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Deep Learning Applications in Maize Disease Detection: A Systematic Review of Trends, Gaps, and Future Research

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Abstract - Maize, a staple crop globally, faces significant threats from various diseases that can drastically reduce yield and quality, impacting food security and economic stability, particularly in regions heavily reliant on agriculture. The search for automated and effective diagnostic tools is driven by the labor-intensive, time-consuming, and error-prone nature of traditional illness detection methods, which frequently rely on visual inspection and expert knowledge. In recent years, deep learning methodologies have emerged as a transformative force in plant disease detection, exhibiting remarkable capabilities in image recognition and classification, surpassing the limitations of conventional machine learning techniques that necessitate manual feature extraction. Deep learning models, highlight key trends, including the increasing use of convolutional neural networks, transfer learning techniques, data augmentation methods, and real- time disease detection using mobile applications. The paper also identifies several gaps in the current research, such as limited diversity in maize disease datasets, insufficient focus on early-stage detection, lack of standardized evaluation metrics, and inadequate consideration of environmental factors. These models have demonstrated proficiency in learning intricate features directly from raw image data, enabling accurate and rapid identification of diseases in maize crops. The paper further outlines potential future directions for research, including the development of more comprehensive datasets, exploration of multi-modal deep learning approaches, investigation of explainable AI techniques, integration with IoT devices, adaptation of models for different maize varieties and growing conditions, incorporation of temporal data, and development of hybrid models. To address the identified gaps, the paper suggests collaborating with agricultural experts, developing models for multiple disease detection, and investigating unsupervised and semi- supervised learning approaches.

Keywords: Convolutional neural networks, Deep Learning, Maize diseases, Disease detection, Transfer Learning,

I. Introduction

The main food supply for billions of people worldwide, maize, often known as corn, is an essential part of animal feed and a raw material for a wide range of industrial uses [1]. Due to the growing need for food and biofuels worldwide, improving maize output is a constant problem [2]. However, a variety of plant diseases can impede the attainment of ideal maize yields, causing significant financial losses and endangering food security, especially in underdeveloped countries where maize is a main crop [3] [4].

In a variety of geographic locations and climates, plant diseases caused by bacterial, viral, and fungal pathogens continue to be a danger to maize production [5]. To mitigate potential yield declines and ensure consistent maize production, it is critical to detect these diseases early and accurately to deploy timely and effective disease management techniques [6].

Conventional approaches to disease identification in maize mostly depend on molecular diagnostics, laboratory-based procedures, and visual inspection by qualified specialists [7]. Despite being easily available, visual inspection is subjective, time-consuming, and frequently insensitive to identify infections in their early stages or distinguish between illnesses that present with identical symptoms. Higher precision can be obtained by laboratory methods including growing pathogens and performing biochemical assays, but these methods are usually costly, labour-intensive, and call for specific tools and knowledge [8].

A vital crop for world food security, maize is seriously threatened by several illnesses that can lower output and cause financial losses. Convolutional neural networks (CNNs), a type of deep learning, have emerged as a successful technique for classifying and diagnosing maize diseases. This research investigates the key developments in maize disease detection, including the use of CNNs, transfer learning, data augmentation, and real-time detection via mobile applications, using data from recent academic publications.

This systematic review aims to provide a comprehensive overview of the state-of-the-art in deep learning for maize disease detection, highlighting dominant trends, identifying gaps, and suggesting potential directions for future research, given that the agriculture industry has greatly benefited from the combination of machine learning and deep learning, particularly in disease management and detection [9] [4].

The evaluation also includes an in-depth examination of the deep learning architecture used, the training, and validation datasets, and the performance metrics documented in pertinent research [10].

II. RELATED WORKS

According to their research, early and accurate detection of maize leaf diseases is necessary to reduce crop loss. Because traditional approaches are often manual and have a narrow scope, automated, image-based procedures are quite beneficial [24]. Nevertheless, achieving high accuracy and generalizability in a range of field scenarios remains a challenge. CNNs are the best deep learning models for identifying and forecasting maize leaf diseases, according to [24]. These algorithms' remarkable capacity to extract information from cropped pictures of leaves enables automated classification.

Deep learning techniques, especially CNNs and transfer learning models, have revolutionized the diagnosis of maize leaf disease by achieving high accuracy and enabling practical, real-time applications. Increasing model generalizability and enhancing robustness under field conditions are the objectives of current research [11,12,13,14,15].

CNNs are the most widely used deep learning models for identifying maize leaf disease. Modified architectures such as LeNet, GoogLeNet, and custom 15-layer CNNs have shown remarkable accuracy (up to 98.9%) in classifying various maize leaf diseases using datasets such as PlantVillage and field-collected photos [12,16,17,18]. By automatically extracting features from unprocessed photographs, these models do away with the necessity for tedious feature engineering.

[12,15] They claim that transfer learning with pre-trained models (like VGG16, ResNet50, InceptionV3, Xception, and EfficientNet) has been shown to significantly improve classification accuracy, often exceeding 99%, when combined with data augmentation and hyperparameter optimization. By using insights from large image libraries, these models can perform well even with limited agricultural data.

Advanced architectures like DenseNet121 with attention modules (like CBAM), MaskRCNN for segmentation, and specialized networks like MaizeNet and SqueezeNet have been introduced in recent studies [15,20]. In real-world situations, these models achieve accuracies of 97% while addressing issues including small sample sizes, complex backgrounds, and mixed disease conditions [21,22].

Deep learning models have been incorporated into mobile applications and Internet of Things platforms, enabling farmers to identify diseases in the field in real time.

For instance, Deep Quantum Neural Networks and YOLOv8n have been utilized for quick and precise disease classification and localization; some models have been shown to achieve up to 99% accuracy [11,23].

[15] reported that managing mixed infections, generalizing models to various field situations, and guaranteeing tolerance to background noise are some of the main obstacles. For better external validity, recent research highlights the value of incorporating segmentation approaches and training on genuine, field-collected information [23]. [24] emphasises the significance of high-quality picture datasets and preprocessing techniques for enhancing model performance. They further agree with the fact that there is need to improve training data, image cropping and augmentation which need to be frequently employed.

The accuracy and resilience of current deep learning models are assessed. Although the current models are promising, the evaluation points out that they should be improved, particularly in real-world situations [24]. The usefulness of CNN-based deep learning techniques for detecting maize leaf disease is highlighted in their review, which also urges further development to overcome existing constraints. The intention is to stimulate additional study that will result in more precise, reliable, and useful solutions for sustainable agriculture [24]. The remainder of the paper is structured as follows: Related works are explained in Section II. Methodology is explained in Section III. Future research directions are indicated in Section IV. The conclusion is provided in Section V.

Table 1: Deep Learning Models and Performance

Approach	Accuracy	Key Features	Citations
YOLOv8n (Mobile App)	99.04%	Real-time, mobile-based detection	11
Modified LeNet (CNN)	97.89%	PlantVillage dataset, 4 classes	12
Improved GoogLeNet/Cifar10	98.9	Reduced parameters, 9 disease classes	13
ResNet50 (Transfer Learning)	99%	Fine-grained, transfer learning	14
MDCDenseNet (Attention)	98.84%	Small sample, complex background	15
SqueezeNet	97%	Lightweight, improved over VGG/ResNet	23
EfficientNet B3	99.66	Augmented dataset, high accuracy	24
MaizeNet (Faster-RCNN)	97.89%	Spatial-channel attention, complex scenes	21

The following research questions are addressed in this work.

RQ1 What deep learning architectures and methods are being used to detect diseases in maize, and how have they changed over time?

RQ2 Which image formats, datasets, and annotation techniques are frequently used to train and validate deep learning models for the identification of maize diseases?

RQ3What are the main obstacles, restrictions, and unmet research needs in the deep learning methods currently used to detect maize diseases?

RQ4 What new technologies and lines of inquiry could improve the precision, effectiveness, and practicality of deep learning-based maize disease detection?

III METHODOLOGY

A. SEARCH APPROACH

A citation systematic search technique was used to find pertinent databases, search terms, and inclusion/exclusion criteria to perform an extensive evaluation of the literature on maize leaf disease detection and classification using deep learning. The following databases were systematically searched: Science Direct, Scopus, IEEE Xplore, and Google Scholar which yielded result.

TABLE2:DATA SOURCES

DATA SOURCES	SEARCH RESULTS
SCIENCE DIRECT	50
IEEE XPLORE	60
SCOPUS	50
GOOGLE SCHOLAR	83
TOTAL	243

Combinations of words like "convolutional neural networks," "disease detection," "research gaps," "deep learning," "convolutional," "future research," and "key trends" were used in the search.

- Original research publications and the use of deep learning techniques were the inclusion criteria for the investigations.
- Published in peer-reviewed journals; 20 papers were reviewed in total.
- Review articles, conference papers, and studies that did not use deep learning techniques were among the exclusion criteria.
  • Research that does not concentrate on maize leaf disease

B. FINDINGS OF RESULTS

1. RQ1What are the current deep learning architectures and techniques applied in maize disease detection, and how have they evolved over time?

Simple convolutional neural networks (CNNs) have rapidly been supplanted by sophisticated attention-based and transformer models as the main deep learning architectures for diagnosing maize diseases.

. Advances in model design, transfer learning, and data augmentation have made it possible for modern methods to attain high accuracy even in challenging real-world situations.

Deep CNNs were used in early studies to extract and classify features, and they produced good results on carefully selected datasets [25]. Accuracy and training time were enhanced using pre-trained models (VGG, ResNet, Inception, and Xception) that were tailored to maize disease datasets, particularly by data augmentation and hyperparameter optimization [26].

Complex, real-world image detection was enhanced by the combination of feature fusion and attention modules (CBAM, state-space attention) [27]. Newer models such as MaxViT and hybrid CNN-transformer architectures perform better than conventional CNNs, providing faster inference and greater generalization [28].

Real-time, in-field disease diagnosis through mobile apps and IoT platforms is made possible by lightweight models (YOLOv8n, MobileNetV2).

Class imbalance and short sample sizes are addressed by methods like rotation, brightness augmentation, and GAN-based synthetic data synthesis.

TABLE3: EVOLUTION OF DEEP LEARNING ARCHITECTURES

Era/Model Type	Architecture & Techniques	Performance	Citations
Early CNNs (2018–2020)	LeNet, AlexNet, VGG, GoogLeNet, Cifar10	High accuracy on simple datasets (up to 98.9%)	[25]
Transfer Learning (2021–2023)	VGG16, ResNet50, InceptionV3, Xception	Leveraged pre-trained models, >99% accuracy	[26]
Lightweight & Mobile Models	MobileNetV2, NASNetMobile, YOLOv3–YOLOv8n	Real-time, mobile deployment, 99% accuracy	[29]
Attention & Hybrid Models	DenseNet121and CBAM, State-Space Attention, MaizeNet (Faster-RCNN and ResNet50), Vision Transformers (MaxViT)	Improved robustness to field conditions, complex backgrounds, and small sample sizes; up to 99.24% accuracy	[30]

2. RQ2 Which image formats, datasets, and annotation techniques are frequently used to train and validate deep learning models for the identification of maize diseases?

Deep learning models are trained and validated using a range of datasets, image kinds, and annotation techniques for maize disease detection. Large, varied, and professionally annotated field image collections with ever-more-advanced annotation techniques have replaced regulated, lab-based datasets in the field.

TABLE 4: DATASETS COMMONLY USED

Dataset Name	Image Types & Collection Methods	Annotation Strategy	References
Plant Village	Lab-captured, uniform backgrounds,	Manual, disease class labels	[31]

	RGB images		
Field-Collected Datasets (e.g., NEAU, ICAR-IIMR, University Research Farm Koont)	In-field images, varied backgrounds, digital cameras, smartphones, drones	Manual expert annotation, lesion-level marking, disease class labels	[31]
Combined/Large Datasets (PlantVillage, PlantDoc, CD&S)	Mixed lab and field images, diverse conditions	Multi-class, expert annotation	[32]

C. IMAGE TYPES

High clarity, regulated lighting, and uniform backgrounds(e.g.PlantVillage)[31].

Field images are taken using handheld cameras, smartphones, drones, or mounted systems and feature a variety of backgrounds, natural lighting, and intricacy of the actual world [31]. These provide both spatial and spectral information and are used to detect seed diseases.

D. ANNOTATION STRATEGIES

This technique, which is frequently applied to both lab and field photos, involves human experts labeling disease kinds, marking lesions, or segmenting affected areas [31]. This improves dataset granularity and facilitates segmentation and localization tasks by precisely labeling specific disease areas or lesions [31]. It is often used in classification tasks, and it involves giving the entire image a disease categorization. To improve scalability, disease areas can be located with little user input by using class activation mapping or AI-assisted methods [32]. Using cropping, brightness adjustments, rotation, and GAN-generated photos, they are artificially increasing the quantity and diversity of datasets.

TABLE 5: DATASETS AND ANNOTATION STRATEGIES

Dataset	Image Type	Annotation Method	Citations
Plant Village	Lab,RGB	Image-level, manual	[31]
Field datasets (ICAR-IIMR, NEAU, Koont)	Field, RGB	Expert, lesion-level, image-level	[31]
Combined datasets	Mixed	Multi-class, expert	[32]
Hyperspectral datasets	Lab/Field,HSI	Manual, spectral features	[33]

3. RQ3 What are the major challenges, limitations, and research gaps in existing deep learning approaches for maize disease detection?

Although maize disease detection has greatly improved thanks to deep learning, there are still a few important obstacles, restrictions, and research gaps, particularly when transferring from controlled to real-world settings.

TABLE 6: CHALLENGES AND LIMITATAIONS

Challenge	Description	Citation
Limited Focus on Severity and Crop Loss	Most research targets disease classification, with few models addressing severity prediction or crop loss estimation.	[31]
Model Interpretability	Because deep learning algorithms are frequently “black boxes” people find it difficult to trust or comprehend predictions	[31]
Class Imbalance	Some diseases are underrepresented in datasets, leading to biased models and poor detection of rare diseases	[33]
Real-Time and Mobile Deployment	Achieving high accuracy with lightweight models suitable for mobile or edge devices remains a challenge.	[33]

E. RESEARCH GAPS

i)Development of Large, Diverse, Expert-Labeled Field Datasets

Large, varied, expert-labeled field datasets are needed to increase the model's resilience and real-world practicality [33].

ii)Synthetic Data Creation and Advanced Data Augmentation

Techniques like augmentation and GANs are being researched to overcome short sample numbers and class imbalance [34].

iii) Integration of Severity and Crop Loss Estimation

[33] stated that only a few models go beyond classification to offer farmers useful information.

iv) Improved Model Interpretability

Using explainable AI methods (such as Grad-CAM, SHAP, and LIME) can increase user confidence and promote adoption [33].

v) Robustness to Environmental Variability

Models need to be able to manage a variety of lighting conditions, backdrops, and occlusions that are common in field photos [34].

vi) Efficient, Real-Time Solutions

Additional investigation is required to refine models for implementation on mobile and Internet of Things devices [34].

4. RQ4What new technologies and lines of inquiry could improve the precision, effectiveness, and practicality of deep learning-based maize disease detection?The accuracy, effectiveness, and practicality of deep learning for maize disease diagnosis are quickly improved by new technologies and future research avenues

Transformer- based models, explainable AI, mobile deployment, sophisticated data augmentation, and the combination of severity/crop loss estimation are some of the major advancements.

TABLE 7: MAJOR CHALLENGES AND GAPS

Challenge/Gap	Description	Citations
Small Sample Sizes	Since many models are trained on little or unbalanced datasets,their accuracy and robustness are diminished particularly in field settings	[31]
Complex and Varied Backgrounds	Field images often have clutter, noise, and lighting variations, making disease localization and classification difficult.	[31]
Lack of Real-World, Labelled Data	Most datasets are lab-based or lack expert annotation; real-life, field-labelled datasets are scarce.	[34]
Generalizability and Robustness	Due to overfitting or a lack of diversity,models trained on controlled datasets frequently perform poorly on unseen real-world data	[34]

TABLE6: EMERGING TECHNOLOGIES

Technology/Approach	How It Enhances Detection	References
Vision Transformers (e.g., MaxViT)	Achieve state-of-the-art accuracy and inference speed, outperforming CNNs, and generalize well to diverse datasets.	[32]
Attention Mechanisms (e.g., CBAM)	Improve focus on disease-relevant regions, boosting accuracy in complex backgrounds.	[35]
Explainable AI (XAI) (e.g., SHAP, LIME, Grad-CAM)	Increases model transparency and user trust by visualizing decision processes.	[37]
Mobile & Edge Deployment (e.g., YOLOv8n)	Enables real-time, in-field disease detection via lightweight, fast models on smartphones.	[36]
Generative Adversarial Networks (GANs)	Create synthetic images to address small sample sizes and class imbalance.	[31]

IV FUTURE RESEARCH DIRECTIONS

i) Larger, Diverse, Expert-Labeled Field Datasets

[34]in their studies state that more extensive, varied, expert-labelled field datasets are needed. They further say that integrating real-world photos and data from various sources will increase the generalizability and robustness of the model.

ii)Integration of Severity and Crop Loss Estimation

There is need to go beyond categorization to give farmers useful information about disease severity and possible yield loss.

ii) Advanced Data Augmentation & Preprocessing

Expanding and balancing datasets using methods like rotation, brightness enhancement, and Gans, particularly for rare diseases [31].

iv) Hyperparameter Optimization & Transfer Learning

[26] also states that optimizing performance with less data and computing by utilizing pre-trained models and automated tuning.

v) User-Friendly Applications

Creating accessible, real-time web and mobile applications for decision assistance and disease detection [36].

V CONCLUSION

In conclusion most researchers suggest that combining sophisticated deep learning architectures (such as transformers and attention models), explainable AI, reliable data techniques, and real-time mobile solutions is the way for the future for maize disease detection. These developments will improve precision detection, effectiveness, and usefulness for actual agricultural applications.

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