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Secure AI-Driven Corn Disease Detection in 5G/6G-Enabled Smart Agriculture: Integrating Deep Learning and IoT Sensor Networks.

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Abstract:
The integration of Artificial Intelligence (AI) into smart agriculture has significantly enhanced crop monitoring and disease management, particularly for staple crops such as corn. However, the increasing reliance on interconnected Internet of Things (IoT) sensor networks and next-generation communication technologies, including 5G and emerging 6G systems, introduces critical security and privacy challenges. This paper presents a comprehensive review of secure AI-driven approaches for corn disease detection, focusing on the convergence of deep learning techniques, IoT-based sensing infrastructures, and 5G/6G-enabled smart agriculture frameworks. The study systematically analyses state-of-the-art deep learning models, including convolutional neural networks (CNNs), vision transformers, and hybrid architectures, for accurate and early-stage disease identification using image and multimodal sensor data. Furthermore, it explores the role of IoT sensor networks in real-time environmental monitoring and data acquisition, enabling precision agriculture practices. A key contribution of this review is the examination of security vulnerabilities across the data pipeline, including data poisoning, adversarial attacks, model inversion, and communication-level threats within 5G/6G networks. In addition, the paper discusses emerging security mechanisms such as blockchain-based data integrity, federated learning for privacy preservation, and intrusion detection systems (IDS) tailored for agricultural IoT environments. The challenges of scalability, latency, energy efficiency, and secure data transmission in ultra-reliable low-latency communication (URLLC) scenarios are also highlighted. Finally, open research issues and future directions are identified, emphasizing the need for robust, secure, and intelligent frameworks to ensure resilient and trustworthy smart agriculture systems.
Keywords: 5G/6G Networks, CNN, Corn Disease Detection, Cybersecurity, Deep Learning IoT, Smart Agriculture, UAV imagery, YoLo

1. Introduction

The prediction and classification of corn diseases are critical for safeguarding crop health and sustainable agricultural practices. Corn (Zea mays L.) diseases significantly impact global food security and farm productivity, necessitating early and accurate diagnostic methods. Advances in deep learning (DL) and computer vision have enabled innovative solutions for addressing these challenges. Helong et al.[1] developed a CNN model optimized from the VGG-19 architecture for diagnosing corn diseases, utilizing convolutional layers, pooling operations, and preprocessing techniques to extract significant features from input images. Such approaches demonstrate the potential of DL models in identifying diseases under controlled experimental conditions. In addition to disease diagnosis, understanding plant density and uniformity is essential for optimizing corn yield, as they are influenced by factors like planting date, hybrid selection, and environmental variables. Traditional manual methods for evaluating plant density are time-consuming and often lack precision,

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prompting the need for automated solutions. U-Net, a convolutional neural network, has shown promise in segmenting plants from complex backgrounds, offering a robust tool for analyzing plant spacing and density in agricultural applications [2]. Similarly, UAV imagery integrated with DL models has emerged as a powerful tool for field-scale monitoring, providing valuable insights into crop emergence patterns and spatial variability [3]. This study focuses on integrating UAV imagery and advanced deep learning tech-niques for predicting and classifying corn diseases. By leveraging automated workflows and scalable solutions, the research aims to address existing limitations, such as dataset variability and the complexity of real-world conditions, to improve decision-making in precision agriculture.

2. Literature Review

The authors in [4] present a deep learning model for classifying healthy and unhealthy corn plant leaves using two pre-trained CNNs, EfficientNetB0 and DenseNet121. The deep features extracted from both networks are fused, and data augmentation techniques are applied to enhance the dataset. The proposed model achieves 98.56% classification accuracy, outperforming larger models like ResNet152 and InceptionV3. The approach demonstrates the effectiveness of combining smaller CNNs for improved accuracy and efficiency in plant disease classification.

The authors in [5] have used deep convolutional neural networks (DCNN) to detect North- ern Corn Leaf Blight (NCLB) in maize. A dataset of 985 leaf images was augmented to 30,655 using techniques like segmentation and resizing. Several DCNN models, including GoogleNet, VGG16, and VGG19, were tested, with GoogleNet achieving 99.94% accuracy using loss functions like ArcFace and A-Softmax. The results, implemented in Pytorch and Keras, demonstrate the effectiveness of DCNNs for early disease detection, with potential applications for other plant diseases and improved crop management.

The authors in [6] have utilized unmanned aerial vehicles (UAVs) and deep learning to monitor corn growth under different management practices. UAVs equipped with RGB and multispectral cameras captured field images, and YOLOv5 was used to count plants. Otsu thresholding was applied to extract plant height and vegetation indices (VIs). The results showed that fertilizer application near seeds and a planting depth of 2.8 cm led to higher germination rates. The study highlighted how management practices and climatic factors affected corn emergence, and how UAVs and deep learning can optimize agricultural practices for improved crop monitoring.

The authors in [7] have developed a corn yield monitoring system using photoelectric sensing and machine learning. EDEM simulations showed kernel variations, necessitating advanced models. DNN, GBM, and RF models were tested, with DNN achieving the highest accuracy and stability. Field tests confirmed the system's effectiveness in real-time yield prediction.

3. Comparison Analysis

Table 1 depicts the comparative analysis among various models and datasets to carry out Agricultural Disease and Detection.

Table 1 Comparative Analysis of Models for Agricultural Disease Detection and Monitoring

Article No.	Model(s) Used	Dataset(s) Used	Accuracy
[8]	Attention-based FCN, CNN, Random	UAV-based MISM	OA: 82.1%, Macro

	Forest		F1: 0.82%
[9]	MMF-Net	Corn-leaf diseases-dataset	99.23%
[10]	YOLOv5,Mask R-CNN, YOLOX, Efficient Det, Haar + Cascade	Image-based corn kernel detection dataset	High accuracy (YOLOv5)
[11]	Random Forest (RF)	Historic sweet corn yield dataset	RMSE: 3.29 Mt/ha, Pearson's correlation: 0.77
[12]	Mobile Net, VGG16,	Baby corn images	99.06%

4. Methodology

The block diagram (as shown in Fig 1) illustrates a deep learning and sensor-based system for corn disease detection in smart agriculture. It begins with Data Acquisition, where images from RGB/multispectral cameras and environmental data from IoT sensors are collected. The next stage is Preprocessing, where the data is normalized and features are extracted to enhance model performance. The Deep Learning Model, typically a Convolutional Neural Network (CNN), processes these inputs to identify disease patterns. The Decision System classifies the disease based on a confidence threshold, determining whether a plant is healthy or infected. Performance Evaluation then assesses the model's accuracy using metrics such as Precision, Recall, F1-score, and Accuracy. Finally, the Smart Agriculture Response provides automated recommendations for disease management and sends IoT-based alerts to farmers, enabling timely intervention and improving crop health [13]. This integrated system enhances precision farming, ensuring early disease detection and optimized agricultural productivity.

The entire workflow is represented by the Algorithm 1 below. The pseudocode for Autoencoder-based Anomaly Detection in Smart Agriculture outlines a structured approach for detecting plant diseases using IoT sensor data.

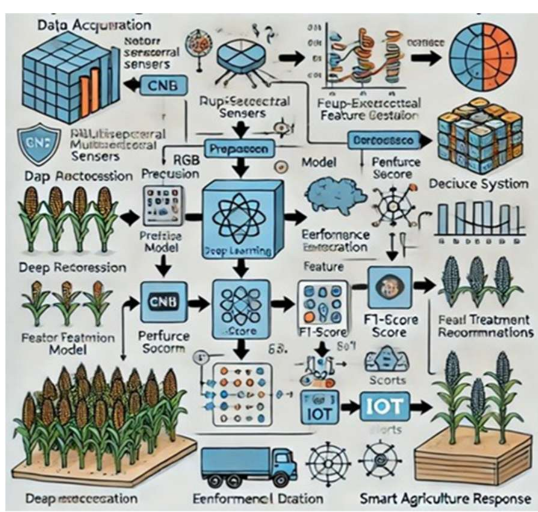

Fig. 1 Deep Learning and Sensor-Based Disease Detection

Algorithm 1. Secure AI-Based Corn Disease Detection

Require: *I, S, M, T, E, K*
Ensure: *D, P, A*1: Collect sensor images *I* and data *S* from IoT devices.
2: Encrypt and validate data using lightweight security and IDS.
3: Normalize *I* and extract features from *S*.
4: Fuse multimodal data (image + sensor features).
5: for *e = 1 to E* do
6: Forward pass: extract features and classify using *M*.
7: Apply adversarial defence and compute loss.
8: Update weights using Adam optimizer.
9: end for
10: Input new *(I′, S′)*, verify integrity, and classify disease.
11: if confidence > *T* then assign disease *D* else mark healthy.
12: Compute Accuracy, Precision, Recall, and F1-score.
13: Evaluate security and latency performance (5G/6G).
14: if disease detected then send IoT alert and recommend treatment.
15: Return *D*, *P*, and recommended actions *A*.

Deep learning as shown in Algorithm 2 which begins with the data acquisition phase, where environmental and crop health data are collected from IoT sensors and images from multispectral cameras. The preprocessing step normalizes the data, extracts features, and prepares it for training. A deep learning-based autoencoder model is then initialized and trained using normal (healthy) data to learn its latent representation. During the anomaly detection phase, the trained autoencoder reconstructs the input data, and the reconstruction error is computed. If the error exceeds a predefined threshold, the system classifies it as an anomaly, indicating a potential disease. The final stage involves performance evaluation, where metrics such as Accuracy, Precision, Recall, and F1-score are used to assess the model's effectiveness. Additionally, the system can trigger real-time alerts for smart agriculture applications, enabling farmers to take timely action and mitigate crop damage. By integrating deep learning with IoT security principles, this approach ensures robust, automated disease detection while securing sensor data from potential cyber threats.[14]Integrating Particle Swarm Optimization (PSO)[16] with autoencoders enhances the efficiency and accuracy of IoT-based anomaly detection in smart agriculture. By optimizing hyperparameters, feature selection, and anomaly detection thresholds, PSO ensures a more robust, adaptive, and resource-efficient corn disease detection system[15]. This hybrid approach strengthens IoT security.

Algorithm 2. Secure Corn Disease Detection using Autoencoder–*PSO*

Require: *I, S, AE* (Autoencoder), *M, T, E, PSO* params
Ensure: *D, P, A*

1: Collect sensor images I and data S from IoT devices.
2: Encrypt and validate data using IDS mechanisms.
3: Normalize I *and extract features from* S.
4: Train Autoencoder AE to learn latent representations.
5: Encode inputs → obtain compressed features F.
6: Initialize PSO particles for hyperparameter optimization.
7: for each iteration do
8: Evaluate fitness (validation accuracy/loss using M).
9: Update particle velocity and position (PSO rules).
10: end for
11: Train optimized model M using best PSO parameters.
12: Input new (*I′, S′*) *→ encode via AE and classify.*
13: if confidence > T *then assign disease D else healthy.*

14: Compute Accuracy, Precision, Recall, F1-score.
15: Send IoT alerts and recommend treatment if disease detected.

5. Imaging techniques available for plant health status detection

Several researchers have used a variety of imaging techniques, including RGB imaging, thermal imaging, and hyperspectral imaging, to collect data for assessing the health condition of plants (Fig. 2). Imaging methods that are helpful include fluorescence, thermal, hyperspectral, multispectral, visible, photo-acoustic, tomographic, thermographic, and MRT [17]. Furthermore, 3D imaging methods can be used in conjunction with other methods. The best techniques for identifying early-stage disease contagions in crops are thermal and hyperspectral sensors. However, RGB, multispectral, and hyperspectral sensors can also identify the severity of an illness at a later stage [18].
Digital RGB imaging sensors are the most widely utilized type of image sensor for plant disease detection. RGB cameras are often more accessible and less costly. Additionally, they can be used to capture crisp still photos[19].
RGB (Red, Green, and Blue) sensors are used by cameras to detect red, green, and blue values in pixels. The evaluation of biomass in crops is made possible by these cameras, which produce images that show the intensity of three distinct colors [20]. RGB cameras are used in combination with multispectral and near-infrared cameras to increase biomass estimation accuracy [21]. In modified RGB cameras, near-infrared filters are replaced with red filters [22]. Although they are cheap, commercial RGB cameras have poor spectral resolution [23]. Not every wavelength in the 380–750 nm electromagnetic spectrum range of RGB cameras is suitable for accurate crop disease detection [24]. Other color spaces, such as hue saturation value (HSV), LAB (lightness), YCbCr (blue difference, luma component, and red difference chroma components), and others that are especially useful for diagnosing plant diseases, are created from RGB color information. It is unable to discern between various illness severity levels due to the low resolution of RGB camera images [25]. Conversely, RGB cameras have the capacity to capture images with a high spatial resolution, which offers superior spatial features for tracking and identifying plant diseases [26]. One of the main benefits of RGB cameras over multispectral systems is the capability. Effective use of RGB cameras guarantees consistent lighting and color in the images. Regularly taking pictures will reduce the inaccuracy in identifying healthy and diseased plants [27].

Fig 2. Techniques for plant disease detection**.**

Corn disease detection in modern smart agriculture is increasingly intertwined with information security due to the reliance on AI models, IoT sensor networks, and 5G/6G communication infrastructures [28]. Deep learning-based systems use data from RGB images, multispectral sensors, and environmental devices to accurately identify diseases at early stages [29]; however, this data-driven approach also introduces vulnerabilities across the pipeline. Malicious attacks such as data poisoning, adversarial image manipulation, and unauthorized access to sensor networks can compromise model accuracy and lead to incorrect disease predictions, ultimately affecting crop yield and food security[30]. Furthermore, the transmission of sensitive agricultural data over wireless networks exposes systems to interception and tampering [31]. To address these challenges, robust security mechanisms—including encryption, intrusion detection systems, federated learning, and blockchain-based integrity verification must be integrated into disease detection frameworks[32]. Ensuring secure data acquisition, transmission, and processing is therefore essential for building reliable, trustworthy, and resilient AI-driven corn disease detection systems in next-generation smart agriculture environments[33]. Various security threats can significantly impact AI-driven corn disease detection systems deployed in smart agriculture environments. One major risk is **data poisoning**, where attackers inject manipulated or mislabelled training data to degrade model accuracy or bias predictions [34]. **Adversarial attacks** are another concern, where subtle perturbations are added to input images, causing deep learning models to misclassify diseased crops as healthy or vice versa. In IoT-based sensing systems, **spoofing and false data injection attacks** can compromise environmental sensor readings, leading to incorrect disease assessment. Additionally, **eavesdropping and man-in-the-middle (MITM) attacks** in 5G/6G communication channels may result in unauthorized access, data leakage, or tampering during transmission [35]. **Model-based attacks**, such as model inversion and model stealing, can expose sensitive training data or replicate proprietary models. Furthermore, **denial-of-service (DoS) attacks** can disrupt real-time monitoring and decision-making processes by overwhelming network or edge devices. These threats highlight the need for robust security measures to ensure the integrity, confidentiality, and availability of AI-powered corn disease detection systems[36]. In next-generation Internet of Things (IoT) networks, modern cellular technologies like 5G and 6G are enabling incredible device density, ultra-low latency, and intelligent edge services. These developments make it possible for autonomous systems, smart cities, industrial automation, and healthcare, but they also present security issues. Device heterogeneity, resource constraints, network softwarization, edge computing, and artificial intelligence make next-generation IoT ecosystems more vulnerable [37]. Next-generation IoT network security concerns such as data privacy, network slicing isolation, DDoS attacks, software-defined and AI-driven network architectural vulnerabilities, and authentication and access control are all covered in this assessment. In large-scale, highly dynamic IoT environments, current security and intrusion detection techniques are assessed. Lastly, the necessity for lightweight, flexible, and intelligent security solutions to ensure reliable next-generation IoT deployments is highlighted by open research issues and future projects [38].

6. Conclusion and Future Scope

This paper reviewed secure AI-driven approaches for corn disease detection by integrating deep learning, IoT sensor networks, and 5G/6G technologies in smart agriculture. The use of multimodal data and advanced models improves disease detection accuracy, while techniques such as Autoencoders and PSO enhance feature extraction and optimization. The study also highlighted critical security challenges, including data poisoning and network vulnerabilities, and discussed solutions such as encryption, intrusion detection systems, federated learning, and blockchain. Overall, combining AI with secure communication frameworks enables efficient, reliable, and scalable smart farming systems. Machine and deep learning over precision agriculture have advanced significantly in the comparison. Using multi-contextual characteristics, MMFNet detects maize leaf diseases with 99.23% accuracy, whereas attention-based FCN monitors Southern maize Rust with 82.1% accuracy. Fast and efficient real-time corn kernel detection using YOLOv5 beats other models. 99.06% EfficientNetB5. Future research shows the need for better agricultural monitoring along with disease detection. For monitoring accuracy and to overcome obstruction and pathogenicity, researchers focus on multi view imaging spectral measurements (MISM) fusion approaches. For IoT applications, MMF-Net and attention-based FCNs show potential but need tuning. Heterogeneous data, feature fusion, and environmental complexity require improvements. Enhancing crop management data, kernel recognition in obstructed situations, and sensor-based smart farming systems might enhance efficiency, minimize resource consumption, as well as promote sustainable agriculture. Future research should focus on lightweight AI models for edge deployment, integration of real-time IDS with detection systems, and privacy-preserving approaches such as federated learning. The use of explainable AI can improve transparency, while 6G-enabled URLLC can support faster and autonomous decision-making. Additionally, blockchain integration and advanced optimization methods can further enhance security and performance in smart agriculture.

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