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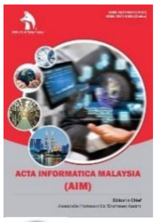

REVIEW ARTICLE

A REVIEW OF CONVOLUTIONAL NEURAL NETWORK IN EMERGING TRENDS AND OPPORTUNITIES IN PRECISION AGRICULTURE

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ABSTRACT

Agriculture has always been integral to life's existence as it directly depends on food production. Precision farming has emerged due to soft computing and information technology development trends. Food security has become a significant issue over the last few decades. Convolutional Neural Networks familiarize new sensations in precision agriculture; based on this, researchers have introduced effective planning, organized cultivation, smart irrigation, faster production, and cost reduction to address the continuously increasing demand for food supplies and to improve environmental as well as food sustainability. This paper contains a systematic review of various Convolutional Neural Network techniques in terms of the inescapable usefulness of modern agriculture to support food production for the ever-growing population, as well as the CNN adaptability in various agricultural sectors.

KEYWORDS

Precision Farming, Convolution Neural Network, ANN

1. INTRODUCTION

In this 21st century, many countries with monetary stability and GDP depend on agriculture. The impact of ever-growing world population demands consistent food supply and daily necessities. Food supply is a crucial challenge in this century to achieve the global development goal of sustainability. By 2050, the world population will be an estimated 9.7 billion (United Nations Department of Economic and Social Affairs, 2019. Managing food supply for this vast increasing population and fighting against poverty will be humans' significant issues in the coming decades. To feed this huge population and overcome food shortages, food production needs to be increased two to four times higher than other sectors by the next two decades (Agriculture Overview: Development News, Research, Data | World Bank, 2022).

Modernization in agriculture has never been a luxury for human beings, but it's necessary to tackle the coming problems. In 2016, it seemed that 65% of poor working-class adults manage their livelihood by directly involving agriculture and indirectly more than 80% are somehow involved with agriculture or agriculture related activities. Whereas, 4% of the global GDP (Gross Domestic Product) depends on agriculture; in some nations, the percentage is as high as a quarter of their entire GDP (Boretti and Rosa, 2019). But recently, it seems that traditional agricultural methods aren't sufficient enough to produce food for this massive population and maintain the economy; that's why food production has been significantly reduced compare to the ever-growing world population. Also, the traditional methods fail to tackle climate change, human error, and costly management.

Artificial Intelligence based precision farming can be a perfect solution to overcome from these crises (Lee et al., 2020). Precision farming is implemented based on observing, responding and measuring by enabling the automatization of technology (Lippi et al., 2021). In actuality, the phrase "precision farming" has been stamped to characterize agricultural approaches that have previously gone by different names, including "prescription farming," "site-specific" practices, "variable rate technology," etc. (Planter and Chew, 1998). In order to reduce agricultural risk, environmental impact, and manage agricultural activities in the cropping system for more effective and maximum production and the betterment of product quality, precision farming is the most desired term for this era (Mantovani et al., 2007).

Researchers proposed different Convolutional Neural Network techniques to ensure food security and modernize the age-old traditional farming techniques from the last few decades. CNN is a deep learning technique which produces modern approaches in various domains (Lecun et al., 2015; Wan et al., 2014). CNN is a part of machine learning and with many similarities with ANN or Artificial Neural Network but with a much deeper hierarchical representation of neural network (Schmidhuber, 2015). In order to overcome the real-world problem, CNN enables superior learning capabilities with multiple functionalities of solving various problems by using visual techniques of images segmentation, classification, disease detection and many more. As a result, the trained model can perform more accurately in terms of different circumstances.

Hundreds of research are being conducted to solve the problem in agricultural land (Boulent et al., 2019). The growing popularity of Convolutional Neural networks sets strong platform in terms of modernizing and increasing productivity (Alzubaidi et al., 2021). Till now, more than a hundred research has been conducted to solve different agricultural problems. The CNN problem-solving approaches are becoming more and more popular as CNN primarily focuses on image analysis techniques. Convolutional Neural networks' contribution is not limited to one or two domains; its diversity in solving problems helps researchers find the solution of multiple disciplines related to agriculture (Zhang et al., 2020). CNN provide solution to disease detection by

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analyzing the plant leaf; application of CNN is capable enough to count the number of fruits, CNN trained models are able to detect weed from an intense environment which might be impossible for a human (Kolli et al., 2021; Kavitha, 2021; Champ et al., 2020; IEEE Staff, 2018). The robustness of the CNN algorithm produces tremendous advantages in farming; now, researchers have found that CNN can be helpful from sowing seeds to harvesting crops (Sharma et al., 2020; Yamashita et al., 2018a).

Furthermore, CNN has made enormous contributions to protecting the environment from pesticides and pollution; as pesticide use is increasing rapidly, pesticide-related pollution is also increasing (Wei et al., 2021; Nam and Hung, 2018). Although people use pesticides to protect crops and increase food production, these substances are very harmful to the environment and negatively impact the soil, air, water, the overall biodiversity, and the living beings of the ecosystem (Popp et al., 2013). Birds, fish, and even human faces chronic effects of pesticides (Aktar et al., 2009). That's where CNN plays a significant role by producing the most accurate and reliable solution for pesticides and disease detection.

The aim of preparing this review is to explore the recent research on using the Convolutional Neural Network in precision farming. The article synthesizes the research that has been conducted using Convolutional Neural networks to modernize agricultural activities, increasing productivity, reducing the cost of cultivation and overall, a reliable and accurate solution for food safety. Furthermore, the article also focuses on evaluating the CNN techniques and approaches for a promising solution to various challenges related to agriculture, as well as the current limitation of the Convolutional Neural networks and future possibilities of CNN in terms of battling food safety for the coming generations.

2. Methodology

The review process in this paper is being involved five steps:

- Gathering all the related works based on precision farming using a convolutional neural network;
- Explicit investigation of those gathered works methods and approaches;
- Brief portrayal of the execution of those works;
- Discussion over advantages and disadvantages of Convolutional Neural Network for farming; Future possibilities.

For the first steps among those five, a search operation is performed to find the related works based on the desired topic. For collecting the papers ScienceDirect, Cambridge University press listed "The Journal of Agriculture Science", Springer, IEEE Xplore, Web of Science and Google Scholar database is being explored with some keyword like ['Convolutional Neural Network' | 'CNN'], ['CNN' | 'Precision farming'], ['Agriculture' | 'Deep Learning'], etc.

By using those keywords and exploring the journals, a total of 73 papers are being collected, and among them, 58 are being selected for the initial review. During choosing the potential works, a few criteria are followed, such as:

I. The research targets CNN or CNN-based techniques to solve agricultural problems or modernize the agriculture industry.
II. The researcher identifies the potential benefits of using CNN on particular issues.
III. The research shows a practical implementation of the proposed solution for the specific problems.
IV. The work shows acceptable accuracy of the solutions being presented.

Following are a few performance metrics that have been noted in corresponding research:

Classification Accuracy: For an equal number of samplings in each class, the accuracy is the division of the number of correct and total predictions (Hossin and Sulaiman, 2015).

Confusion Matrix: A confusion Matrix is a particular table configuration that makes it possible to see how an algorithm performs (Ting, 2017).

F1 Score: For the dataset accuracy measurement F1 score is being used (Hand et al., 2021).

Root mean square Error (RMSE) or MAE (Mean absolute Error): The difference between expected and observed values, expressed as a standard deviation (Chai and Draxler, 2014).

Also, Quality Measure (QM), LifeCLEF metric (LC), and Ratio of total fruits counted (RFC) is being evaluated.

The second step is an Explicit investigation of those gathered works methods and approaches; some research questions are being followed to carry out the most relatable connection between Convolutional Neural networks and precision farming. The research problem is being explored, and the source of data, percentage of accuracy and comparison of the different algorithm is being measured.

3. Literature Review

3.1 Principle of CNNs in Precision Farming

In the section of this review, the fundamental of CNN is discussed by referencing the researcher's work that was completed earlier. The relationship between precision farming and Convolutional Neural networks discovered by the researchers is being explored. The importance of CNN in modern agriculture and how the CNN models are being trained and implemented by the researchers are being discussed.

3.1.1 Convolutional Neural Network

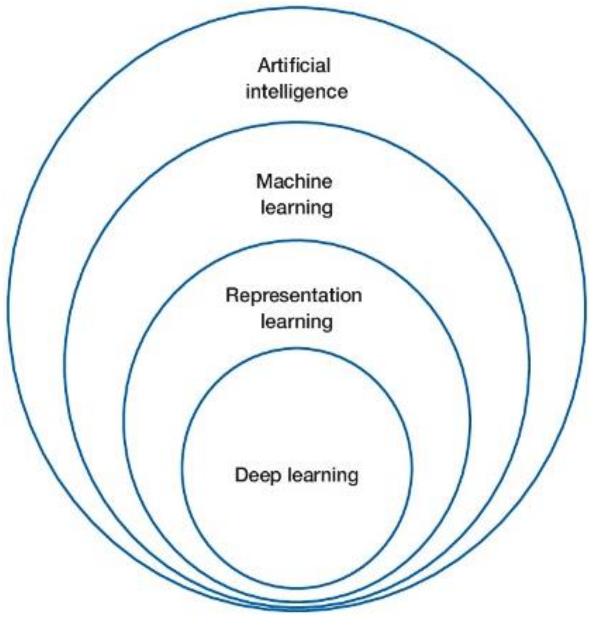

Figure 1: Venn diagram of AI and its subsets, here if AI is a set, then Machine learning is the subset of AI and Representation learning is the subset of Machine learning where as Deep learning is the subset of Representation learning and CNN is in DL (Popper et al., n.d.)

Convolutional Neural Network is a layer-based feed-forward Artificial neural network that falls under the deep learning category. Convolutional neural networks have evolved into one of the most prominent deep learning algorithms, playing a significant role in the evolution of deep learning due to its attributes of minimal input parameters, a straightforward architecture, and ease of adaptation (Lei and Peng, 2020). CNN has been successfully enforced in computer vision and image recognition applications (Schmidhuber, 2014). In recent years the use of Convolutional Neural Networks has been expanded from handwriting recognition techniques (Microsoft deployed) to target detection, gesture Identification and facial expression recognition (Yong-jie et al., 2021). SeNet, GoogleNet, VGGNet, AlexNet, and ImageNet are some recent networks developed by the Convolutional Neural Network (Krizhevsky et al., 2017; Szegedy et al., 2015; Simonyan and Zisserman, 2014; Alom et al., 2018). Convolutional Neural Network changes the traditional structure of the neural network. Traditionally, CNN was divided via a weight-sharing process into an input layer and the output layer, and in between, convolutional, pooling, and full connection layers are present. In CNN, the fully connection layer is replaced with the convolutional layer, leading to an error reduction of up to 10% more than in traditional CNN (Basha et al., 2020; Lei and Peng, 2020). The modern Convolutional Neural Network design has three different layers: the Convolutional layer, the Pooling layer, and the Fully connected layer.

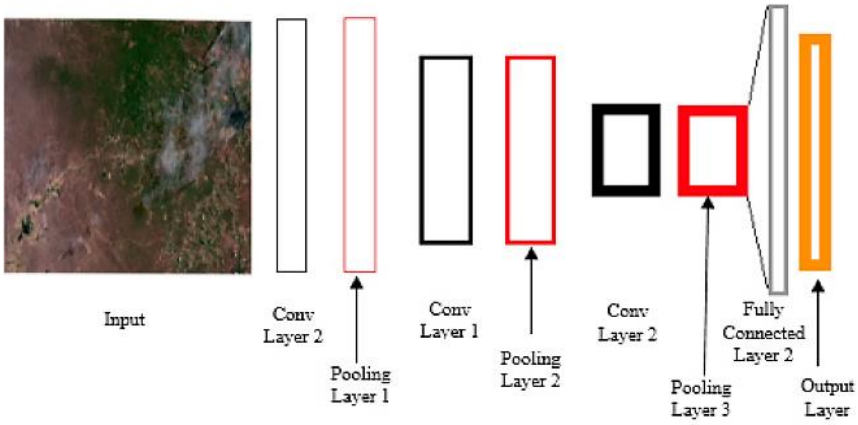

Figure 2: Convolutional Neural Network's architecture starts from the input image, then the convolution layer, then the pooling layer, and finally the fully connected layer (Cobeña et al., 2019).

The convolution layer is the fundamental structure obstruction of CNN. It carries the majority of the network's computational load. This layer computes the dot product of two matrices, one representing the kernel (a collection of parameters that can be learned) and the other the constrained area of the receptive field. Although the kernel is more profound than an image, it occupies less space. If a picture has three (RGB) channels, the kernel height and width will be fair, but the depth will span all three channels, the output from this layer is a feed-forwarded sub-sampling layer (Neforawati et al., 2019). Rather than that, Pooling layer is a type of down - sampling that reduces the dimensionality of a feature map. The rectified feature map is now processed by a pooling layer to produce a pooled feature map (Milioto et al., 2018). Then the fully connected layer, also known as the hidden layer in the CNN architecture, provides the final out for each of the layers consisting of the CNN architecture (Yamashita et al., 2018b). This layer is the combination of Non-linear like Sigmoid, TanH and ReLU and affine functions.

The diverse architecture of the Convolutional neural network can accept any form of data like audio, video, images, etc. A group researcher which helps the CNN to be more comprehensive in terms of working field and the availability of data for different purposes (Kamilaris et al., 2017). CNN does have the capacity to modify according to the dataset needs; for the different datasets, CNN operation and the methods of implementation can be changed accordingly. Furthermore, the researchers use various tools and experimental platforms to conduct the research; most choose TensorFlow, PyTorch, and MATLAB. Also, the Application Programming Interface or API on top of TensorFlow is being used for some of the research performed for real-time implementation; Pylearn2 has also been seen in some of the experiments. Different libraries and framework is also being introduced.

3.1.2 Convolutional Neural Network and Precision Agriculture

In recent studies, it has been seen that Convolutional Neural Network provides significant benefits to agricultural sectors. In this review article, the collected research paper has been selected based on different types of work on implementing CNN in agriculture. Five papers are being collected that focus on implementing the CNN application on Unmanned Aerial Vehicles (UAVs) for pesticides, seeds and detections. Thirteen papers are being found for the disease identification from a plant leaf. Seventeen papers are for plant recognitions based on different environments. At the same time, seven research work is being collected for weed plant and leaf identification. Fourteen research work is being collected for the classification and categorization of different plant and disease. And another five-research work for fruit counting using CNN.

Most of the research has been conducted in recent years, and that's what proves that the implementation of CNN in agriculture is a contemporary technique. The majority of the papers are based on image classification and detection like pest detection, fruit counting, prediction like yield and protein prediction, image recognition like image recognition for citrus disease etc. (Meen et al., 2020; Lippi et al., 2021; Peerlinck et al., 2019).

3.1.3 Training and testing the CNN models with Agricultural Datasets

By analysing the research work, it has been seen that most of the researchers focus on the large dataset while working with Convolutional Neural networks related to precision farming, one of the main reasons for using a large dataset while working with agricultural implementation as well as any other interpretation of CNN is to get the higher accuracy (Boulent et al., 2019). The large image dataset is used in most cases; some researchers have used publically available datasets like LifeCLEF, MalayaKew, UC Merced, and PlantVillage datasets (Champ et al., 2020; Lottes et al., 2018; Mhango et al., 2021; Neforawati et al., 2019; Peerlinck et al., 2019). At the same time, some of them collected data via different approaches, for example collect data for pest detection, crop health related data (Lippi et al., 2021; Zhang et al., 2020).

3.1.4 CNN Architectures and Framework Evolutions

As CNN provides a wide range of architectural variations, the researchers have used ImageNet, AlexNet, GoogleNet, ResNet, VGG and many other architectures. Some of the research with the large visual database are executed with ImageNet as it has been designed for large-scale visual database object recognition software. AlexNet was created in 2012 with more filters per layer and introduced stacked in Convolutional layers. GoogleNet, also known as Inception, has recently been used in lots of research because of its high accuracy or human-like performance. Then VGG or VGGNet is also being used because of its uniform architecture. The Residual Neural Network or ResNet also can be seen in different research. Moreover, some of the researchers used CNN with other combined approaches such as SVM (Support vector machine), linear regression, etc.

Table 1: Collected Research Article Percentages of Different CNN Architectures and Their Creators, The Year of Creation, and Some Examples of Referencing Research.

Developed Year and developer	CNN Architecture and number of research (used in this review)	Research (Some of them.)	Percentage of collected research
2006, Fei-Fei Li	ImageNet	(Lippi et al., 2021)	13.79% (8)
2012, Alex Krizhevsky, Geoffrey Hinton, Ilya Sutskever	AlexNet	(Francis and Deisy, 2019)	20.69% (12)
2014, Google	GoogleNet	(McCool et al., 2017)	15.52% (9)
2015, Kaiming He	ResNet	(Hu et al., 2020)	10.34% (6)
2014, Simonyan, Zisserman	VGG	(Paymode and Malode, 2022)	13.79% (8)
	Others	(Al-Amin et al., 2019; Li et al., 2020; Xie et al., 2019; L. Zhang et al., 2021)	25.86% (15)
Total			100% (58)

Numerous deep learning architectures are compatible with typical operating systems like Windows, macOS, and Linux-based systems and include bindings for different programming languages. Python is currently the most popular language in deep learning research, such as for CNN; python is one of the most used programming languages for implementing CNN. Convolutional Neural network models are trained and inferred using millions of simple computations, such as multiplications and additions. The researchers preferred GPU or graphics processing units over CPU or central processing units for CNN. Because GPUs are optimized to handle concurrent operations as it does have thousands of simple cores for different operations. Among the GPUs developed by different companies, NVIDIA is the most popular among data scientists and machine learning experts because it features the cuDNN or CUDA Deep Neural Network library, which is operated by common deep learning frameworks.

For example, the cuDNN library provides convolutional, pooling, and activation functions in the CNN operation. Furthermore, Google provides Google Colab, which gives the free online GPU without any setup. Moreover, CNN can be implemented in a different framework based on the datasets used, the dataset's size, and the technology's availability. PyTorch, TensorFlow, and Keras are some of the examples that have been used in most of the research related to Convolutional Neural Networks. Because of the features of visualization and data augmentation, the use of those frameworks is much more user-friendly compared to others.

3.1.5 Performance Evaluation of CNN

For the performance evaluation, different researchers utilized different performance metrics; some have used percentages of correct prediction based on training, testing and validation datasets, some of them focused on RMSE, some on F1 score and various other implementations. The majority of the research can be seen based on correct prediction or CA, which generally indicates the promising success of the performance of Convolutional Neural Network (Garg et al., 2021; Milioto et al., 2018). It has been seen that in statistical measurements, some of the research produces as high as 99% or more CA accuracy (Chen et al., 2014; S. H. Lee et al., 2015; Steen et al., 2016a). The performance of CNN in different datasets proves the capability of showing highly accurate results in the farming field. CNN's performance in disease detection, classification, and prediction is remarkable. As well as the performance comparison with different algorithms gives the superiority of CNN in agricultural-related problems. The robustness of CNN produces much more reliable and precise performance than others. Some of the research can be seen as a comparison with CNN and other techniques such as SVM, Linear Regression, Image processing, etc.

Table 2: Comparison Study with CNN and Other Techniques in Agricultural Problems

Reference	Research area	Problem Statement	Used models	Other techniques	Data Used	Accuracy
(Hassan et al., 2021)	Leaf Disease identification	Identification of disease from 14 different plant species and 38 diseases class.	InceptionV3	Transfer learning with InceptionResNetV2	Plant Village	98.42% (2-6% better performing)
(Sethy et al., 2020)	Leaf Disease identification	Rice Leaf disease identification	AlexNet	SVM (Support Vector Machine)	500 collected (authors) images	98.38% (2% better performing than SVM)
(Prashar et al., 2019)	Leaf Disease recognition	Cotton Leaf disease recognition in America	ResNet50	Vector Machine (SVM), Neural Network with Multi-layer Perceptrons and K-nearest Neighbor (KNN)	Collected cotton images (authors)	96% (CNN shows better accuracy than others)
(Ahil et al., 2021)	Leaf Disease Classification	Apple and Grape Leaf Disease Classification	AlexNet	Multi-layer Perceptrons	3171 images of apple leaf disease and 4062 images of grape's (authors)	95.66% (The MLP shows only 82% overall accuracy)
(Pan et al., 2020)	Land cover classification	Identifying land cover from 13 different classes and nine Pavia classes	Researcher's own framework	RBF-SVM	KSC collected mixed vegetation data	98% (1.50% more accurate)
(Rahnemoonfar and Sheppard, 2017)	Fruit counting	Number of tomatoes in an image	Inception-ResNet	ABT (Area-based technique)	24000 collected (authors) images	93% (RFC) and 2.52 (RMSE) which shows better accuracy than ABT (Area-based technique)
(Xinshao and Cheng, 2016)	Weeds identification	Classification of weeds from 91 types of weed seeds	AlexNet and VGG	PCABet and LMC	3980 collected (authors) images	90.96% (Better result than PCANet)
(Steen et al., 2016b)	Obstacle detection	Identifying obstacles in row crops and grass	AlexNet	Not mentioned	437 collected (authors) images	99.9% in row crops and 90.8% for grass
(Kuwata and Shibasaki, 2015)	Estimation of crop yield	USA county level maze yield estimation	Researcher's own framework	SVM	2001-2010 maize yield data in Illinois	RMSE = 6.298 (Better than SVM's RMSE value)

Table 2 shows some of the research comparing the performance of Convolutional Neural Network and other techniques; many other researchers have tried to implement CNN in different circumstances, and the performance of CNN can be seen as promising compared to other methods.

4. Discussion

Recent research shows that Convolutional Neural Network produces more accurate and reliable answers than any other algorithm of its kind. The accuracy and performance of the algorithm created a strong belief among the industries and research. Deep learning-related agricultural problems are more likely to be solved using CNN because of its variety of use and promising results. In this review analysis, it has been proven that CNN provides superior performance in terms of precision and accuracy. Although the current study is small, satisfactory precision has been observed in most agricultural challenges, especially when compared to other techniques used to solve the same problem like SVM, ABT, etc., which illustrates the successful application of CNN in various agricultural domains. Especially on fruit counting, plant recognition, leaf disease identification, weeds detection, etc.

Among the research analyzed in this review article, it has been seen that the researchers use various ways of implementing CNN for the particular dataset and based on the dataset either collected by the researchers or the public, the researchers are able to modify the CNN layers easily, which is highly impactful in terms of user-friendly behaviors of CNN application. Although in some research, it has been seen that CNN is associated with other techniques such as image processing, computer vision, etc., the performance remains satisfactory. Among the research, it has been seen that for comparing the performance, it is crucial to stick to the same experimental conditions in terms of precision. CNN provides a simple and highly accurate system compared to other traditional techniques; CNN is capable enough to automatically enable the essential features while training the models, giving superior advantages to CNN compared to others. On the other hand, the main disadvantage of CNN is the lengthy training process, especially when the dataset is large. But the modern architecture of CNN reduces the training times by using different hardware configurations.

The convolutional neural network has many possibilities in agricultural domains, but the research has not been widely spread. By 2022, it has been seen that CNN resembles only 15 agricultural-related problems. Still, there are lots of other agriculture-related issues that can be evaluated by using CNN, such as the greenhouse monitoring system, pesticides identification in the agricultural field after use, irrigation system assessments, plant water stress identification, food defects detection (Already some research is being conducted but still the accuracy and dataset not that much reliable), crop phenology, seed classifications, etc. Furthermore, CNN can also be a good solution for aerial imagery as drones are becoming increasingly popular; it can significantly impact fast food production and cost reduction in the agriculture industry.

5. Conclusion

In this study, a survey has been conducted among the research in the Convolutional Neural Network-based agriculture domain. After analyzing the research, it is seen that researchers focus on different techniques of CNN to solve various problems. This paper shows the overall CNN reliability in precision agriculture from the brief investigation of their study, focus area, technical aspects, used models, data sources, and performance measurement techniques. In the context of precision, the study describes convolutional neural networks to other available methods using various measures of performance. The results show that Convolutional Neural Network achieved high accuracy in the vast majority of cases where it was used, outperforming numerous prevalent image-processing methodologies and other techniques of detecting leaf disease, classifying plants, fruit counting, etc. It has been seen that CNN provides high effectiveness in highly complex problems based on agricultural domains.

In the future, researchers intend to apply Convolutional Neural networks in various areas of agriculture where it has not been used till now. Some of the possibilities for implementing CNN are discussed in this article's discussion section. The main focus of this study was to evaluate the application of convolutional neural networks from the general perspective of being used in agricultural domains to ensure food safety for the coming generations. The overall evaluation shows CNN's advantages and numerous possibilities in the agriculture sector. CNN's potential advantages are reassuring for its's continuous use in intelligent, more sustainable farming and more stable food production.

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