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Application of Robotics, Artificial Intelligence and Deep Learning in Modern Agriculture Technology: A Review

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Review Article

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ABSTRACT

In order to determine their potential impact in the field of agriculture, the proposed work aims to review the various artificial intelligence (AI) techniques, with a focus on expert systems, robots designed specifically for agriculture, and sensors technology for data collection and transmission. These techniques include fuzzy logic (FL), artificial neural network (ANN), genetic algorithm (GA), particle swarm optimisation (PSO), artificial potential field (APF), simulated annealing (SA), deep learning. The application of AI techniques and robots in cultivation, monitoring, and harvesting is not highlighted in any literature, making it difficult to compare each one simultaneously based on popularity and usefulness while also understanding how each contributes to the agricultural industry. With knowledge of the extent of AI engaged and the robots used, this paper compares three crucial agricultural phases: cultivation, monitoring, and harvesting. The current study offers a comprehensive analysis of over 200 publications that cover the use of automation in agriculture as of 1960 and 2021. It draws attention to the unmet research needs for developing intelligent, self-governing agricultural systems. The frequency of various AI, robotics and deep learning techniques for particular applications in the agriculture industry round out the article.

Keywords: precision agriculture; smart farming; deep learning; CNN; RNN; SVM.

1. INTRODUCTION

The phrase "smart agriculture" describes the widespread use of artificial intelligence (AI), which includes deep learning, big data, the internet of things (IoT), and numerous other digital technologies [1]. Food production needs to rise significantly in order to keep up with the global population growth [2–3]. It is difficult for current technologies to guarantee the steady and reliable supply and quality of food on a worldwide scale without negatively impacting natural ecosystems. A novel, state-of-the-art technique for data analysis and picture processing is deep learning. It has been effective in a number of industries, including agriculture, and has produced encouraging results and tremendous potential [4].

Deep learning-based agricultural applications, or "smart agriculture," have been incredibly successful in recent years. These systems deal with managing various agricultural tasks by using data gathered from various sources. The ability of various AI-based intelligent systems to capture and analyse data and help farmers make the best decisions at the right moment varies. Installed IoT nodes (sensors) can record data, which can then be processed using any deep learning technique and used by actuators to enforce judgements on operational regions. The AI system is enhanced by other cutting-edge technologies to monitor and manage agriculture in real-time, including automated computer control, global satellite positioning, and remote sensing geographic information.

Additionally, by scheduling the best use of resources like water, fertiliser, and pesticides, AI-based smart agriculture may maximise output while reducing pollution and production costs. Plant illnesses can be detected and prevented early with the use of AI, which means that less treatments would be needed to stop their spread, which would drastically lower environmental contamination [5]. For plants to be healthy, grow, and yield, agronomic inputs like water, nutrients, and fertilisers must be continuously available [6]. Both biotic and abiotic stress may result from the lack of any of these sources. Only artificial intelligence (AI) can make the decision to apply a certain resource in the correct amount at the right time while taking future projections and the current state of affairs into account. This study looked at deep learning and artificial intelligence's application in agriculture as well as its future prospects. We also looked into the agricultural metrics that IoTs tracked and fed the deep learning algorithms with them for additional analysis.

This research uses deep learning techniques to offer a survey of recently created systems in smart agriculture. The significance of deep learning applications and the creative solutions that deep learning approaches can offer in resolving agricultural issues are what inspired the preparation of this survey. In recent publications, the use of deep learning techniques to smart agriculture has gained prominence and is still in its early stages of development. As a result, we have emphasised the contributions that deep learning approaches have made to solving the issues with data processing and decision making in smart agriculture. The absence of early detection and classification of plant leaf diseases is one of the primary problems we discovered when reviewing the most recent research publications. We offer a suggested method for resolving this problem that makes use of a hybrid deep learning model that combines support vector machines and convolutional neural networks.

2. DEEP LEARNING

Deep learning, which is basically a neural network with three or more layers, is a subset of AI and machine learning. While these neural networks try to replicate brain activity, they are far from matching the brain's capacity for large-scale data learning. Additional hidden layers can help optimise and improve the accuracy, even though a single-layer neural network can only make rough predictions. A branch of artificial intelligence called machine learning enables a system to pick up knowledge and concepts without explicit programming. In order to improve future outcomes and judgements, data aspects and patterns are first observed, such as through in-person interactions. Multiple nonlinear transformations are used by machine learning algorithms to model high-level abstractions in data, and this is the foundation of deep learning [7]. One important benefit of deep learning is feature learning, or the automatic extraction of characteristics from unprocessed data. Lower-level components are composed to yield features from higher hierarchy levels [8]. Two common deep learning networks used in agriculture are recurrent neural networks (RNNs) and convolutional neural networks (CNNs).

2.1 CNN, or Convolutional Neural Network

Multiple convolutional layers, pooling layers, and fully linked layers make up a CNN, a deep learning method [9]. The animal visual cortex serves as the foundation for this multi-layer neural network [10]. The two primary applications of CNNs are handwritten character recognition and picture processing. CNNs have been utilised for image classification, object detection, picture segmentation, text and video processing, speech recognition, and medical image analysis, among other tasks, in a number of computer vision studies. Typically, convolutional, pooling, and fully linked layers make up a CNN architecture [11]. The architecture of CNNs, where the layers are briefly described:

2.2 Layer of Convolution

In a CNN, the convolutional layer is both the most fundamental and important. An activation map for the given image is constructed by twisting or multiplying the resulting pixel matrix for the supplied item or picture. The primary benefit of the activation map is that it reduces the quantity of data that needs to be processed at once while storing all of the unique characteristics of a particular image. A features detector matrix is constructed by combining the data, and different feature detector levels are used to create distinct image versions. Backpropagation is also used in the training of the complex model in order to minimise error in each layer. The error set with the fewest errors determines the depth and padding [11]. The extraction of visual features is handled by the convolutional layer.

2.3 Layer of Pooling

This is a critical stage that aims to further reduce the activation map's dimensions while preserving only the most important elements and reducing the striking invariance. As a result, the model's learnable feature count is decreased, which helps to alleviate the overfitting problem. Through pooling, a CNN may use all of an image's dimensions to identify the given object even when the form is distorted or viewed from an unusual perspective. There are several methods for pooling, such as spatial pyramid, max pooling, average pooling, and stochastic pooling. Max pooling is the most often utilised technique [11].

2.4 Completely Networked Layer

The neural network is fed into this last layer. The matrix is typically flattened before being given to the neurons. After this, the data get more complicated to follow because of multiple hidden layers whose weights for each neuron's output vary. This is where data reasoning and computation take place [11].

2.5 Neural Network with Recurrence

An RNN is a neural sequence model that excels at important tasks like machine translation, speech recognition, and language modelling [12]. Unlike typical neural networks, RNNs leverage the sequential information of the network; this feature is important in many situations where the structure of the data sequence itself provides important information. For example, you have to grasp the context of a sentence before you can comprehend a word in it. Thus, an RNN with input layer x, hidden (state) layer s, and output layer y can be thought of as a short-term memory unit [10]. An RNN architecture called long short-term memory (LSTM) is designed to more accurately imitate temporal sequences and their long-term associations than regular RNNs [13].

3. DEEP LEARNING APPLICATIONS IN AGRICULTURE

In smart agriculture, deep learning algorithms are being utilised to observe and monitor multiple linked parameters from any location in the world. Recent surveys have shown that the main focus was on the advantages of deep learning for agricultural applications. We have provided an overview of deep learning's contributions to the many known applications of smart agriculture in this review. Among other things, we attempted to analyse which deep learning model is more efficient and effective and which one is appropriate for specific applications. We have seen that the CNN algorithm has produced amazing results and that researchers are becoming more interested in applying it for plant disease detection and classification applications.

Because the CNN algorithm is based on time series and produces useful results, it is also widely used in weather forecasting applications. We looked into the various uses of deep learning in agriculture as well as the various domains of smart agriculture.

3.1 Plant Disease Identification and Classification

The energy that disease-causing fungi, bacteria, and microorganisms draw from the plants they live on has an impact on agricultural yield. Farmers may experience large financial losses if this is not identified in a timely manner. Farmers face significant financial strain when using pesticides to eradicate diseases and restore crop functionality. Overuse of pesticides damages the ecosystem and interferes with the water and soil cycles in agricultural areas [14]. When it comes to improving accuracy over time, deep learning seems to have a lot of promise. A large number of novel DL architectures as well as enhancements to already-existing ones are put forth. Plant disease signs are being recognised and categorised using a variety of contemporary visualisation approaches [15].

The author of [16] offered a CNN-based technique for identifying and categorising banana illnesses. It can help farmers identify the invading disease quickly, affordably, and efficiently. This method used a deep neural network model to identify two banana illnesses, Sigatoka and speckle, by taking a picture of a leaf that was afflicted. With a high degree of accuracy, the authors of [17] classified the type of plant disease from photos of the leaves using another deep learning model, AlexNet. In order to categorise the diseases of sunflowers, such as Alternaria leaf rot, Downy mildew, phoma rot, and verticillium wilt, a deep learning hybrid model is described in [18]. The stacking ensemble learning technique was employed by the author to create a hybrid model of MobileNet and H.VGG-16. They used Google Photos to create their dataset, and they said that their suggested model outperformed other models with an accuracy of 89.2%.

The study described in [19] examined and contrasted the output from five distinct deep learning models, among them H. Using both simulated data and photos taken from rice fields in the Pakistani city of Gujranwala, Vgg16, Vgg19, ResNet50, ResNet50V2, and ResNet101V2. ResNet101V2 achieved an accuracy of 86.799 on the real dataset, while the ResNet50 model achieved 75% accuracy using a fake dataset.

A mobile device with machine learning capabilities was created by the author of [20] to automate the diagnosis of illnesses affecting plant leaves. The developed system uses CNNs as the core deep learning engine and is able to classify 38 different types of sickness. For the CNN model's training, validation, and testing, the researchers collected an image dataset of 96,206 pictures of plant leaves from both healthy and sick plants. Farmers might utilise the Android smartphone application's user interface to take pictures of ill plant leaves. The 90% confidence level and the disease category were then shown. With this method, farmers should have a better chance of maintaining the health of their crops and avoiding overusing fertilisers that could damage them.

A pre-trained deep neural network model for transfer learning was utilised in study [21] to detect crop diseases and learn crucial features like leaf characteristics straight from the input data. They looked into different deep learning techniques as well as CNN topologies, including MobileNet, Wide ResNet, DenseNet, and ResNet. The suggested solution works better than previous methods in terms of precision and memory, according to the results.

In [22], a different CNN method for identifying, categorising, and detecting plant diseases is provided. For thirteen distinct plant diseases, it has demonstrated output result accuracy ranging from 91% to 98% with an average performance of 96.3%. Additionally, it can tell good leaves from unhealthy ones and set them apart from their surroundings. Utilising a CNN model, the author of [23] was able to identify and categorise plant photos with the maximum accuracy possible—99.58 percent. They used commercially available ConvNet representations to assess a maize crop's plant development. In [24], an SVM classifier with 94% accuracy is proposed for autonomously identifying plant diseases by picture analysis. A dataset of 500 pictures of plant leaves from thirty distinct native plant species was used for the experiment. By defining a single healthy class, the other deep learning studies [25,26-35] built automatic plant detection and recognition algorithms to identify nine different diseases. With an accuracy of above 91%, all of these research used the PlanVillage dataset for testing and training.

4. IDENTIFICATION AND CATEGORIZATION OF CROPS

Harvesting a crop at the right time and according to market demand is a crucial step for farmers when it has been fully cured of all illness and stress. When creating a harvesting plan, deep learning may also be very helpful in taking into account many factors including soil type, quality, and pH, weather forecasts (which include temperature, precipitation, humidity, and sunshine hours), and fertiliser schedules. Such a paper is a research paper [36]. In [37], a multi-layer DL architecture was suggested. It uses satellite images from many sources to classify various crop species in a land-covered area. The RF classifier and a chorus of MLPs were defeated by an ensemble of 1-D and 2-D CNNs, enabling a more precise categorization of summer crops, primarily maize and soybeans [38]. CNN models classify primary crops (wheat, corn, sunflower, soybeans, and sugar beets) with an accuracy rate of over 85%.

Using the Seed-lings dataset—which includes images of about 960 distinct plants from 12 species at various growth stages—the authors of [39] presented a deep learning classification system for diverse plants. For the aforementioned aim, three pre-trained models were used: InceptionV3, VGG16, and Xception. With an accuracy score of 86.21%, Xception was found to be the best classifier. In a study [40], a CNN model prototype was created to categorise various flowers. It classified publicly available flower datasets using the transfer learning technique, VGG16, MobileNet2, and Resnet50 architectures, and it yielded good results with respectable accuracy. In order to effectively anticipate agricultural yield, a hybrid MLR-ANN model was presented in [41]. It receives weights and bias as input from the MLR intercept and coefficients. Rice crop yield is estimated via a feed-forward artificial neural network using backpropagation training. The collected findings demonstrated that the hybrid MLR-ANN model performs more accurately than the conventional models.

In [42], a different deep learning system based on leaf pictures was published for the purpose of classifying plant images and identifying plant species. Both CNN and transfer learning were applied as methods of classification. The results of the experiment showed that the proposed model was able to successfully extract and classify features from photos. The cited article [43,44] used deep neural networks to classify summer crops based on EVI time series. Long short-term memory (LSTM) and the Landsat enhanced vegetation index (EVI) time series are two new DL models that were created. Three gradient boosting machines—support vector machine (SVM), XGBoost, and random forest (RF)—were employed as classifiers. This model was said to outperform others in terms of overall accuracy and crop-specific identification skills. In order to classify summer crops, a study [45] used hybrid CNN-RF networks with optimal feature selection and multi-temporal Sentinel-2 data to create a novel crop-classification approach [46]. The OFSM model was utilised in this investigation to choose the best characteristics, and both temporal and spatial dimensions were applied to produce classification results that were satisfactory in terms of total accuracy, reaching up to 94.27%.

The faster region-based convolutional neural network (FRCNN) framework was created in [47] in order to estimate plant densities over a UAV orthomosaic and provide a plant detection model. The findings demonstrate that UAV photography may be used to create precise two-dimensional maps of plant density that are strongly linked with key yield components.

4.1 Recognising Weeds

It is not always essential or easy to identify every weed on a farm. On the other hand, identifying giant weeds correctly can be an essential first step in successful management. There are times when distinct weed species can look surprisingly alike. However, there are still significant differences in their life cycle, manner of reproduction, effects on plants, and susceptibility to management strategies. Using an RGB + NIR camera, a CNN-based classification system was developed in [48] to identify and separate sugar beetroot plants from weeds in natural settings. When identifying sugar beetroot plants among the weeds, the method provided accurate results [49].

4.2 Determining the Water Stress

Water is a critical resource for agricultural output, and water hazards are becoming more prevalent. It is also the industry that uses the most water and pollutes the most since fertilisers and pesticides can contaminate both surface and subsurface water supplies. Therefore, ensuring the agricultural sectors are productive and sustainable requires better water management in agriculture. A convolutional neural network model was presented in article [6] to identify the water-stressed and typical locations in the maize crop field. A comparison of the suggested framework's performance against ResNet50, VGG-19, and Inception-v3 reveals that, with an accuracy of 93%, the suggested model produced superior results. In contrast, study [50] used images of chickpea plant shoots to create and evaluate a novel deep learning-based pipeline model for phenotyping plant water stress zones.

A deep learning method was presented in [51] to identify irrigation system water requirements from aerial photos. This automatic detection could help with irrigation system management, which lowers the system's maintenance costs and duration. The preliminary results indicated that it could be able to identify water from UAV-taken photos using the Mask R-CNN neural network. The intention was to identify and prevent irrigation malfunctions that could lead to either overwatering or underwatering through the appropriate application of irrigation plans.

4.3 Forecasting the weather

In the rapidly developing field of agriculture, weather data is becoming more and more important since it emphasises precision and control during crop cultivation. An essential part of this method is the use of information technology, which includes plant health indicators, sensors, drones, GPS guidance, satellite and aerial imagery, weather forecasts, and other elements. By monitoring low temperatures, authors [52,53] created LSTM deep learning models to forecast plant frost. The LSTM models yielded good time-series prediction results to detect/expect ice in the plants, despite their high computational cost.

4.4 Counting Fruit

When estimating crop production in agriculture, the challenge of correctly identifying and counting the fruits on trees is critical. Manual counting requires a lot of work and effort. In order to boost output and profit margins, harvesting schedules and yield projections can be better organised with the aid of automated crop counting. To determine the precise quantity of fruits, a simulated model of a deep convolutional neural network is created and evaluated in [54]. According to testing data, it employed a modified version of the Inception-ResNet architecture and had an average test accuracy of 91%.

5. DEEP LEARNING'S PROSPECTS IN AGRICULTURE

One of the more difficult application areas is agriculture since every region has unique climate conditions, natural features, and other characteristics. To identify the relevant components and evaluate the gathered data, technology is thus desperately needed. To investigate this, taking into account changes in real-time, a significant amount of data is needed. As a result, deep learning is among the most significant technologies in this area that can perform these tasks utilising suitable algorithms like CNN and RNN. An algorithm creates a probabilistic model before making a judgement when it is fed field data, such as climate parameters, soil types, weather patterns, and other variables. Prior to suffering food or money losses, early and correct identification is crucial for tracking various illnesses. Upon sifting through ten years' worth of photos of ill plants, this system can identify the kind and extent of the sickness. This also holds true for how the weather develops. A deep learning model's primary benefit is that the software generates the chosen feature automatically and without assistance. Unsupervised learning improves our knowledge and readiness to operate in the dynamic and uncertain real-world workplace. It is crucial as the Internet of Things (IoT) is becoming increasingly significant and since the majority of data produced by machines and people is unstructured and unclassified. Deep learning performs better than conventional techniques like ANN, SVM, RF, etc. Deep learning models provide automatic feature extraction that is more efficient than traditional feature extraction [55].

5.1 Advantages of AI Techniques to Crop Protection

The way crops are cultivated and safeguarded has been completely transformed by the introduction of robotics and artificial intelligence (AI) into agriculture. It is important to understand that robotics and artificial intelligence (AI) may support entire crop protection strategies, even though the title "Sustainable Crop Protection via Robotics and Artificial Intelligence Solutions" suggests a concentration on pest management. We can improve agricultural practises and guarantee a sustainable future for food production by utilising these technology. Even while we concentrate mostly on crop protection—that is, weed and disease control—we must recognise the larger picture of total crop protection and monitoring. Here, we hope to give a brief synopsis of these extra elements and emphasise how much AI solutions have contributed to these fields [56].

Beyond weeds and diseases, there are other elements that greatly affect crop health and productivity that are included in crop protection. To ensure comprehensive crop protection methods, factors like plant physiology, cultural activities, nutrition optimisation, and climate conditions are essential. We can make strides and open up new opportunities in each of these fields by utilising AI technologies [57].

5.2 Resilience and Climate Adaptation

Significant obstacles to agricultural output are presented by climate change. Robotics and AI have important roles to play in risk mitigation and adaptation related to climate change. Large-scale meteorological data can be processed by sophisticated algorithms, which assists farmers in choosing crops, planting dates, and water use. Robots fitted with environmental sensors are able to track pest outbreaks, soil moisture content, and weather patterns, giving agricultural managers access to real-time information. Farmers can minimise crop losses and make appropriate adjustments by anticipating weather patterns with AI-driven climate modelling [32].

Optimising crop nutrition is essential for achieving high yield and high quality. By examining soil composition, plant nutrient requirements, and growth trends, artificial intelligence and robotics can optimise nutrition management. With the use of intelligent systems, one can precisely apply fertilisers or other supplements by keeping an eye on nutrient excesses or shortfalls. Robotics can also automate processes like nutrient supply, weeding, and precise seeding, which reduces waste and increases resource efficiency. Artificial intelligence (AI) and robots lower environmental consequences while promoting sustainable agriculture by customising nutrition solutions to individual crop demands. [43].

5.3 Cultural Activities and Labour Optimisation

Successful crop production depends on a variety of cultural activities, which are included in agriculture. AI and robots can automate and simplify a variety of processes, minimising labor-intensive work and maximising the use of available resources. For instance, robotic systems are more accurate and efficient at time-consuming tasks like pruning, sorting, and harvesting. Farmers may concentrate on higher-value duties like crop planning, disease control, and market analysis by automating monotonous processes. The combination of robotics and AI increases productivity while also improving farmers' quality of life, which attracts more people to the agricultural industry [44].

The crop protection system based on AI and robotics consists of multiple modules that collaborate to improve agricultural practises:

5.3.1 Module for gathering data

The system gathers information from a variety of sources, such as weather reports, soil sensors, satellite photos, and digital bug traps, in order to produce insightful reports. Accurate forecasts of weed growth, disease outbreaks, pest infestations, and weather conditions are made possible by this extensive dataset.

5.3.2 Module for developing and interpreting machine learning models

Developing automated systems that analyse data and draw insightful conclusions is the focus of this topic. The system interprets machine learning model outputs to deliver concise and useful insights to support decision-making.

5.3.3 Module for making decisions

AI systems evaluate the information gathered to identify the best crop protection tactics. Crop type, development stage, insect, weed, or disease severity, as well as environmental and risk assessment factors pertaining to pesticide use, are among the factors taken into account. The possible emergence of pesticide resistance as well as legislative restrictions are considered.

5.3.4 Robot module

The technology can be included into self-governing robots that have cameras, sensors, and spraying tools. These robots are trained to precisely identify and target pests, weeds, and illnesses using machine learning algorithms, maximising the efficacy of crop protection techniques.

5.3.5 Monitoring Module

Artificial Intelligence is used to track the performance of crop protection tactics and instantly adapt as needed. This ongoing observation guarantees peak performance and permits prompt action when required.

5.3.6 Module for user interface

A user interface is offered to help with communication between farmers, agricultural scientists, and other stakeholders. The interface displays the system's conclusions and recommendations, enabling users to offer feedback and alter the results to suit their own requirements.

6. CONCLUSION

The review covers some of the vital research articles and developed solutions in the field of Ai and Robotics for the agriculture sector till today. To address this multi-dimensional domain, only a few innovations and solution approaches were considered. This review paper is created to provide a glimpse of innovations that are taking place in Ai and robotics for agriculture. Furthermore, its social, economic, environmental impacts along with the problems for the broad adoption of these techniques were discussed. The rule-based expert systems were widely used in the early 1980s and 1990s, while the artificial neural network was used from 1990 onwards. Deep learning models and computer vision systems have played a dominant role in the development of various application in the agriculture sector. For example, Plant disease and pest identification and detection system using ai powered smartphone application, Target spraying of pesticides robots, Precision weeding robot, smart irrigation using of IoT devices, Robotic harvesting system and many more. The transition from labour-intensive to advanced technology in agriculture tend to accelerate int the upcoming years and will give rise to new growth possibilities and creative business models, with a range of creative offerings in the sector.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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