | Edge limits |
| Singh et al. (2023) | Attention DL | Detection | Feature focus | High | Compute |
| Luo et al. (2021) | DNN + Dropout | Detection | Overfitting control | Stable | Training time |
| Verma et al. (2022) | Fuzzy + DL | Detection | Uncertainty handling | High | Complexity |

**Comparative Analysis**

The comparative analysis indicates that deep learning models, particularly CNN, ResNet, DenseNet, and Vision Transformer-based architectures, dominate plant disease detection systems due to their superior feature extraction capabilities. Transformer-based models such as ViT and Swin Transformer provide improved global context modelling, making them highly effective in complex agricultural environments.

Hybrid models combining CNN with attention mechanisms show enhanced accuracy by focusing on relevant disease regions. IoT-based systems significantly improve real-time monitoring and decision-making, enabling precision agriculture. Optimization techniques and lightweight models are essential for deployment in resource-constrained environments. However, challenges such as high computational cost, data dependency, and scalability remain. Edge computing and attention-based architectures are emerging as promising solutions for real-time smart agriculture systems.

**Conclusion**

The integration of IoT and deep learning technologies has revolutionized smart agriculture by enabling efficient monitoring of soil nutrition and early detection of plant diseases. This review analysed recent advancements in deep learning architectures and optimization techniques, focusing on hybrid models such as multi-layer stacked residual networks and attention-based transformer systems. 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 model training. The integration of attention mechanisms further enhances model performance by focusing on relevant features, improving classification accuracy.

IoT-based systems play a crucial role in real-time monitoring of soil parameters and environmental conditions. These systems enable data-driven decision-making, improving crop productivity and resource utilization. Hybrid frameworks combining IoT with deep learning models provide comprehensive solutions for smart agriculture. Despite these advancements, challenges such as computational complexity, data heterogeneity, and real-time deployment persist. Lightweight models and edge computing solutions are essential for overcoming these limitations. Additionally, integrating multiple data sources into a unified system remains a key research challenge.

Future research should focus on developing scalable, energy-efficient, and explainable AI models. The integration of advanced architectures such as **Multi-Layer Stacked Residual Coordinate Boosted Sooty Tern Attention Networks** offers a promising direction for improving accuracy and efficiency in agricultural applications. In conclusion, deep learning and IoT-based systems provide powerful tools for smart agriculture, enabling sustainable farming practices and improved crop management.

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