Application of Convolutional Neural Networks (CNNs) in Agriculture

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Abstract

AI and machine learning applications are on the rise. Especially, deep learning is used very frequently in research these days. Convolutional Neural Networks (CNNs) are one such popularly used deep learning approach in the agricultural domain. In smart agriculture, CNNs find its use in identification, classification and mapping problems. It is used for disease & weed: identification and classification. It is also utilized for crop yield prediction. Its combination with IoT and Drone devices enhances its application perspectives. Hence, this paper provides insights into the CNN methodology. It reviews the available datasets and the effectiveness of existing CNN application in the agricultural domain.

Keywords: *Deep Learning, Convolutional Neural Networks, Smart Agriculture, Crop Disease, Weeds Detection, Yield Prediction.*

1. Introduction

Agriculture is widely regarded as the cornerstone of every economy, as it is the primary source of food and livelihood for a significant portion of the global population. With the increasing population, food security is emerging as a primary challenge that needs to be addressed. The methods used in the agricultural practices must evolve and transform to tackle this situation. Crop production loss due to various diseases, pests, and abiotic stresses accounts for 40% of the global yield, estimated roughly as an economic loss of 220 billion USD annually [1].

The emergence of Artificial Intelligence has made traditional agricultural practices smarter with intelligent and data-driven systems. Along with the Internet of Things (IoT), it can enhance resource optimization, such as water, fertilizers, pesticides, and weedicides for sustainable agricultural practices. Artificial Intelligence combined with image processing is helpful in the detection of crop disease, weeds, pests, and the prediction of yield, which has proven to be more accurate and efficient as compared to traditional/conventional methods involving manual inspection of crop phenotypes, including shape deformation, discoloration, and other deformities. The visual assessment requires knowledge about plant physiology, which is not readily accessible to farmers worldwide.

Given its ability to handle highly complex and multidimensional data, Deep Learning, a subfield of Artificial Intelligence, has attracted significant attention in the agricultural domain. The Deep Learning models are widely known for extracting required features from the data and then learning from the extracted features, unlike conventional Machine Learning, which requires extracted features for learning. Among different DL models, Convolutional Neural Networks (CNNs) have gained popularity for efficient processing of spatial and spectral information from RGB, Multispectral, and Hyperspectral data. These are widely used in the detection of crop disease, weeds, pest infestation, and nutrient deficiency, which represent the crucial aspects of agriculture.

This paper reviews CNN based agricultural applications from 2019 to 2025 with the focus lying on crop disease detection, weed segmentation, yield prediction and crop classification, and discuss challenges and future research directions. The papers is further divided into 6 sections. Section 2 covers an overview followed by section 3 including commonly used datasets, section 4 elaborates application of CNNs in agriculture, followed by section 5,6, and 7 discussing challenges, future research directions and conclusion.

2. Overview of Convolutional Neural Networks (CNNs)

2.1 Fundamentals

CNNs are named as a variant of Deep Learning models, which are applied to spatial or image data. These are based on the convolution operation in which filters are applied to the input to obtain the output, unlike the matrix multiplication used in conventional neural networks. These are multi-layered networks that are efficient in extracting spatial features from the data or visuals. It makes them perfect for any tasks related to the visual aspect, including object detection, anomaly detection, segmentation, & classification.

A CNN consists of Convolution Layers, Activation Function, Pooling Layers, and a Fully Connected Layer, each having its own significance. In CNN, Feature extraction is done through convolutional layers, which identify the underlying patterns through filters and generate a feature map. An activation function is used that introduces non-linearity to the extracted features, enabling the model to learn complex and non-linear data. The spatial dimension of the feature map is reduced by pooling layers while retaining the essential information. The fully connected layer combines the extracted output for classification or regression. The deeper layers learn complex features while the lower layers extract simple attributes. The main aim of CNNs is to minimize the loss for which the parameters are optimized by the backpropagation algorithm. They are robust in learning and provide a generalized representation of image features.

2.2 Evolution of CNN Architectures

The evolution of CNN has been rapidly transforming since its inception. The starting of CNN with digit and digit recognition task was performed by an early efficient model, LeNet-5, introduced by LeCun et al. [2]. A ground-breaking performance was given by AlexNet [3] in 2012 by winning the ImageNet Large Scale Visual Recognition Challenge (ILSVRC). Deep layers, usage of the ReLU activation function, and dropout regularization made the AlexNet the flagbearer of modern deep learning.

After that, numerous models came with various innovations and transformations in their architectures. A model named the Visual Geometry Group Network (VGGNet) was proposed by Simonyan & Zisserman (2014) [4], which used small convolution filters of size 3x3 that remained the same throughout the network. It focused on the key idea that deeper networks would learn important features. The inception module was introduced through GoogleNet [5], where multiple filter sizes were used in parallel and by combining their output, multi-scale features were extracted.

For the problem of vanishing gradient, ResNet [6] was introduced, which had a residual connection that liberated the training of networks to a very deep level and also simplified optimization to further improve feature propagation. DenseNet [7] was introduced, in which every layer received output from all the previous layers. It helped in the reusability of features by improving, reducing parameters, and improving gradient flow.

For smaller systems, including mobiles and edge devices, the concept of MobileNet [8] (small and portable) was proposed. It introduced convolutions that are separable according to depth, leading to reduced computation. It is widely used in real-time applications owing to its lightweight structure.

The idea of compound scaling was introduced through EfficientNet [9], which achieved better accuracy with fewer parameters. Due to its high accuracy and efficiency, it is considered good for Agricultural drones, UAVs, or the data collected through sensors.

The state-of-the-art technique in deep learning is Transformers [10], which is completely formed on the idea of self-attention without any convolution layers. It enabled parallel computation and calculated long-term dependencies using multi-head self-attention.

These architectural advances have made the CNNs robust, powerful, and efficient for real-world problems, including the agricultural field.

2.3 Why CNNs Fit Agricultural Problems

The agricultural domain deals with the analysis of heterogeneous, complex and variable data, which includes images captured through cameras, drones, and satellites. Images captured through various angles and media exhibit variations in texture, soil background, crop canopy density and lighting. As traditional machine learning faces problems in generalization due to its dependence on manually extracted features, deep learning efficiently gives improved performance due to its self-extracting automated feature learning capability from raw data [11].

They are capable of both detecting low-level features such as edges and textures, as well as higher-level features, including the structure of leaves, spots caused by disease, or clusters of weeds. It is helpful in identifying unhealthy and diseased plants, crops, and weed plants.

Their capability of handling RGB, multispectral, and hyperspectral data makes them suitable for agricultural data. These models can be helpful in monitoring crop health and growth over time as they are capable of handling temporal data. These architectures are robust to noise and environmental variations such as shadows, soil, and background clutter, and give stable and accurate predictions.

The manageability of the deployment of these CNNs on IoT is another major advantage of CNNs. These CNNs can simulate the human brain in identifying crop patterns and abnormalities with greater accuracy and efficiency than human eyes.

3. Data Sources and Image Modalities in Agricultural CNN studies

As discussed earlier, the agricultural data images can be obtained from different sources such as ground-based cameras, unmanned aerial vehicles (UAVs), integrated sensor systems and satellites. Different data source provides different aspects of information for the analysis of disease, weeds and crop yield.

Ground-based RGB Images are the most easily accessible data source in the agricultural domain. Captured through mobile phones or digital cameras, these are helpful in plant disease classification and phenotype-related work. To overcome the environmental noise and factors, pre-processing techniques such as segmentation, colour normalization, and contrast enhancement are used to improve data quality.

UAV imagery is widely used to collect high-resolution images of vast agricultural fields. These can help in crop health monitoring at different growth stages and extract the features signifying spatial variability, which cannot be captured through a ground-based camera. These images are essentially helpful in detecting plant stress, canopy-related information and chlorophyll content.

Satellite and Multispectral Imagery are responsible for capturing the information beyond the visible spectrum range, sensitive to chlorophyll content and vegetation stress. It often requires cloud masking and radiometric correction as pre-processing steps before analysis to remove the effect of environmental factors. There are various crop datasets publicly available on the internet, which can be used for classification and identification purposes for different crop conditions.

Table 1 shows the type of data captured along with the crop species and the purpose of the datasets. These datasets represent various imaging modalities and application domains ranging from disease detection to yield estimation.

Table 1: Commonly used datasets for CNN-based agricultural research (2019–2025).

Dataset Name	Data Type	Crop	Purpose
PlantVillage[12]	RGB leaf images	14 crop species (Apple, Cherry, Grape, Potato, Corn, Tomato, etc.)	Disease classification
DeepWeeds[13]	UAV & ground RGB images	8 weed species (Snake weed, chine apple, Rubber vine, etc.)	Weed detection
WeedMap[14]	UAV multispectral images	Weeds in crop fields	Weed segmentation
Sentinel-2[15]	Multispectral satellite imagery	Multiple crops vegetation indices	Large-scale field weed mapping
Landsat-8[16]	Multispectral satellite imagery	Broad agricultural coverage	Crop classification, vegetation analysis and weed infestation mapping.
Rice Leaf Disease Image Samples [17]	RGB leaf images	Rice (Bacterial Blight, Blast, Brown Spot and Tungro)	Disease detection
Disease Dataset of Wheat [18]	RGB images	Wheat (Healthy, Leaf Blight, Wheat	Disease detection

		Blast, Black Point and Fusarium Foot Rot)	

4. Application of CNNs in Agriculture

4.1 Crop Disease Detection

Crop disease detection is the most extensively explored application of CNNs in agriculture. Early and accurate identification of diseases enables timely treatment and prevents yield loss. CNN architectures have been trained on large datasets of leaf images, such as PlantVillage [11], to classify healthy and diseased crops under various conditions.

A comparative study between CNN and AlexNet was proposed [19] for disease detection through potato and mango leaf imagery. The hybrid dataset of 4004 images was formed by taking potato data from PlantVillage and mango data from the field. The results showed that the AlexNet performed better than the CNN architecture.

DeepCrop [20], a crop disease prediction system with a web application, was proposed on the Plant Village Dataset, which contained 10,000 images of various crops, including Bell Pepper, Tomato, and custom CNNs. VGG-16, VGG-19, and ResNet-50 were applied. ResNet-50 achieved the highest accuracy of 98.98% for all models, while CNN, VGG-16, and VGG-19 achieved 98.60%, 92.39%, and 96.15% respectively. EfficientNet Deep Learning Model [21] and its variants were used for the classification of 39 different classes of crops through the PlantVillage Dataset, constituting 55,448 images. Data augmentation was performed to manage class imbalance, which led the total image count to 61,486. Through the transfer learning approach, B4 and B5 outperformed all the other models with an accuracy of 99.97% and 99.91% respectively.

These CNN architectures are being widely used in disease detection through UAV imagery. MobileNet model was used to detect anthracnose disease of chilli leaf imagery captured through UAV [22], which achieved the accuracy of 99.6%.

A location-wise soft attention mechanism-based Crop disease recognition model was proposed by Chen et al. [23] along with a two-phase progressive training strategy, which achieved an accuracy of 99.71% on the standard dataset, while 99.13% in complex background conditions. These experiments show the variety of applications of CNN in the agricultural field in the domain of crop disease detection.

4.2 Weed Detection and Segmentation

Weed detection plays a significant role in the growth of the crops by enabling the detection at early stages and minimizing the use of weedicides by selective spraying. The widely used datasets for the studies that are open to all are DeepWeeds and WeedMap. Various CNN models are being used for their detection using ground-based cameras and UAV cameras.

YOLO architecture is widely used in the field of weed detection. YOLO-Sesame [24], a customised framework, was proposed to detect weeds. Integrated with attention mechanism, local importance pooling, and an adaptive spatial feature fusion module, it can be helpful in handling large differences in size and morphology of weeds. The proposed model outperformed all the models by achieving an accuracy of 96.16% and a detection speed of 36.8 FPS, making it suitable for real-world applications.

A study proposed a soybean-based novel weed detection framework [25] with a visible colour index and encoder-decoder instance segmentation architecture. Multi-scale semantic features extraction was improved through the ResNet101 and DSASPP module. It outperformed all the other models by 90.5% accuracy on real field imagery of weeds, which showed its potential in dense crop environments. Another vision-based weed detection system for soybean crop [26] used MobileNetV2, ResNet50, and three custom CNN models, which were later deployed on Raspberry Pi. With the accuracy of 97.7%, the proposed 5-layer custom CNN outperformed all the models, giving directions to improved performance through customisation.

A multiclass weed identification framework [27] was introduced using semantic segmentation in a study conducted in the brinjal plantation fields in Gorakhpur, India. A customised dataset with various growth stages of weeds was used for evaluating four deep learning models. U-Net-based Inception-ResNetV2 achieved the highest accuracy of 96.78%.

Silva et al. [28] used deep learning models to detect and segment weeds in soybean and bean crops with images captured by UAVs. The study compared the YOLOv8 variants (n, s, m, l), Mask R-CNN, and U-Net using a publicly available dataset of 3,021 annotated images. YOLOv8 produced the best results among all the other models by achieving mAP50 of 97%, precision of 99.7%, and recall of 99%. The findings show the strong potential of object detection and segmentation algorithms for effective weed identification in aerial imagery.

4.3 Yield Prediction and Estimation

A study proposed in the state of Missouri [29], USA, looked at how UAV-based data fusion can predict soybean yields using RGB, multispectral, and thermal imagery. Features like canopy spectral, structural, and thermal information were combined into various models, including PLSR, RFR, SVR, and Deep Neural Networks (DNNs). The intermediate-level fusion DNN (DNN-F2) achieved the highest accuracy, with $R^2 = 0.72$ and RMSE = 15.9%. It performed better than traditional regression methods. The results show that combining multimodal UAV data with DNN frameworks improves prediction accuracy, decreases spatial dependency, and offers a solid solution for high-throughput phenotyping and precise yield estimation.

More than 1,800 counties that produce soybeans were included in a U.S. study [30] that suggested employing deep learning models to enhance crop production forecast using MODIS satellite data from 2003 to 2018. Two hybrid architectures are being proposed: one that combines 3D-CNN with ConvLSTM-Attention, and the other that combines 2D-CNN, skip connections, and LSTM-Attention. CNN-LSTM (7.002), ConvLSTM (6.05), and DeepYield (6.003) were all surpassed by the top model, which had an MAE of 4.3. According to these findings, spatiotemporal deep networks have significant promise for improving agricultural planning decision-making and yield forecasting accuracy. A hybrid CNN–Bi-LSTM_CYP model [31] was proposed for sugarcane yield prediction in India, combining convolutional layers for spatial feature extraction with Bi-LSTM layers to capture long- and short-term temporal dependencies. Using historical data (1950–2019) from major sugarcane-producing states, the model achieved superior performance **(**RMSE = 4.05**,** MSE = 16.40**)** compared to Stacked-LSTM, ARIMA, GPR, and Holt-Winter models, demonstrating high accuracy and minimal relative error in yield estimation.

A deep learning framework was proposed by Neethu and Ravind [32] for mango crop yield prediction. The dataset comprised of 4000 mango fruit images from eight cultivars, along with data augmentation technique. The proposed FRNN pre-trained architecture model was compared with nine other ResNet-50 models and surpassed all of them by achieving an accuracy of 98.35% on the testing dataset of 800 images.

4.4 Crop Classification and Mapping

One of the essential components of precision agriculture is accurate crop classification and mapping that enables the identification of crop type, cultivation area approximation, and crop distribution monitoring. A drone-based study proposing deep ResNet architectures for crop type identification was done by Ajayi et al [33]. It used remotely sensed data images collected by the DJI Mavic. The maize dataset was trained on three different ResNet-50, ResNet-101, and ResNet-152 models. The ResNet-50 outperformed others by achieving an accuracy of 82%, while ResNet-101 and ResNet-152 achieved 77% and 74% accuracy, after two hours of initial training.

With the recent advancements in remote sensing and deep learning, particularly CNN, the area of automated crop type recognition has achieved significant growth. CNNs, along with custom changes in architecture, are being widely used in crop mapping. A new deep metric learning model based on attention was developed by Zheng et al. [34] for mapping of crops in complex agricultural landscapes. In this study, data were taken from multiple sources, including Sentinel-2, Sentinel-1, Landsat-8, and ground imagery for more comprehensive information. A 2-D CNN network model with CBAM attention was proposed to improve spatial feature extraction and cross-field generalization. It outperformed six models, including RF, SVM, XGBoost, ResNet18, and other methods. It achieved the overall accuracy of 93.99% and a kappa coefficient of 0.9253, outperforming the models, including RF, SVM, XGBoost, ResNet18, and DML, OHM methods.

Li et al. [35] proposed a model enhancing ResNet-50, integrated with ACmix self-attention and coordinate attention mechanisms for crop classification using UAV multispectral imagery. Multispectral image data of sunflower, corn, beet, and pepper were used to overcome the limitations of RGB images. The proposed model surpassed traditional and RGB-based approaches by achieving an accuracy of 97.81%. It shows that the ResNet architecture integrated with an attention mechanism can be potentially useful for crop mapping.

The hybrid model combining two or more CNN architectures is also gaining popularity. A hybrid deep learning model combining InceptionResNetV2 and U-Net was proposed for land use classification in the Kafkaji region for the period 2017–2024[36]. Multi-scale feature fusion and test-time augmentation were employed through the model. The model outperformed U-Net, ResU-Net, and Attention–U-Net models by achieving an accuracy of 98.21%, DSC (Dice similarity coefficient) of 88.96%, precision of 94.71%, and recall of 89.19%.

5. Challenges

The CNNs showed remarkable growth in agricultural problems. However, a few challenges still hinder their real-world application. Lack of a large, well-annotated, variable dataset is one of the major issues in agricultural research. Mostly CNNs are trained on small and region-specific datasets, which leads to a drop in generalizability. The large datasets are only available for some crops and for particular purposes. Obtaining agricultural data is labour-intensive and needs expert knowledge, making it expensive and time-consuming.

The images captured from various means, including drones, satellites, and other devices, exhibit variations in crop density, illumination, and growth stages, which lead to CNNs misinterpreting features. For real-world applications, the proposed system needs to be deployed on edge devices or low-power systems; for that purpose, Deep CNN architectures are difficult to use. Light models like MobileNet or ShuffleNet can help, but sometimes they trade off depth of feature extraction for speed, affecting the performance. Multimodal data integration is an effective but challenging way to improve the efficiency and quality of data because of its different spatial resolution, data volumes, and preprocessing requirements. The constraints for real-world deployment of models are also a challenge, which includes limited network connectivity, delays in data transmission, etc. All these constraints need to be taken care of to make a good agricultural application.

6. Future Work

The rapid evolution of DL, CV, and sensory technologies shows promising opportunities to overcome the existing limitations of CNN-based agricultural applications. Future work should address the challenges in the field of agricultural research. Large publicly available and well-annotated agricultural datasets should be created and integrated with multi-season and multi-regional crop imagery acquired through different devices. A combination of RGB, multispectral, hyperspectral, and LiDAR data can help in providing comprehensive insights into plant physiology and stress, surpassing the capability of any single data source. Optimization of lightweight CNNs should be focused on improving their efficacy on real-world applications. In recent studies, hybrid architectures have shown strong potential in capturing long-range dependencies and spectral correlations. Vision Transformers integrated with CNN architectures can deliver superior performance in crop classification, disease detection, and yield estimation. The upcoming research should prioritize climate-adaptive and sustainable AI frameworks capable of learning long-term and environment-related data.

7. Conclusion

The emergence of CNNs can be regarded as one of the transformative tools in smart agriculture, integrating automation, scalability, and precision across diverse applications in crop management. Their decision-making ability has been significantly enhanced by their capability to extract spatial and spectral patterns from multimodal image data.

All the CNN architectures, from classical to advanced, have shown exemplary performance in agricultural image analysis. Despite its performance, data scarcity, environmental variability, and real-world deployment constraints are some challenges faced by CNNs. Bridging these gaps requires large-scale multimodal agricultural datasets and optimized lightweight edge-based CNN models. Furthermore, integrating transformer architectures and hybrid CNN models can help in better generalization and spatiotemporal understanding. CNNs have already revolutionized the field of agriculture. Combined interdisciplinary efforts will help in advancing AI-driven smart farming.

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