Application of Deep Learning-based Techniques for Precision Agriculture

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Abstract: Agriculture is a vital industry that adds significantly to the global economy. Researchers are currently starting to investigate the prospect of integrating deep learning techniques and machine learning into agriculture, due to recent developments in technologies for deep learning. The paper examines several deep neural network designs and machine learning techniques used in agriculture, including irrigation, weeding, pattern recognition, and crop disease identification. The primary goal of this study is to determine multiple uses of deep learning in agriculture and to summarise existing state-of-the-art approaches. The review addresses the particular deep learning algorithms utilized, the sources of data used, study achievement, the equipment used, and the possibility for immediate application as well as integration with autonomous mechanical platforms. According to the results of the chapter, the use of deep learning research outperforms typical machine learning techniques in terms of reliability. In general, the study indicates the enormous potential of deep learning and machine learning in agriculture and the necessity for additional study in this field. It may be able to improve agricultural efficiency, decrease waste, and raise the yields of crops by utilizing the potential of these methods, ultimately enhancing the worldwide availability of food.

Keywords: Precision Agriculture, Image Processing, Object Detection, Data Fusion

I. Intoduction: As the world's population grows, so does the demand for food and agricultural products. Meeting this need necessitates an increase in agricultural production that does not jeopardize the nutritional value of food or hurt the natural world. As a result, image collection and interpretation are critical study areas in this sector. Many characteristics of agricultural fields and plant parts can be examined by analyzing photographs of agricultural areas and parts of plants. Without the use of dangerous pesticides, automatic image analysis of the field can assist in examining soil quality and taking effective actions to improve the fertility of the soil and compatibility for crop production. Furthermore, diagnosing diseases in plants using image analysis can assist in taking critical actions to improve crop quality and reduce the health risks connected with unhealthy plants. Pests are a big threat to crops grown in agriculture, and recognizing them through image analysis can allow for a prompt intervention to safeguard crops and people. Image capturing and processing is an important tool in meeting the increasing need for food and agricultural goods. It has the potential to improve productivity in agriculture, reduce environmental impact, and improve the safety and purity of food. Remote sensing, the Internet of Things (IoT), cloud computing, and big data analysis are some of the developing information and communication technology (ICT) fields that might help us comprehend agricultural ecosystems. Remote sensing, which uses aircraft, satellites, and drones to give accurate and non-invasive images of the agricultural environment, may provide extensive and non-invasive views of the agricultural environment. This approach may cover broad geographical regions, especially difficult-to-reach locations. In contrast, the Internet of Things (IoT) employs modern technology for sensors to collect data on numerous aspects of the field. Cloud computing is used to gather, store, pre-process, and model massive volumes of information from many sources. These technologies offer various advantages and can be very useful in agricultural assistance. Producers as well as scientists may use these tools to make educated decisions regarding crop management, soil health, and other crucial elements affecting agricultural ecosystems. Big data analytics and the use of cloud computing are becoming more prevalent for analyzing massive volumes of data stored in the cloud as technology advances. This is especially true for data and images collected using remote sensing and the Internet of Things (IoT). Image analysis has shown to be a significant tool in the agricultural sector for solving several issues since it provides a full perspective of agricultural areas. As a result, researchers are focusing more on creating smart scanning algorithms that can effectively recognize and categorize images, as well as detect any anomalies that may exist in various uses in agriculture. In general, combining big data processing and cloud computing with image analysis has the potential to greatly boost agricultural output. Machine learning approaches paired with high-performance computers enable the effective analysis of enormous volumes of visual data. Traditional machine learning algorithms, which entailed manual feature extraction, were utilized in the early phases of computer vision. A Deformable Part-Based Model (DPM), Histogram of Oriented Gradient (HOG), Scale-Invariant Feature Transformation (SIFT), Speeded Up Robust Features (SURF), and Haar-like features were among the most popular. To categorize each pixel in a picture, these attributes were integrated using classifiers such as Support Vector Machine (SVM). While classic methods are very simple and have seen major advancements, they are typically better suited for low and medium-density pictures, and their performance may need to be tweaked to accommodate specific scenarios. Traditional methods for dealing with dense scenes either ignore the difficulties faced by these circumstances or apply naive heuristic approaches based on size and form, which are ineffective in natural contexts with considerable occlusion and scale fluctuations. As a result, typical machine learning algorithms are unsuitable for dealing with dense pictures. Deep learning approaches, on the other hand, have been proven to be more successful than manually produced features in many applications, and they address various challenges inherent in the dense processing of images. Deep learning is a sort of machine learning in which artificial neural networks with many hidden layers and large quantities of data are trained to pick up data models. Deep neural networks' success in a variety of domains, including computer vision, natural language processing, bioinformatics, automatic control, machine translation, and autonomous driving, is due to their unique structure, which can acquire high-level characteristics through the combination of lower-level features acquired through input data. Deep learning learns complex feature representations from raw data using multiple levels of concepts, and various layers of characteristics could be related to various objectives. To summarise, deep learning is a sophisticated technique that uses deep network architecture to learn feature representations from data dynamically. Deep learning is a technique that focuses on building complex algorithms with multiple layers of detail to effectively and quickly train and collect information. It has been demonstrated to be very versatile and capable of tackling a broad range of complicated issues, particularly those involving the analysis of images and videos, such as traffic patterns and tiny creatures. Because of factors like skill, available resources, and specialized application demands, DL's success in one sector may frequently inspire advancements in other ones. For example, the application of DL in This transformation has changed agriculture chores into agriculture-vision, which utilizes computer vision techniques to tackle agricultural problems. Several evaluations have examined the application of deep learning in agriculture and computer vision, emphasizing its ability to advance both sectors. analyzing dense scenes has spread into the agriculture industry, where higher-density imagery has grown in significance. Deep learning (DL) literature in agriculture has generally focused on giving a thorough review of DL methods employed in the industry or analyzing the most recent research on DL technologies in specific agricultural domains. However, nothing has been said about how DL works in dense agricultural landscapes with a huge number of items. While several research summarised the use of DL for fruit recognition and yield calculation, they ignored other agricultural applications involving a high density of objects. As a result, the purpose of the current review is to address this vacuum in the literature by investigating the uses and methodologies of DL in agriculture. Deep learning (DL) literature in agriculture has generally focused on giving a thorough review of DL methods employed in the industry or analyzing the most recent research on DL technologies in specific agricultural domains. 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The fourth segment delves into the uses of DL in agriculture. Finally, part five reveals the study's findings. The primary goal of this study is to give agricultural researchers a fast and precise overview of the DL approaches associated with their research problems.

Literature review: In paper [5] suggested an Agri-IoT framework for smart farming real-time reasoning over different sensor data streams. It combines cross-domain data streams to provide interoperability across sensors, services, processes, farmers, and other stakeholders. In paper [6] examined deep learning applications in precision agriculture, emphasizing the technology's significant potential for real-time applications, tools, and datasets. The purpose of this study is to explain the importance of smart farming in environmentally friendly farming and to provide a unique technique to forecast fruit yield using quick and reliable deep neural networks. Researchers reviewed the usefulness of deep learning approaches for identifying remote sensing images in agriculture-related uses in a study stated in reference [7]. Using 60 training photos, the performance of two models, FCN8s and U-net, was compared. The findings indicated that FCN8s detected weeds with an accuracy of 75.1%, which was higher than U-net's accuracy of 66.72%. However, when it came to detecting crops, U-net beat FCN8s with an accuracy of 60.48% vs 47.86% for FCN8s. As a result, the study stated that the model should be based on the specific job and should be based on the specific job and kind of item detected in remote sensing pictures. To put it another way, [8] offered an in-depth examination of a variety of essential metrics in use cases, yielding important conclusions such as energy consumption autonomy from design and batch size, the exaggerated connection between precision and deduction time, and a trustworthy relationship that exists between the number of operations and inference time. Furthermore, the study found that the greatest attainable accuracy and model complexity is limited by power constraints. They provide a unique technique to yield determination based on a simulated deep convolutional neural network. By properly calculating the number of fruits, flowers, and trees in their orchards, farmers may make educated judgments about cultivation practices, plant disease control, and labor force allocation. The proposed method counts the number of fruits on a coffee branch by using digital images of a single side of the branch and its developing fruits, and it utilizes the Faster R-CNN object recognition framework for fruit detection in orchards including other crops such as mangoes, almonds, and apples. A CNN architecture is also proposed for distinguishing plant kinds from images gathered by intelligent agriculture stations. Using affordable technology and deep learning, this model can deliver direct advising services to farmers, even those with tiny agricultural plots. To build a recommendation model, the suggested method employs a classification algorithm and classifier optimization. The MDNN technique is proposed to increase the precision of predictions by including L2 regularization for weight matrix computations and PSO for modifying MDNN the hyperparameters and network architecture [9]. A study found that robots and Deep Learning methods may be used to harvest date fruits in orchards. According to the findings, two pre-trained Convolutional Neural Network techniques, Alex Net and VGG-16, can be used for this purpose. To put it another way, the paper recommends using robotics and Deep Learning techniques with pre-trained CNN models like AlexNet and VGG-16 to automate date fruit harvesting in orchards[10]. In this chapter, we explored deep neural network applications in agriculture and classified them into five categories: diagnosing plant illnesses, identifying weeds, identifying plants, counting fruit, and categorizing crop kinds.

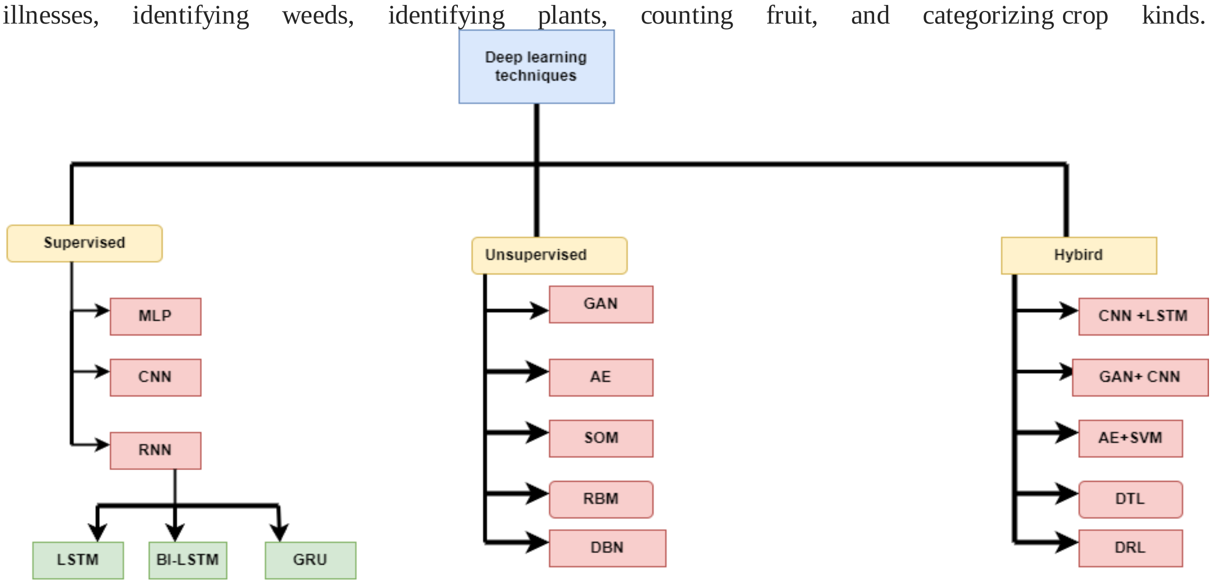

Figure 1. Classification of deep learning techniques.

3 Application of Deep Learning in Plant domain

3.1 Crop Prediction: The prediction of crop yields is an important part of successful agriculture, and various researches has concentrated on increasing yield prediction using deep learning (DL) approaches. One such research recommended using an RNN DL method called DRQN to calculate agricultural yield, with the objective of lowering mistakes and boosting precision for greater food production[11] Another study used the DL approach to create a model for forecasting wheat and barley crop yield based on NDVI and RGB data collected by UAVs[12]. Similarly, utilizing CNNs and RNNs, DL architecture has been proposed to estimate yield based on environmental data, yielding encouraging results for maize and soybean crops. Other research integrated multiple DL architectures, such as CNN, LSTM, and 3D-CNN, to accurately forecast crop production, while another presented a DNN-based model for crop selection and yield prediction. Overall, deep learning approaches have a lot of potential for improving agricultural output predictions and increasing food production.

3.2 Soil management: Deep learning (DL) is a strong method for predicting and recognising various soil qualities that might help with agricultural planning and management. To reliably predict parameters like as soil moisture, temperature, and organic carbon content, DL models may be trained using data from sensors, remote sensing technologies, and other sources. Another study assessed soil dryness using meteorological data to assist farmers in making educated irrigation and water management decisions [13]. Another study used a collection of soil samples and accompanying measurements to test four regression models for predicting soil organic carbon, moisture content, and total nitrogen [14]. Finally, the most recent work [15] offered a unique approach for assessing soil moisture using force sensors on a no-till chisel opener [16]. Based on the force sensor data, the study most likely utilized an ANN model to forecast soil moisture. Overall, machine learning can be a useful tool in soil management and agriculture. ML models can forecast soil qualities accurately, allowing farmers and land managers to make intelligent choices regarding irrigation, fertilization, and other agricultural practices.

3.3 Disease Detection: Deep learning is becoming more prevalent in precision farming to identify illnesses in crops such as tomatoes, wheat, and grapevines. For example, a deep convolutional neural network (CNN) was trained to identify late blight sickness in tomato plants using leaf pictures, obtaining a disease categorization accuracy of 99.4% [13]. A deep learning model was employed in wheat crops to identify and categorize different forms of leaf diseases, with an overall accuracy of 97.78% [14]. Deep learning algorithms have also been applied in grapevines to identify diseases such as downy mildew, powdery mildew, and black rot with excellent accuracy [15].Deep learning applications in agricultural disease detection represent a viable strategy for early disease diagnosis, enabling timely and effective management of crop diseases.

3.4Agriculture Robitics: Agricultural robotics is the application of robots to farm tasks such as tracking crops, sprinkling, and gathering[16]. Deep learning techniques, such as convolutional neural networks (CNNs), have been used to teach these robots to recognize crops, insects, and weeds and to decide what actions to take based on this knowledge [17].The application of CNNs to identify and categorize weeds in crops is one example of deep learning in agricultural robotics. Targeting focusing only on the regions that require medication can assist decrease the usage of pesticides while increasing crop output. Another use of deep learning algorithms is the training of robots to recognize and divide agricultural produce for collecting [18].

3.5 Plant Breeding: Deep learning has demonstrated encouraging outcomes in plant breeding by assisting in the prediction of yield possibilities for novel crop types. A deep-learning algorithm was built in a study by [19] to forecast the yield of soybean cultivars based on their genetic composition. The algorithm was trained on vast datasets of soybean genetic data and yield data, and it predicted the productivity of new soybean varieties with outstanding precision. Similarly, the paper [20] employed deep-learning models to forecast the yield of wheat and maize varieties based on genetic data. The algorithms outperformed standard mathematical methods in properly forecasting the yield of novel kinds. These results show that deep learning has the potential to improve the productivity and reliability of plant breeding programs by allowing for the quick and precise estimation of the yield potential of novel varieties of crops based on their genetic profile.

3.6 Image-Based Plant Identification: Deep learning methods, notably CNNs, have shown tremendous promise for accurately and efficiently identifying plant species from images in plant recognition algorithms. These devices have been utilized for a variety of purposes, such as agricultural monitoring, plant disease detection, and environmental studies. The PlantCLEF rivalry, requiring competitors to design algorithms that can identify plant species from images, is one example of the effective utilization of CNN-based detection of plants. On a dataset of over 10,000 plant species, the most accurate algorithm in the 2019 contest attained a success rate of 90.21%. Other research has yielded encouraging results for CNN-based plant identification systems. Joly et al[21], for example, built a system that obtained an accuracy of 97.31% on a dataset of 10,000 plant species. Similarly, Singh et al.[22]obtained 96.45% accuracy on a dataset of 100 plant species. Overall, these findings show that CNN-based plant identification systems can accurately and effectively classify plant species from images, with uses in a variety of agricultural science and agribusiness domains.

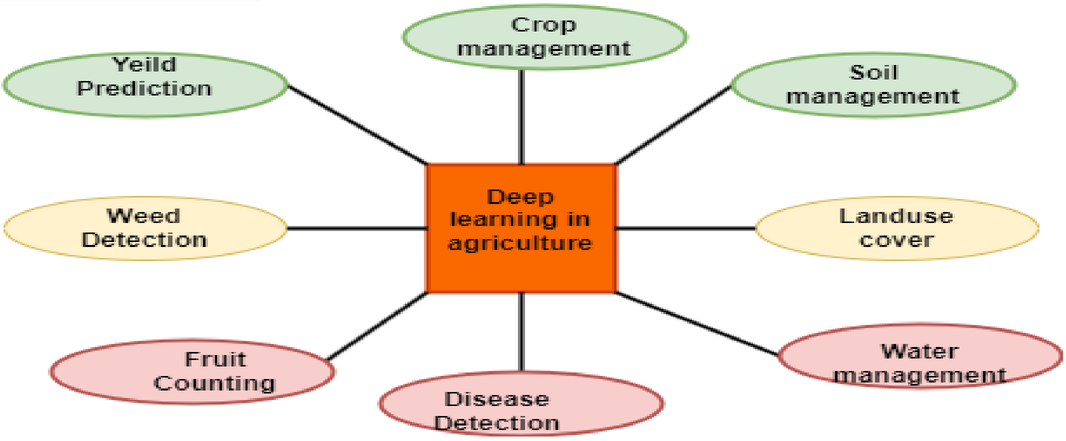

Figure.2. Deep learning in Agriculture domain

4 Application of deep learning in the Animal domain

Deep learning, a subset of machine learning, has found numerous applications in the animal domain.

4.1Object recognition: Deep learning object identification has already proved to be successful in recognizing and distinguishing between animals in images and movies. Deep learning techniques, such as convolutional neural networks (CNNs), have been used to recognize animal characteristics such as lines, areas, or face traits. This technique is very important in the preservation of animals and study because it allows researchers to monitor and track species that are threatened. Olafsson et al. [23], for example, utilized deep learning to recognize particular humpback whales in photographs, which might aid in the study of their routes of migration and behavior.

4.2 Behaivour Analysis: Behavior analysis is an important part of the animal study because it helps scientists comprehend the intricate interpersonal and environmental mechanisms that regulate the number of animals. Deep learning is a strong technique that has been created to help with this study. It employs artificial neural networks to simulate and analyze patterns in enormous data sets.Deep learning algorithms may be taught to recognize and categorize various animal behaviors based on visual cues or other sensory inputs, such as enmity, a relationship, and scavenging. They may also be applied to follow the movements of animals and forecast potential behaviors based on historical data. In paper[24] utilized deep learning to analyze the actions of fruit flies, discovering particular types of behavior throughout courting that weren't previously recognized using standard approaches. Another research employed deep learning to follow the motion of dolphins, showing previous unseen patterns of social interaction as well as communication [25].Overall, deep learning algorithms offer a strong and adaptable tool for studying behavioral data from animals, and they are expected to play a growing role in future research on biodiversity and habitat.

4.3 Disease Detection: Deep learning algorithms have demonstrated encouraging outcomes in animal illness diagnosis, notably in animal radiography. These computer algorithms may analyse medical pictures like as X-rays and MRI scans to detect patterns or anomalies that may signal the development of illnesses such as cancer or bone fractures.Several research has shown that deep learning algorithms are effective in veterinary care[25]. Research published in the Journal of Veterinary Internal Medicine, for example, demonstrated that a deep learning system could reliably detect elbow dysplasia in dogs using elbow radiographs. Another research published in the Journal of the American Veterinary Medical Association discovered that utilising radiographs, a deep learning system could reliably detect cranial cruciate ligament damage in dogs[26]. Overall, deep learning has demonstrated remarkable promise in the animal realm and has the ability to significantly assist animal studies as well as conservation activities.

4.5 Land Cover: Land cover identification is an important topic in remote sensing since it seeks to detect and map various types of land cover and land use in a given region. Deep learning approaches such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks, and Generative Adversarial Networks (GANs), (RNNs) have been used successfully to classify land cover.Deep learning algorithms for land cover categorization based on Sentinel-2 time series data have shown substantial growth in recent years. Sentinel-2 is a satellite system that produces high-resolution multi-spectrum imagery that may be used to map various land use and land cover types. The publication "Land Use and Land Cover Classification Using Deep Learning Techniques on Sentinel-2 Imagery" by Gao et al.[27] provides one example of a deep learning strategy for land cover classification using Sentinel-2 data. Using Sentinel-2 time series data, the authors suggested a deep learning architecture based on a mix of CNNs and RNNs for land cover categorization. The suggested strategy outperformed standard machine-learning algorithms in terms of classification accuracy. Another example may be found in Liu et al.'s [28] a Novel Deep Learning-Based Approach for Land Use and Land Cover Classification of Sentinel-2 Imagery. The authors suggested a novel deep learning-based technique for land use and land cover. Overall, deep learning methods have shown great potential for land cover classification using remote sensing data, and are likely to play an increasingly important role in agriculture and environmental monitoring applications in the future.

6.Applications of deep learning in other domains: Deep learning has been applied to a wide range of domains beyond agriculture, including computer vision, natural language processing, speech recognition, healthcare, finance, and more. Deep learning has evolved into a potent technique in computer vision for image and video analysis[29]. Faster R-CNN and YOLO object detection algorithms have been employed in a variety of uses, notably self-driving vehicles, CCTV cameras, and imaging for medical purposes[30]. Image segmentation technologies such as U-Net and Mask R-CNN have been used for recognizing and distinguishing certain regions inside an image in medical image analysis and autonomous driving purposes[31]. Convolutional Neural Networks (CNNs) categorised pictures has enabled accurate detection of objects and scenes in images, while recognition systems such as Google's InceptionV3 and ResNet models have been employed in image searching and content-driven image retrieval[32]. Deep learning algorithms have considerably increased the precision as well as the effectiveness of recognition of face systems, which are a vital component of computer vision.[33].Safety and monitoring, as well as identification and access control, are all applications for these systems. Deep learning techniques such as machine translation using neural networks have been used to create captions that are contextually and semantically appropriate in imagine captioned[35].

Table 1 Summary of BP, CNN, RNN, and GAN

Type	**References**	**Variants**	**Network structure**	**Applications**
BP	Rumelhart[37]	GRNN	Input layer Output layer Hidden layer	Data fitting Pattern recognition Classification
CNN	Krizhevsky[38]	AlexNet, VggNet	Input layer Convolution layer Pooling layer Full connected layer	Image processing Speech signal Natural Language Processing
RNN	Sundermeyer[36]	LSTM	Input layer Hidden layer Output layer	Time series analysis Emotion analysis Natural Language Processing
GAN	Goodfellow[34]	DCGAN	Discrimination model Generation model	Image generation Video generation

7.Conclusion: The author has examined the development of deep neural-based work attempts in the agricultural area in this research. Analysed the studies on deep learning systems and the technical nuances of their execution. Each effort was contrasted with current efficiency approaches. Deep learning has been shown to produce far superior outcomes than previous illustration-processing approaches. Deep learning will also benefit from developments in technology for computers. In a practical sense, neural networks are one of the greatest answers to a few agricultural challenges. Without a doubt, the application of ANN to precision agriculture plays a critical part in the prospective appraisal of agricultural precision farming as a realistic approach of meeting the world's dietary demands. However, additional research on the effects of ANN on agricultural problems is needed to assure the viability of future food needs, farmer welfare, and economic expansion. The purpose of this work is to inspire additional researchers to investigate deep learning for agricultural concerns such as identification, categorization, or forecasting, relevant image analysis, and statistical analysis, or more general computer vision tasks.

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