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Advancements in maize disease detection: A comprehensive review of convolutional neural networks

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ABSTRACT

This review article provides a comprehensive examination of the state-of-the-art in maize disease detection leveraging Convolutional Neural Networks (CNNs). Beginning with the intrinsic significance of plants and the pivotal role of maize in global agriculture, the increasing importance of detecting and mitigating maize diseases for ensuring food security is explored. The transformative potential of artificial intelligence, particularly CNNs, in automating the identification and diagnosis of maize diseases is investigated. Various aspects of the existing research landscape, including data sources, datasets, and the diversity of maize diseases covered, are scrutinized. A detailed analysis of data preprocessing strategies and data collection zones is conducted to add depth to the understanding of the field. The spectrum of algorithms and models employed in maize disease detection is comprehensively outlined, shedding light on their unique contributions and performance outcomes. The role of hyperparameter optimization techniques in refining model performance is explored across multiple studies. Performance metrics such as accuracy, precision, recall, F1 score, IoU, and mAP are systematically presented, offering insights into the efficacy of different CNN-based approaches. Challenges faced in maize disease detection are critically examined, emerging opportunities are identified, and future research directions are outlined. The review concludes by emphasizing the transformative impact of CNNs in revolutionizing maize disease detection while highlighting the need for ongoing research to address existing challenges and unlock the full potential of this technology.

1. Introduction

Plants hold immense significance in the ecosystem, showcasing various benefits for the planet and human health as outlined in the provided abstracts. In the ecosystem, plants function as primary producers, transferring carbon energy up the food chain, protecting the environment by reducing greenhouse gas emissions and pollutants, contributing to the oxygen cycle through photosynthesis, stabilizing soil, preventing erosion, and promoting biodiversity [1]. Regarding the oxygen cycle, plants act as the "lungs of the Earth" by filtering the air and releasing oxygen. They also contribute to the balance of oxygen and carbon dioxide in the atmosphere through photosynthesis [2]. Plants offer numerous advantages for human health, providing therapeutic substances and pharmaceuticals, serving as a vital source of food crucial for human sustenance, acting as educational hubs in botanic gardens, and being historically used for medicinal benefits. In addressing climate change, plants play a pivotal role in mitigating its effects by altering biological and physical processes, enhancing soil stabilization, reducing flooding and storm surges, and restoring degraded ecosystems. The strategic planting and maintenance of specific plant species further aid in conserving ecosystem function and mitigating the impacts of climate change. In conclusion, plants are indispensable for the planet, contributing significantly to the ecosystem, oxygen cycle, human health, and climate change mitigation. Their ability to transfer energy, filter the air, and stabilize the environment underscores their crucial role in ensuring the well-being of both the planet and its inhabitants [1,3–6].

Maize stands as a critically important crop for various compelling reasons. Firstly, it claims the title of the largest grain crop globally, leading in terms of cultivated area, production, and overall yield. This prominence has resulted in substantial economic benefits, further expanding cultivation into previously unused areas [7]. Additionally, maize plays a pivotal role as a high-yield commodity crop, acting as a vital source of food security in numerous developing countries [8]. Secondly, the significance of maize extends to its diverse applications in

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both food and industrial realms. Used in the production of human foods, animal feeds, biofuels, and various industrial products, maize is processed into raw materials for breakfast cereals, snacks, bakery items, corn syrups, beer, and distilled spirits. Moreover, maize contributes significantly to the food cultures of various civilizations [9]. Lastly, the wide genetic variability and adaptability of maize make it a crucial model organism in plant biology and genetics. Extensively studied, maize has been instrumental in major advances in fundamental knowledge and breeding practices [10,11]. maize's economic significance, versatility in food and industrial applications, and genetic adaptability collectively establish it as a globally important crop.

Maize diseases are important due to their significant impact on maize production and the resulting economic losses for farmers. Several factors contribute to the prevalence of maize diseases, including climate change, insect attacks, and various bacterial and fungal diseases. These diseases can affect different parts of the maize plant, from the leaves to the panicle. The fungal diseases of maize, such as Anthracnose stalk rot, brown spot, downy mildew, and maize rust, can significantly reduce both the yield and quality of the produce. Additionally, viruses can cause significant losses in maize production. Developing disease-resistant maize varieties is an effective and economical strategy for disease prevention. Understanding the genetic components controlling disease resistance and the interactions between maize pathogens and the plant's immune system is crucial for developing genotypes with durable resistance. Overall, addressing maize diseases is essential for maintaining maize productivity and ensuring global food security [12–14].

The largest maize producer is Northern America, with the highest production region being in the United States. Africa dominates as the major consuming area, with 10 of the top maize consuming countries per capita. In terms of imports, Asia and Africa are more dependent on maize imports. The leading maize exporters are the United States, Canada, Australia, Argentina, and the EU. South Africa has also seen a significant increase in maize production over the years. Overall, Northern America is the largest maize producer, while Africa is the major consumer, and the United States is one of the leading exporters [15–17].

Artificial intelligence (AI) is a popular topic lately [139–147]. AI can be used for disease detection like maize, potato, rice, tomato [18–20]. Several researchers have proposed state-of-the-art solutions based on AI techniques such as CNNs artificial neural networks, and deep learning to detect diseases in various crops, including maize. The use of AI in agriculture can have a positive impact on disease detection, leading to early diagnosis and treatment of diseases in crops. AI-based techniques, such as machine learning and image processing, have been shown to be more reliable, accurate, fast, and economical compared to traditional methods. These techniques can automatically identify and monitor diseases in crops at an early stage, improving crop quality and productivity. By harnessing the power of AI, farmers can adopt a proactive stance in disease control, reducing their reliance on pesticides and mitigating the environmental footprint of agriculture. Overall, AI offers promising approaches for the detection and management of maize diseases, contributing to improved agricultural practices and crop yields [21–24].

CNNs are a method used in agriculture to detect diseases in plants by analyzing images of plant leaves. CNNs have been shown to be effective in identifying and classifying diseases in various crops, including maize. By taking a picture of the plant leaves and feeding it to a CNN model, the presence of a particular disease can be detected with an high accuracy. Maize leaf diseases, such as northern corn leaf blight, common rust, and gray leaf spot, can be recognized and classified using CNNs. CNNs offer advantages over other machine learning approaches, such as k-NN and decision trees, due to their ability to handle a wide array of inputs. The use of CNNs in maize disease detection helps simplify the process and provides a quick and easy implementation for farmers [25,26].

Established standards for systematic literature reviews in the field of agricultural technology and artificial intelligence are adhered to in this review. A comprehensive search was conducted using two premier academic databases: Web of Science and Scopus. The search criteria were designed to capture relevant papers published between 2014 and 2024, focusing on maize disease detection using artificial intelligence, with a particular emphasis on CNNs. The search terms included combinations of keywords such as "maize," "corn," "disease detection," "artificial intelligence," "machine learning," and "convolutional neural networks." Over 150 papers were initially identified, which were then screened based on their titles and abstracts. The papers were thoroughly reviewed, and their relevance was assessed based on the novelty of the approach, the robustness of the methodology, and the significance of the results. This rigorous selection process resulted in the final set of papers included in this review, ensuring a comprehensive and up-to-date analysis of the state-of-the-art in maize disease detection using AI and CNN technologies is provided. Fig. 1 shows the general methodology of the paper. Fig. 2 shows the comparison of the algorithms.

2. Literature review

2.1. Dataset analysis

Table 1 presents a comprehensive overview of the datasets used in various maize disease detection studies, showcasing the diversity in both size and composition. The datasets range from relatively small collections of 200 images [27] to extensive compilations of 54,000 images [28], reflecting the varied scales of research efforts. The number of disease classes also varies significantly, from binary classifications [29,30] to more complex multi-class problems involving up to 14 distinct categories [28]. Most datasets include a 'Healthy' class alongside various disease classes, allowing for differentiation between healthy and infected plants. Common diseases such as Gray Leaf Spot, Northern Leaf Blight, and Common Rust appear frequently across multiple datasets, indicating their significance in maize cultivation. Notably, some datasets [31–33] incorporate severity levels or specific disease stages, providing more granular information for disease progression analysis. The diversity in dataset composition highlights the complexity of maize disease detection and the importance of comprehensive, well-balanced datasets in developing robust detection models.

2.2. Preprocessing strategies

Table 2 provides an overview of various preprocessing strategies employed in maize disease detection studies. Preprocessing strategies for maize disease detection images are crucial for enhancing the performance of machine learning models, particularly CNNs. These strategies typically include several key techniques aimed at improving image quality and ensuring that the models can effectively learn from the data.

1. Image Resizing: Resizing images to a uniform dimension is a common preprocessing step. This ensures that all input images have the same size, which is essential for batch processing in CNNs. emphasize the importance of maintaining consistent image dimensions to facilitate effective feature extraction during model training [34].
2. Normalization: Normalizing pixel values is another critical preprocessing step. This involves scaling the pixel values to a range, often between 0 and 1, which helps in accelerating the convergence of the training process. highlight that normalization can significantly improve the performance of CNNs by reducing the sensitivity of the model to the scale of input data [36].
3. Data Augmentation: To combat overfitting and enhance the robustness of the model, data augmentation techniques such as rotation, flipping, and cropping are employed. This artificially increases the size of the training dataset and introduces variability, which helps the model generalize better. note that data augmentation is particularly beneficial in agricultural applications where obtaining large datasets can be challenging [31].

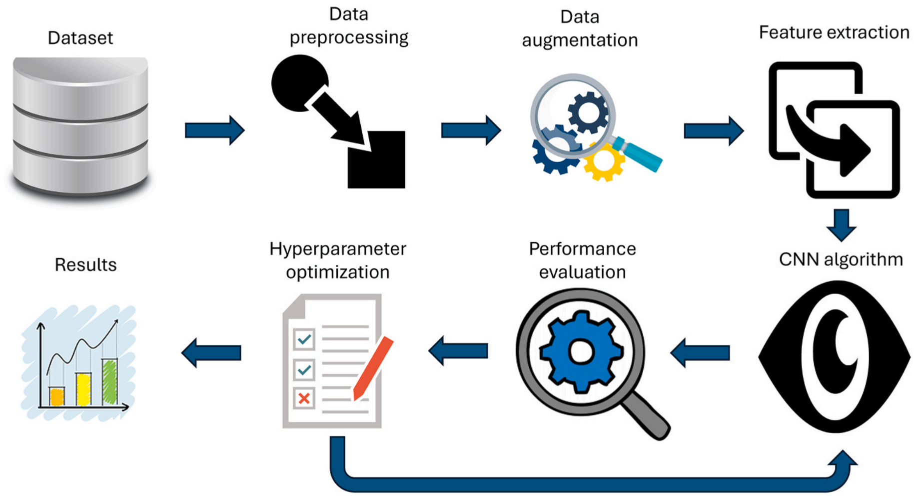

Fig. 1. General methodology of CNN applications [20].

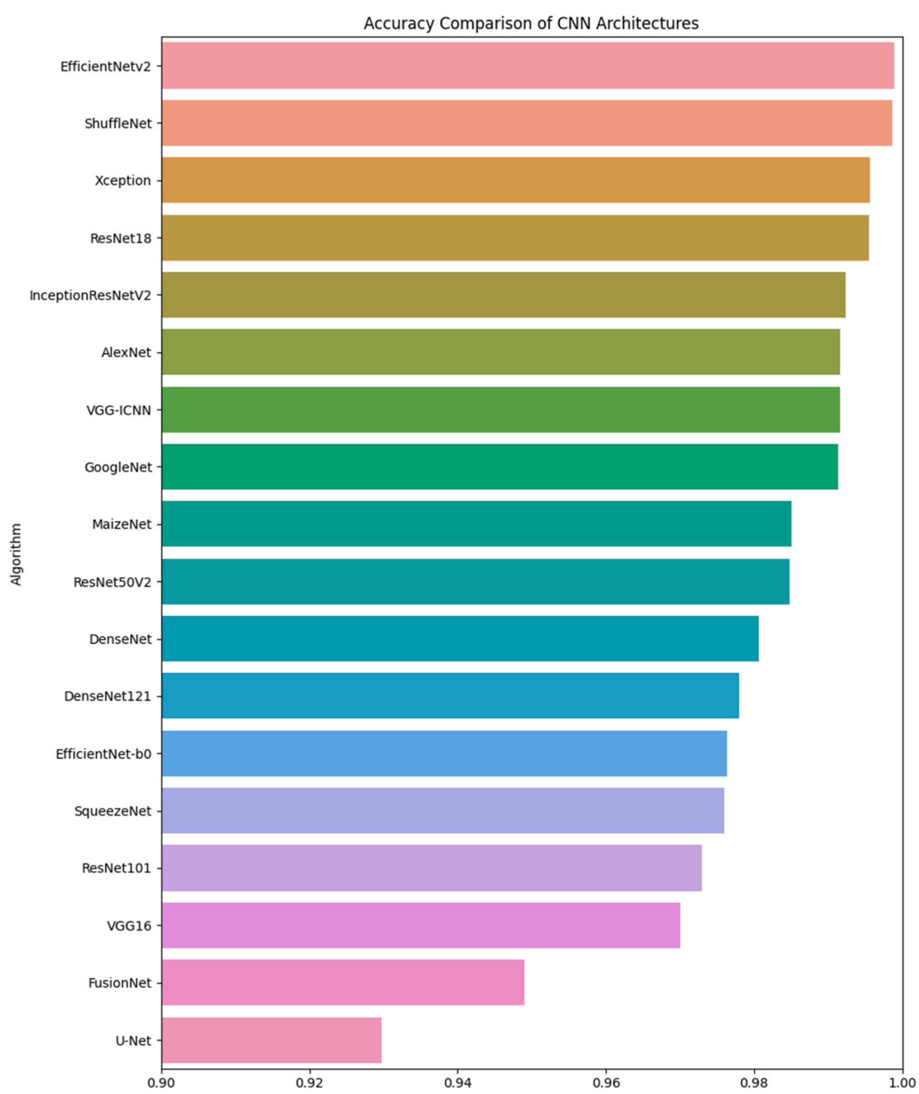

Fig. 2. Algorithm comparison.

Table 1
Number of images and classes in the datasets.

Paper	Number of Images	Number of Classes	Class Names
[32]	10000	4	Healthy: 3000, Maculopathy: 3500, Rust: 2500, Blight: 1000
[34]	4000	4	Cercospora leaf spot: 1000, Common rust: 1000, Northern Leaf Blight: 1000, Healthy: 1000
[33]	370	5	Common Rust: 100, Southern Rust: 50, Gray Leaf Spot: 70, MLB: 30, Turcicum Leaf Blight: 30, Healthy: 90
[27]	200	4	Healthy: 50, Cercospora: 50, Common rust: 50, Northern leaf blight: 50
[35]	10000	5	Healthy: 2000, Gray leaf spot: 2000, Northern leaf blight: 2000, Common rust: 2000, Southern leaf blight: 2000
[36]	5000	5	Healthy: 2000, Gray Leaf Spot: 1000, Northern Leaf Blight: 1000, Northern Rust: 1000, Southern Leaf Blight: 1000
[29]	6267	2	Healthy: 3134, Diseased: 3133
[28]	54000	14	Healthy: 10000, gray leaf spot: 4000, northern leaf blight: 4000, common rust: 4000, leaf blight: 4000, tar spot: 4000, downy mildew: 4000, leaf spot: 4000, bacterial leaf streak: 4000, blight: 4000, fusarium ear rot: 4000, anthracnose: 4000, stalk rot: 4000, ear rot: 4000
[37]	10000	5	Healthy: 2000, Gray leaf spot: 2000, Northern corn leaf blight: 2000, Common rust: 2000, Southern corn leaf blight: 2000
[38]	3852	4	Healthy: 1000, Gray leaf spot: 1000, Common rust: 1000, Northern leaf blight: 852
[30]	5000	2	Corn anthracnose: 2500, Brown spot: 2500
[21]	10000	5	Healthy: 2000, Northern Leaf Blight: 2000, Gray Leaf Spot: 2000, Common Rust: 2000, Southern Leaf Blight: 2000
[22]	30000	6	Healthy: 10000, Gray leaf spot: 4000, Northern leaf blight: 4000, Common rust: 4000, Southern leaf blight: 4000, Maize dwarf virus: 4000
[31]	1760	4	Healthy: 440, Low severity: 440, Medium severity: 440, High severity: 440
[26]	30000	5	Healthy: 10000, Gray leaf spot: 5000, Northern leaf blight: 5000, Common rust: 5000, Southern leaf blight: 5000

Table 2
Preprocessing strategies.

Preprocessing Strategy	Papers
Image Enhancement and Normalization	[23,34,39,41–68]
Resizing and Cropping	[22,35,38,69–88]
Noise Reduction and Filtering	[21,32,42,47,72,74,77,79–86,89–91]
Color Space Transformations	[32,36,41,85,87,90,92]
Feature Extraction and Selection	[40,44,93–98]
Background Removal	[21,38,66,68,99]
Brightness/Contrast Adjustment	[35,43,48,70,73,75,78,80–82,100,101]
Rotation and Flipping	[39,54,55,57,59,66,68–72,76,82,87,88,92,101]
Specialized Techniques	[33,36,37,45,60,63,65,67,70,91,99,102,103]

4. Image Filtering: Applying image filtering techniques can help in enhancing the features relevant to disease detection. For example, Gabor filters or other edge-detection filters can be used to highlight the boundaries of lesions or other disease symptoms on maize leaves. discuss the effectiveness of using filters to improve the clarity of features that CNNs need to learn [21].
5. Background Removal: Removing or minimizing background noise is essential for focusing on the relevant features of the maize leaves. This can involve techniques such as thresholding or segmentation to isolate the leaf area from the background. emphasize that effective background removal can lead to better classification accuracy by reducing distractions in the image [39].
6. Color Space Transformation: Transforming the color space of images (e.g., from RGB to HSV or LAB) can sometimes enhance the visibility of certain features associated with diseases. This transformation can help in better distinguishing between healthy and diseased areas of the leaf. suggest that different color spaces can provide more informative features for disease classification tasks [32].
7. Histogram Equalization: This technique improves the contrast of images, making it easier for models to detect subtle differences in color and texture that may indicate disease. Histogram equalization redistributes the intensity values of the image, enhancing the visibility of features that are crucial for accurate classification [32].
8. Noise Reduction: Applying noise reduction techniques, such as Gaussian blurring, can help in smoothing the images and removing irrelevant details that may interfere with the detection process. This is particularly important in agricultural images where environmental factors can introduce noise [21].
9. Feature Extraction: Advanced preprocessing may also involve extracting specific features from the images that are known to correlate with disease symptoms. This can include texture analysis or using pre-trained models to extract features before feeding them into a classification model [40].

By implementing these preprocessing strategies, researchers can significantly enhance the performance of CNNs in maize disease detection, leading to more accurate and reliable outcomes in agricultural practices.

2.3. Source of the data

Table 3 provides a comprehensive overview of the geographical distribution of data collection for maize disease detection studies using convolutional neural networks. The data spans across multiple continents, including Asia, Africa, Europe, and North America, highlighting the global nature of this research. Countries such as China, India, and the United States feature prominently, with multiple studies conducted in various cities within these nations. The diversity of locations ranges from rural agricultural areas to major urban centers, encompassing a wide variety of environmental conditions and farming practices. This geographical spread is crucial for developing robust and generalizable models for maize disease detection, as it captures the variability in disease manifestation across different climates, soil types, and agricultural techniques. The inclusion of both developed and developing countries in the dataset also reflects the universal importance of maize cultivation and the global effort to improve crop health through advanced technologies.

2.4. Algorithms and models

In the domain of maize disease detection, various CNN architectures have been employed, particularly leveraging transfer learning to enhance model performance. The following algorithms are commonly used.

1. VGG: The VGG architecture, particularly VGG16 and VGG19, is known for its simplicity and depth, utilizing small convolutional filters and a deep network structure. These models have been widely adopted for image classification tasks, including maize disease detection, due to their ability to capture intricate features in images. note that VGG models are often used as benchmarks in comparative studies of CNN architectures [109].
2. ResNet (Residual Networks): ResNet, particularly ResNet50 and ResNet101, introduces skip connections that help mitigate the vanishing gradient problem, allowing for the training of very deep

Table 3
Data collected country and cities.

Paper	Data collected country	Data collected city
[42]	Bangladesh	
[104]	Bangladesh	
[105]	Belgium	East-Flanders Province
[30]	China	Harbin
[100]	China	
[76]	China	Hefei
[32]	China	Changchun
[49]	China	Gaojia Village, Lishu County
[103]	China	Harbin
[106]	China	
[98]	China	Hebei Province
[65]	China	Changsha
[87]	Ghana	Sunyani
[64]	Ghana	
[107]	Ghana	
[108]	India	West Bengal, New Delhi
[28]	India	Coimbatore
[73]	India	Madurai
[45]	India	Punjab
[31]	India	New Delhi
[26]	India	Erode
[46]	India	Chennai
[109]	India	New Delhi
[75]	India	Bengaluru
[110]	India	Punjab
[78]	India	Punjab
[79]	India	Pune
[111]	India	
[82]	India	Kolhapur
[59]	India	Warangal
[60]	India	Telangana
[68]	India	
[52]	Indonesia	Bangkalan, Madura
[112]	Indonesia	
[80]	Japan	Nagoya
[85]	Kenya	Nairobi
[83]	Malaysia	Shah
[26]	Nigeria	Ota
[113]	Pakistan	Sahiwal
[114]	South Africa	Southern Africa
[115]	South Africa	Pretoria
[81]	Sri Lanka	Colombo
[116]	Sub-Saharan Africa	
[40]	Tanzania	Morogoro
[54]	Tanzania	
[117]	Thailand	
[72]	United Kingdom	Ormskirk
[29]	United States	Ithaca
[102]	United States	
[101]	United States	Davis
[84]	United States	Chicago

networks. This architecture has been shown to perform well in various image classification tasks, including the identification of maize diseases. highlight the effectiveness of ResNet in extracting features from maize leaf images [27].

3. Xception: This architecture is an extension of the Inception model and utilizes depthwise separable convolutions, which significantly reduce the number of parameters while maintaining performance. Xception has been applied in maize disease detection, providing a balance between computational efficiency and accuracy. emphasizes the importance of selecting appropriate CNN architectures like Xception for optimal performance in disease classification tasks [51].
4. Inception (GoogLeNet): The Inception architecture, known for its multi-scale feature extraction capabilities, has been effectively utilized for maize disease detection. It combines multiple convolutional filters of different sizes in parallel, allowing the model to learn features at various scales. This adaptability makes it suitable for complex agricultural images, as discussed by Ref. [29].
5. DenseNet: DenseNet architectures, such as DenseNet121, are characterized by their dense connectivity pattern, where each layer receives inputs from all preceding layers. This design promotes feature reuse and improves gradient flow, making DenseNet a strong candidate for maize disease detection tasks. propose an optimized DenseNet model for recognizing corn leaf diseases, demonstrating its effectiveness in this context [72].
6. MobileNet: MobileNet architectures are designed for mobile and edge devices, focusing on lightweight models that maintain accuracy while reducing computational load. These models are particularly useful in agricultural applications where deployment on mobile devices is essential. highlights the applicability of MobileNet for deep learning-based maize visualization and classification [118].
7. EfficientNet: This family of models scales up the network width, depth, and resolution in a balanced manner, achieving state-of-the-art accuracy with fewer parameters. EfficientNet has been applied in maize disease classification, providing a robust solution for real-time applications. discuss the use of EfficientNet for maize plant leaf disease classification, emphasizing its efficiency [75].
8. U-Net: Originally designed for biomedical image segmentation, U-Net has been adapted for plant disease detection tasks, including maize. Its architecture allows for precise localization of disease symptoms on leaves, making it suitable for applications requiring detailed segmentation. describes the application of U-Net models for quantifying disease incidence on maize leaves [119]. Table 4 provides a comprehensive overview of the algorithms employed and the corresponding performance metrics in various studies on maize disease detection.

Fig. 1 shows algorithm comparison for the CNN models. EfficientNetV2, ShuffleNet, Xception gives the top results.

2.5. Hyperparameter optimization

Hyperparameter optimization is a critical step in the training of CNNs for maize disease detection, as it directly influences the model's performance and accuracy. Various methods have been developed to optimize hyperparameters, each with its own advantages and applicability. Below are some of the commonly used hyperparameter optimization methods.

1. Grid Search: This is one of the most straightforward methods for hyperparameter tuning. It involves specifying a set of hyperparameters and their possible values, and the algorithm evaluates all possible combinations to find the best configuration. This exhaustive search can be computationally expensive, especially with a large number of hyperparameters. highlight the effectiveness of grid search in optimizing hyperparameters for deep learning models [38].
2. Random Search: Unlike grid search, random search samples a fixed number of hyperparameter combinations from the specified ranges. This method is often more efficient than grid search, as it can find good hyperparameter settings without evaluating every combination. It is particularly useful when dealing with high-dimensional hyperparameter spaces.
3. Bayesian Optimization: This method uses a probabilistic model to find the minimum of a function. It builds a surrogate model of the objective function and uses it to select the most promising hyperparameters to evaluate next. This approach is more efficient than grid or random search, especially for expensive-to-evaluate functions. discuss the application of Bayesian optimization in optimizing CNN hyperparameters for maize disease detection [32].
4. Genetic Algorithms: This optimization technique mimics the process of natural selection. It starts with a population of hyperparameter sets and evolves them over generations, selecting the best-performing sets to create new ones. Genetic algorithms can effectively explore large search spaces and have been applied in various studies for hyperparameter tuning [51].

Table 4
Used algorithms and performances.

Paper	Used algorithms	Accuracy	Precision	Recall	F1	AUC	mAP	IoU
[21]	EfficientNetv2, EANet	**0.9989**	–	–	–	–	–	–
[23]	ResNet50V2, DenseNet169, VGG16, VGG19, Xception, MobileNetV2, ViT-B/16, ViT-B/32	0.9848	–	–	–	–	–	–
[26]	Xception, Inception	0.965	–	–	–	–	–	–
[27]	AlexNet, VGG16, VGG19, ResNet50, ResNet101, GoogleNet, Inception-V3	0.935	–	0.9508	–	–	–	–
[30]	3D-2D hybrid CNN (Y-Net)	0.9834	–	–	–	–	–	–
[31]	VGG16, VGG19, InceptionV3, ResNet50, Xception, MobileNetV2, DenseNet121, NASNetMobile	0.9913	–	–	**0.9897**	–	–	–
[32]	HSCNN+	0.92	0.93	0.91	0.92	0.95	0.91	0.89
[33]	P-CNN (PSPNet + CNN), YOLO + CNN, VGG16+CNN	0.9985	–	–	–	–	–	–
[35]	CNN-LVQ, VGG-16, ResNet-50	0.94	0.93	0.95	0.94	0.92	0.91	0.9
[39]	VGG-16	0.9563	–	–	–	–	–	–
[45]	Federated Learning CNN	0.894	–	–	–	–	–	–
[46]	SqueezeNet	0.976	0.974	0.978	0.976	0.965	0.955	0.945
[48]	VGG-ICNN	0.9916	–	–	–	–	–	–
[51]	ResNet101, XceptionNet	0.973	–	–	–	–	–	–
[52]	ResNet18	0.9955	**0.9953**	**0.9973**	–	–	–	–
[54]	VGG16, InceptionV3, XceptionNet, Resnet50	0.9698	–	–	–	–	–	–
[55]	InceptionResNetV2, MobileNetV2, ResNet50, VGG19, InceptionV3, VGG16, DenseNet201	0.9956	–	–	–	–	–	–
[57]	DenseNet201, SVM, Bayesian optimization algorithm	0.946	–	–	–	–	–	–
[60]	SVM, DenseNet-121, Inception V2, ShallowNet-8, CNN-SVM, Modified LeNet, DICNN, SoyNet, Adaptive CNN	0.8872	–	–	–	–	–	–
[61]	GoogleNet	0.9987	–	–	–	–	–	–
[62]	SEYOLOX-tiny, YOLOX	–	–	–	–	–	0.95	–
[63]	AlexNet, ResNet, GoogLeNet, VGGNet	0.9747	–	–	–	–	–	–
[65]	MFaster R-CNN, Faster R-CNN, SSD	0.9718	–	0.9719	–	–	–	–
[67]	EfficientNet	0.9385	0.9356	0.9623	0.9385	–	–	–
[68]	InceptionV3, VGG19, Xception, InceptionResNetV2	0.9556	–	–	–	–	–	–
[69]	MaxViT, DenseNet-121, Global Response Normalization (GRN), CD-Mobilenetv3 model, Convolutional Block Attention Module (CBAM)	0.9924	–	–	–	–	–	–
[70]	AlexNet	0.9916	–	–	–	–	–	–
[71]	Support Vector Machine (SVM), GoogLeNet, ResNet18, MobileNetV2	0.9795	0.95	–	0.96	–	–	–
[72]	DenseNet	0.9806	–	–	–	–	–	–
[75]	DenseNet121	0.978	0.976	0.98	0.977	0.968	0.955	0.945
[77]	EfficientNet-b0	0.9763	–	0.9799	0.9648	–	–	–
[78]	VGG16, VGG19, Inception V3, EfficientNetB7	0.9877	–	–	–	–	–	–
[80]	Faster R-CNN, ResNet-50, EfficientNet-B7	0.945	0.952	0.94	0.945	0.93	0.94	0.92
[81]	VGG19	0.92	0.91	0.93	0.91	0.95	0.89	0.88
[82]	VGG16, ResNet50, YOLOv3	0.975	0.972	0.978	0.974	0.965	0.96	0.945
[83]	VGG16, ResNet50, InceptionV3	0.975	0.972	0.976	0.974	0.965	**0.96**	**0.95**
[87]	LBP-capsule networks with K-Means routing	0.945	0.948	0.943	0.945	0.942	0.936	0.928
[88]	HCA-MFFNet, Inception-V3, MobileNet-V2, ResNet-50, DenseNet-121, ResNeXt-50, AlexNet, VGG-16, DMS-Robust Alexnet, B-ARnet, MFFNet	0.9775	–	–	0.9703	–	–	–
[90]	Random Forest, SVM, KNN	0.9925	–	–	–	–	–	–
[92]	VGG16, ResNet50, InceptionV3, MobileNet, DenseNet	0.92	0.93	0.91	0.92	0.95	0.91	0.89
[93]	MaizeNet	0.985	–	–	–	–	–	–
[95]	K-means clustering, NN classifier, SVM	0.9976	–	–	–	–	–	–
[98]	ResNet	0.982	–	–	–	–	–	–
[99]	ResNet, MobileNet, GoogLeNet, DICNN, Inception-v4, Inception-resnet, DenseNet, Xception	0.9948	–	–	–	–	–	–
[100]	DenseNet121, ResNet50, MobileNetV2, NASNetMobile, ACGAN, MDCDenseNet	0.9884	–	–	–	–	–	–
[104]	Xception, VGG16, ResNet152V2, InceptionResNetV2, DenseNet201, MobileNetV2	0.9552	–	–	–	–	–	–
[108]	GoogleNet	0.9914	–	–	–	–	–	–
[110]	SVM	0.965	0.9519	0.9536	0.9551	–	–	–
[111]	U-Net	0.8335	–	–	–	–	–	–
[112]	Squeezenet, Grad-CAM	0.952	0.9403	0.9428	–	–	–	–
[114]	GA-SVM, LeNet	0.9789	–	–	–	–	–	–
[117]	Inception v3	0.833	–	–	–	**0.9905**	–	–
[119]	U-Net	–	–	–	0.6669	–	–	0.5002
[120]	InceptionResNetV2	0.87	–	–	–	–	–	–
[121]	VGG16	0.97	–	–	–	–	–	–
[122]	FusionNet	0.949	–	–	–	–	–	–
[123]	GoogleNet, AlexNet, ResNet50, VGG16	0.992	–	–	–	–	–	–
[124]	AlexNet, VGG16, ResNet50, DenseNet121	0.9727	–	–	–	–	–	–
[125]	SVM, KNN, ELM, BP, LSTM, 3DCNN, MSR-3DCNN, SATNet, CNN-LSTM	0.95	–	–	–	–	–	–
[126]	U-Net, Vgg16, MobileNet	–	–	–	–	–	–	0.71
[127]	CNN-BiLSTM	0.9902	–	–	–	–	–	–
[128]	Alexnet, VGG-16	0.9211	–	–	–	–	–	–
[129]	U-Net	0.9298	–	–	0.8991	–	–	0.8461
[130]	ResNet	0.9887	–	–	–	–	–	–
[131]	ResNet, Xception, VGG, ENet	0.9869	–	–	–	–	–	–
[132]	VGG	0.93	–	–	–	–	–	–
[133]	DenseNet, VGG, ResNet	–	–	–	–	–	–	–
[134]	ShuffleNet	0.9986	–	–	–	–	–	–
[135]	ShuffleNet	0.984	–	–	–	–	–	–

5. Particle Swarm Optimization (PSO): This is a population-based optimization technique inspired by social behavior patterns of birds and fish. In the context of hyperparameter optimization, each particle represents a potential solution, and they move through the search space based on their own experience and that of their neighbors. This method has been shown to be effective in optimizing CNN hyperparameters [30].
6. Cosine Annealing: This technique is often used for learning rate scheduling. It gradually decreases the learning rate following a cosine function, allowing the model to converge more effectively. This method can be combined with other optimization techniques to enhance performance [77].
7. Network Pruning: This method involves removing less important neurons or connections from the network after training, which can help in optimizing the model's performance and reducing overfitting. While not a traditional hyperparameter optimization method, it can be used to refine the model after initial training [32].

Table 5 outlines the diverse hyperparameter optimization techniques employed in maize disease detection studies, underscoring the importance of tuning model parameters for optimal performance.

3. Discussion

3.1. Challenges

The challenges associated with employing CNNs for maize disease detection present intricate hurdles that require careful consideration. Firstly, the inherent variability and diversity of maize diseases pose a significant challenge. The wide array of potential diseases affecting maize crops demands a nuanced approach to model development, making it challenging to create a one-size-fits-all solution. The complexity is further heightened by the need for robust models that can accurately classify various diseases under diverse conditions [34].

Secondly, the scarcity and imbalance of labeled datasets emerge as a critical challenge. Developing accurate and generalizable CNN models relies heavily on large, well-annotated datasets. The limited availability of such datasets, especially for less common or region-specific diseases, hampers the training and validation processes, potentially resulting in biased models [116].

Addressing the geographical and environmental variations in maize cultivation regions is another substantial challenge. Climate, soil conditions, and agricultural practices vary widely, impacting disease manifestation. Building models that can adapt to these variations requires a comprehensive understanding of the contextual factors influencing disease development, adding an extra layer of complexity to the development process [18].

Moreover, the real-world applicability of CNN-based solutions in agriculture faces obstacles. Implementing these technologies for on-field, real-time detection demands computational efficiency, scalability, and integration with existing agricultural practices. Overcoming these challenges is crucial for ensuring that CNNs can provide practical and timely support to farmers in disease management [33].

Ethical considerations and socio-economic factors also play a role. Ensuring data privacy, addressing technology literacy among farmers, and evaluating the economic viability of adopting advanced AI solutions are pivotal aspects that need careful attention. Striking a balance between technological advancement and the socio-economic realities of agriculture is essential for the successful adoption of CNNs in maize disease detection [20].

By recognizing and articulating these challenges, the review paper aims to provide a comprehensive overview of the current obstacles in the field, guiding future research efforts and technological advancements in maize disease detection using CNNs.

3.2. Opportunities

The exploration of CNNs for maize disease detection presents a multitude of opportunities that hold promising implications for agricultural practices and food security. Firstly, the integration of CNNs offers the opportunity to revolutionize disease detection efficiency. The speed and accuracy of CNN models enable timely identification of diseases, empowering farmers to take proactive measures and mitigate potential crop losses. This can contribute significantly to enhancing overall crop yield and agricultural productivity [29].

The development of open-access datasets and collaborative initiatives provides a unique opportunity for collective advancement. Collaborative efforts in curating extensive and diverse datasets can address the challenge of data scarcity, fostering a shared knowledge base that benefits the entire research community. Open-access datasets also promote transparency and reproducibility, enabling researchers to validate and compare models effectively [99].

Additionally, CNNs offer the potential for early disease detection, even before visible symptoms manifest. This early detection capability is crucial for implementing timely interventions, preventing the spread of diseases, and minimizing the need for extensive pesticide use. By integrating CNN-based solutions, agriculture can transition towards more sustainable and environmentally friendly practices [36].

The use of CNNs in maize disease detection aligns with the broader trend of precision agriculture. The ability to precisely identify and localize diseases allows for targeted interventions, optimizing resource utilization and minimizing the environmental impact of agricultural practices. This not only enhances the economic efficiency of farming but also aligns with sustainable agricultural goals [72].

Furthermore, the ongoing advancements in hardware technology, cloud computing, and edge computing present opportunities for improving the scalability and accessibility of CNN models. The deployment of models on edge devices can enable on-site disease detection, providing real-time insights to farmers directly in the field. This decentralization of computation enhances the practicality and applicability of CNN-based solutions in diverse agricultural settings [123].

In conclusion, the integration of CNNs in maize disease detection opens up exciting opportunities for transforming agricultural practices. From early disease detection to collaborative data initiatives, these

Table 5
Hyperparameter optimization.

Paper	Hyperparameter optimization
[30]	Network pruning
[32]	Grid search, Hyperparameter tuning
[35]	Grid search, Hyperparameter tuning
[46]	Biogeography-based Optimization
[47]	Bayesian optimization
[51]	Grid search, random search, Bayesian optimization
[53]	Orthogonal learning particle swarm optimization (OLPSO), Particle Swarm Optimization (PSO)
[57]	Bayesian Optimization
[75]	Grid search, Hyperparameter tuning
[79]	Particle swarm optimization, Genetic algorithm
[81]	Grid search, Bayesian optimization
[82]	Genetic algorithm, Bayesian optimization
[83]	Random search, Bayesian optimization
[84]	Genetic algorithm, Bayesian optimization
[87]	Genetic algorithm, Random search, Hyperparameter tuning
[88]	Orthogonal Learning Particle Swarm Optimization (OLPSO), Exponential Decay Learning Rate (EDLR)
[92]	Grid search, Bayesian optimization
[104]	SAM
[121]	Bayesian optimization
[125]	Grid search
[130]	Cosine annealing
[136]	AOSMO algorithm
[137]	Genetic algorithm
[138]	Slicing-aided fine-tuning (SF) approach

opportunities pave the way for a more resilient and sustainable future in agriculture. The review paper seeks to highlight these prospects, encouraging further exploration and development in this dynamic field.

3.3. Future directions

The future directions of maize disease detection through CNNs present intriguing avenues for research and technological advancements.

3.3.1. Multi-modal and multi-sensor approaches

One promising direction is the exploration of multi-modal and multi-sensor approaches. Integrating data from various sources, such as satellite imagery, drone-based imaging, and ground-based sensors, can provide a more comprehensive understanding of crop health. Research endeavors should focus on developing CNN models capable of efficiently assimilating and processing diverse data types to enhance the accuracy and robustness of maize disease detection [29].

3.3.2. Explainable AI and model interpretability

Continuing research efforts in the direction of explainability and interpretability of CNN models is crucial for wider acceptance and practical implementation. Developing models that can provide clear and interpretable insights into the decision-making process will foster trust among end-users, especially farmers and agricultural stakeholders. This entails investigating methods to visualize and explain the features contributing to disease predictions [112].

3.3.3. Transfer learning and domain adaptation

The adoption of transfer learning and domain adaptation techniques presents another compelling avenue. Leveraging pre-trained models on related tasks or domains and fine-tuning them for maize disease detection can address challenges related to limited labeled data in specific contexts. Future research should explore transfer learning strategies tailored to the unique characteristics of maize diseases and agricultural settings [99].

3.3.4. Real-time monitoring and decision support systems

Furthermore, the integration of real-time monitoring and decision support systems is a key area for future exploration. Developing CNN models that can operate in real-time and provide actionable insights to farmers during the growing season can significantly enhance disease management strategies. This involves addressing challenges related to computational efficiency, model deployment on edge devices, and communication infrastructure in agricultural settings [33].

3.3.5. Advanced machine learning techniques

The incorporation of advanced machine learning techniques, such as ensemble learning and meta-learning, holds promise for further improving the robustness and generalization of maize disease detection models. Ensembling multiple CNN models or designing meta-learning approaches that adapt to varying conditions and data distributions can contribute to more reliable predictions in diverse agricultural scenarios [72].

3.3.6. Socio-economic impact and adoption

Lastly, the socio-economic impact of CNN-based disease detection in maize farming communities is an essential aspect that merits attention in future research. Assessing the adoption barriers, economic feasibility, and practical implications of implementing these technologies in different regions and farming systems will contribute to the development of solutions that align with the needs and realities of agricultural communities [123].

3.3.7. Integration with other agricultural technologies

The future of maize disease detection lies in its seamless integration with other agricultural technologies. Researchers should explore the potential of incorporating CNN-based disease detection systems into broader precision agriculture frameworks. This integration could lead to more comprehensive farm management solutions. Additionally, investigating the synergies between disease detection models and crop yield prediction systems could provide farmers with a more holistic view of their crop health and expected productivity. The development of integrated farm management systems that incorporate disease detection alongside other crucial agricultural data points will be a significant step towards more efficient and sustainable farming practices [44].

3.3.8. Adaptation of models from other domains

Adapting successful models from other domains presents an exciting opportunity for advancing maize disease detection. Furthermore, investigating attention mechanisms and self-supervised learning techniques from natural language processing could improve CNN performance in detecting subtle disease patterns. Researchers should also consider adapting object detection models from autonomous driving for identifying multiple diseases or pests in a single image, which could significantly streamline the disease detection process in complex field environments [44].

3.3.9. Sustainable and environmentally-friendly practices

The development of CNN models for maize disease detection should align with sustainable and environmentally-friendly agricultural practices. Future research should focus on creating models that can optimize pesticide use based on precise disease detection, potentially reducing chemical inputs and environmental impact. Integrating disease detection systems with climate prediction models could enable more proactive and sustainable disease management strategies. Additionally, exploring CNN applications in identifying drought-resistant or disease-resistant maize varieties could contribute to the development of more resilient and sustainable farming systems in the face of climate change [18,20].

3.3.10. Data quality and augmentation

Improving data quality and augmentation techniques will be crucial for the continued advancement of CNN-based maize disease detection. Researchers should investigate advanced data augmentation techniques to address the challenge of limited labeled data, which is often a bottleneck in developing robust models. The development of synthetic data generation methods using generative adversarial networks (GANs) could provide a valuable solution to data scarcity. Furthermore, the creation of standardized, high-quality datasets for maize diseases across different regions will be essential for developing models that can perform consistently across diverse agricultural environments. These efforts in data quality and augmentation will be fundamental in enhancing the reliability and generalizability of maize disease detection models [86].

The future directions of the paper encompass exploring multi-modal approaches, enhancing model explainability, leveraging transfer learning, integrating real-time monitoring, embracing advanced machine learning techniques, and considering the socio-economic dimensions of technology adoption. These directions aim to advance the field of maize disease detection and foster innovations that can benefit farmers and contribute to global food security.

Key Findings and Future Directions.

- Challenges:
  - Variability and diversity of maize diseases
  - Scarcity and imbalance of labeled datasets
  - Geographical and environmental variations
  - Real-world applicability and integration with existing practices
  - Ethical considerations and socio-economic factors
- Opportunities:
  - Improved disease detection efficiency
  - Development of open-access datasets and collaborative initiatives

- Early disease detection capabilities
- Alignment with precision agriculture trends
- Advancements in hardware and edge computing
- Future Directions:
  - Exploration of multi-modal and multi-sensor approaches
  - Focus on explainable AI and model interpretability
  - Adoption of transfer learning and domain adaptation techniques
  - Integration of real-time monitoring and decision support systems
  - Incorporation of advanced machine learning techniques (e.g., ensemble learning, meta-learning)
  - Assessment of socio-economic impact and adoption barriers
  - Integration with other agricultural technologies
  - Adaptation of successful models from other domains
  - Alignment with sustainable and environmentally-friendly practices
  - Improvement of data quality and augmentation techniques

4. Conclusion

In conclusion, this review paper provides a comprehensive overview of the current state of maize disease detection through CNNs and underscores the significant strides made in leveraging artificial intelligence for agricultural applications. The exploration of data sources, diverse datasets, preprocessing strategies, and the geographic distribution of research efforts has shed light on the global landscape of maize disease research. The thorough examination of algorithms, hyperparameter optimization, and performance metrics has contributed to a nuanced understanding of the technological approaches employed in this domain.

Despite the progress made, the challenges outlined in this review, such as limited labeled data, interpretability concerns, and the need for real-time applications, underscore the complexity of integrating AI solutions into agricultural practices. However, these challenges also represent opportunities for innovation and research, with potential solutions lying in collaborative efforts between researchers, practitioners, and policymakers.

The opportunities identified in this paper emphasize the transformative potential of CNNs in revolutionizing maize disease detection. The prospect of providing timely and accurate insights to farmers, enhancing decision-making processes, and contributing to sustainable agricultural practices holds promise for addressing global food security challenges.

Looking forward, the future directions proposed highlight key areas for continued research and development. The exploration of multimodal approaches, advancements in model explainability, integration of real-time monitoring, and the consideration of socio-economic factors are pivotal for ensuring the practical implementation and widespread adoption of CNN-based disease detection technologies.

In essence, this review not only consolidates existing knowledge but also charts a course for future research endeavors that can shape the trajectory of maize disease detection. By addressing challenges, capitalizing on opportunities, and delineating future directions, this paper contributes to the ongoing discourse on the intersection of artificial intelligence and agriculture, aiming to make meaningful contributions to sustainable and technology-driven agricultural practices. As the field continues to evolve, collaboration and interdisciplinary efforts will play a central role in harnessing the full potential of CNNs for maize disease detection and, ultimately, in securing global food supplies.

Data availability statement

No data was used for the research described in the article.

CRediT authorship contribution statement

Burak Gülmez: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Resources, Investigation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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