Crop Management System

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Abstract:

Smart agriculture is emerging at a significant rate in recent times. It is a part of the information and communication technologies (ICT) movement that is ushering in agriculture in many ways, referred to as the Third Green Revolution. By enriching the crop yield process, smart farming enhances its manufacturing of high-quality food. This article focuses on crop cultivation techniques as well as applies deep learning (DL) and machine learning (ML) algorithms so as to offer responses to a number of challenges that emerge all through the cultivation process. Machine learning is a cutting-edge technological innovation that assists farmers in reducing crop losses by providing specific crop recommendations and keen insight. Soil and water management, crop cultivation, crop disease detection, weed control, crop distribution, robust fruit counting, and yield prediction are all examples of smart agricultural applications that employ deep learning. Farmers have experienced lots of new challenges recently, along with crop failure due to scarcity of rain, soil fertility issues, and etc. As a result of the changing environment, this proposed study will assist by finding the most effective way to handle crops and harvest them.
Keywords: Smart farming , ICT (Information and Communication Technologies), ML (Machine Learning) , DL (Deep Learning).

1. Introduction to Crop Management System

During the past two decagon, extensive research has concentrated towards future farming techniques on agronomic crops. Cropping system changes will have a big impact on insect population trends and administration [1]. Crop production has been one of agriculture's most important branches. Crop production is essential for providing feed for livestock as well as food for the common people. Improving the economic efficiency of agricultural activities has been a primary goal over human agrarian history. Agricultural production sites must be examined regularly to obtain high-quality products, and they can also adopt every necessary crop-production measures. Farmers increase the crop's cost by spending time as well as resources to each visit. Due to intensive monitoring and evaluation of crops that farmers do, smart agriculture has risen to become a necessity. Digitalization will encompass the majority of engineering fields, with a bigger impact over wide-area communication network involving fast data transmission [2] – [4].

Smart farming would be a novel model that uses advanced information technologies to make agriculture highly effective and efficient [5]. Farmers can better monitor various procedures as well as apply specific treatments chosen through machines of superhuman efficiency due to recent improvements in artificial intelligence, automation, and connectivity. Engineers, data scientists, and Farmers are all working on ways to reduce the amount of human labor needed in agriculture. Agricultural firms, despite tough production conditions induced by high prices of production factors, limited attractiveness for rural locations, as well as difficulty in obtaining, have a large output potential. The Crop products have been used for plant-based raw materials together in wide range of sectors, which includes pharmaceuticals, food as well as fuel. Crop production would be a subset of agriculture that involves field crop cultivation, vegetable production, and fruit production, among other things [6].

Artificial intelligence was introduced early in the history that intellectually demanding tasks of humans are simple to computers provided has to be expressed like a set of mathematical or logical rules. Machine learning, a subset in the artificial intelligence, employs an self-learning method for extracting the data. Machine learning employs learning rules like reinforced learning, supervised learning, hybrid learning and unsupervised learning, which obtain useful associations of data [7]. Artificial neural network concepts have been used in machine learning, which is termed as deep learning. Deep networks distinguish from the neural networks for its depth. Because of these characteristics, deep learning networks may detect latent structures in unlabeled and unstructured data. The deep learning networks particularly perform feature extraction while requiring human interaction, providing a substantial advantage over earlier techniques. Due to the rise of broadband wireless transmission networks, customer demands in high-speed wireless communication have risen significantly [8] – [10].

The Deep Anomaly method is more effective than region-based convolution neural networks at detecting humans at distances of 45-90 meters (RCNN) [11]. This algorithm generates homogeneous field characteristics and detects anomaly. The deep learning categorization for land cover as well as crop types employing remote sensing data was described in this article [12]. CNN was compared to a traditional fully linked MLP as well as random forest. The use of self-learning convolutional neural networks to recognize individual plant classes based on visual sensor data is discussed [13]. In UAV images of line crops, automatic weed detection employing deep learning using unsupervised data labeling is presented [14]. Therefore the fully automatic weed detection will conduct when CNNs are used to unsupervised training datasets. A crop disease classification system based on a mobile capture device due to deep residual neural network was introduced. Extensive testing improved the balancing accuracy between 0.78 and 0.8 [15].

The deep neural network including transfer learning is used to detect the mildew illness on millet crop images in order to identify the mildew disease [16]. The experimental result accuracy is 95%, precision as 90.0%, recall got 94.50% as well as the f1-score has been 91.75%. NDVI and RGB data collected through UAVs were used to estimate crop yields using deep convolutional neural network [17]. The RGB images outperform NDVI images while using CNN architecture. Rice grain productivity CNN architecture as well as low altitude remote sensing -based images were discussed as essential features [18]. Deep CNN performed much better and was more stable during the ripening stage. A multi-temporal crop classification based on deep learning has been studied [19]. XGBoost, SVM and RF parameters were compared to LTSM and Conv1D deep learning models. Another crop vision collection using deep learning categorization as well as precise farming recognition has been developed [20]. This suggested methodology outperformed VGG, DenseNet, ResNet, SqueeztNet and Inception on crop datasets, with the precision by 99.81%. The Deep learning technology is used to properly recognize as well as distinguish crops in soil. As a data source, data from a high-resolution digital surface model is used. The transfer learning methodologies with convolutional neural networks are employed with automatic feature extraction for crop pest categorization [21]. Xie1, NBAUR and Xie2 datasets have the highest accuracy of 94.47%, 96.75% and 95.9% respectively.

We evaluate the specific crop management system using deep learning technique and its model as well as frameworks used, nature, pre-processing and data sources as well as the performance attained using the metrics are studied. Since most agricultural firms have switched completely to crop production, the problem of crop production management has become increasingly relevant. The original study goal is to develop suggestions for enhancing crop production planning and management with modern business situations using deep learning models. The purpose of the study will be whether the deep learning technique has been utilized to improve crop management systems, rank the areas to encourage new researchers, to guide future research in agriculture production.

This article is structured that, Section II introduces the Deep learning architecture using CNN. In section III, the role of deep learning in crop management system is discussed. The scope and challenges of artificial intelligence and deep learning in the crop management system has been described through section IV. In the end, Section V concludes with remarks and future work for crop management system.

2. Insights of Deep Learning

Deep structured learning or hierarchical learning is a subset of the machine learning which focuses upon artificial neural networks (ANN) algorithms that are inspired by the structure as well as activity of the human brain [22]. It performs excellently on a variety of complex cognitive tasks, approximating and even outperforming human performance. The ability to learn huge quantities of data is the advantages in Deep learning technique. Deep learning popularity has been increased over the last decade, but it is effectively used for various traditional applications. In several sectors, including natural language processing, cyber security, bioinformatics, medical information processing, and robotics and control, deep learning has excelled over well-known machine learning techniques.

The three main deep learning techniques are partially supervised (semi-supervised), unsupervised and unsupervised. Additionally, deep reinforcement learning (DRL), commonly referred to Recursive Learning, would be a form of learning approach that is typically classified as occasionally unsupervised learning and partially supervised techniques. Recurrent neural networks (RNNs), Convolutional neural networks (CNNs), Recursive neural networks (RvNNs) are among three most well-known types of deep learning networks used. The most extensively used algorithm is CNN which has key advantage over its predecessors would be automatically detecting significant features without the need for human intervention. The features have been extracted by various approaches in traditional machine learning algorithms, however the convolutional neural network trains the filters for itself, indicating that the network extracts features autonomously. CNNs have now employed in various applications, such as computer vision, audio processing, and facial recognition. CNNs are closely related neural networks in their structure which is inspired from neurons in animal and human brains. Convolutional neural networks were extensively deployed in the deep learning network type, which discusses the evolution for CNN architectures as well as their main characteristics. The model of a basic Convolutional Neural Network Architecture is shown in Figure.1.

A convolution layer is typically used in CNN, and it employs convolutional filter collections to recover numerous local features from each input region, resulting in a large number of feature maps. The layer has been represented in mathematically as [23]

$$(cn)_{ij} = (Xn * q)ij + dk \qquad (1)$$

where $(Cn)_{ij}$ indicates the n_{th} output feature map of (i, j) element.
The input feature maps are represented by q. The n-th filter and bias are indicated by Xn and dk, respectively. A 2-D spatial convolution operation is represented by the * symbol.

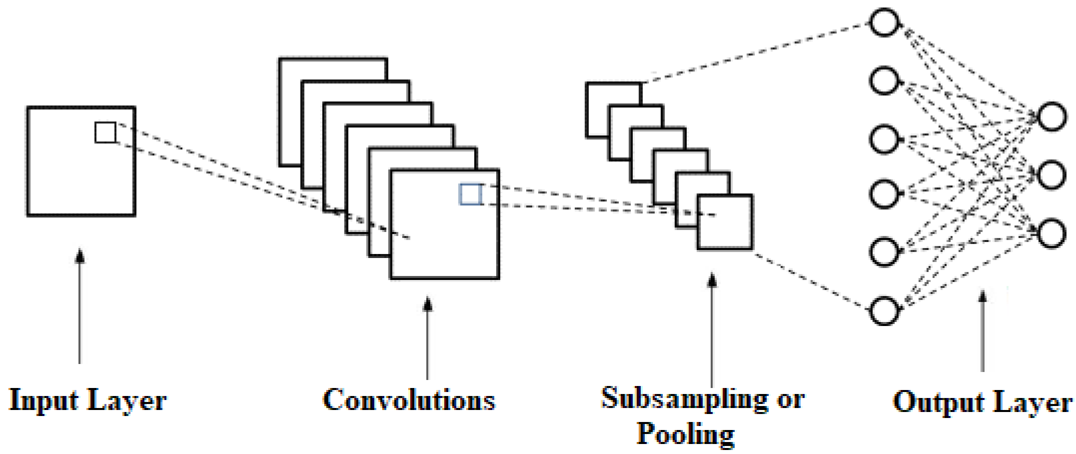

Figure.1. Model of a basic Convolutional Neural Network Architecture

CNN architecture is divided into two components. Feature Extraction is a convolution method which extracts and detects the image distinct characteristics of an image during evaluation. The fully connected network which employs its convolution result for predicting image classification based on characteristics obtained earlier in the process. A CNN is made up of three layers namely pooling layers, fully-connected (FC) layers and convolutional layers. These layers are combined to form the CNN architecture. The convolutional layer is being used to extract input image information. The mathematical operation of convolution has been carried out among the input images as well as filter of MxM size. A Pooling or Subsampling layer has been commonly used after our convolutional layer. The pooling layer which reduces convolved feature map size with the reduced computational costs. While connecting both weights and biases in neurons, the Fully Connected (FC) layer will be connected with neurons between two layers. The CNN Architecture's final few layers were usually placed prior to output layer. Finally, in the CNN model, an activation function employs important component which estimates any kind of continuous and complex link across network variables.

The CNN includes three distinguishing characteristics which make the potentially valuable tool in additional crop yield modeling. i) A CNN model has been developed which represent environmental elements as well as the genetic transformation in seeds through time despite knowing their genotype. ii) The model has proved the capacity that extends yield prediction across untested conditions while maintaining high accuracy. iii) When combined with the back propagation approach, the model was able to demonstrate the level toward which weather prediction accuracy, weather conditions, management practices and soil characteristics may influence crop production variation. During 2008 and 2016, Khaki and Wang [24] developed the deep convolutional neural network technique which estimates the corn yield in 2,247 locations. A deep learning architecture was developed by Kim et al. [25] during 2006 and 2015 on agricultural yield prediction. The soybean crop production in Argentina and Brazil, which uses deep learning and transfer learning approach have been estimated by Wang et al. [26]. With remote sensed pictures, Yang et al. [27] evaluated effectiveness for yield of rice grain and yield prediction in ripening process by the CNN model.

3. Crop Management System - A Deep Learning Approach

As the world's population continues to grow, a significant increase in food production is required to ensure worldwide availability and good nutritional quality while also safeguarding natural ecosystems through sustainable agricultural practices [28]. The application of crop management methods guarantees the crop's productivity with higher yields and better quality. Crop management is a set of agricultural operations aimed at improving crop growth, development, and yield. As indicated in figure. 2, it begins with Land preparation, seed selection, seed sowing, irrigation, crop development, together with crop management and concludes with crop harvest, storage, along with commercialization.

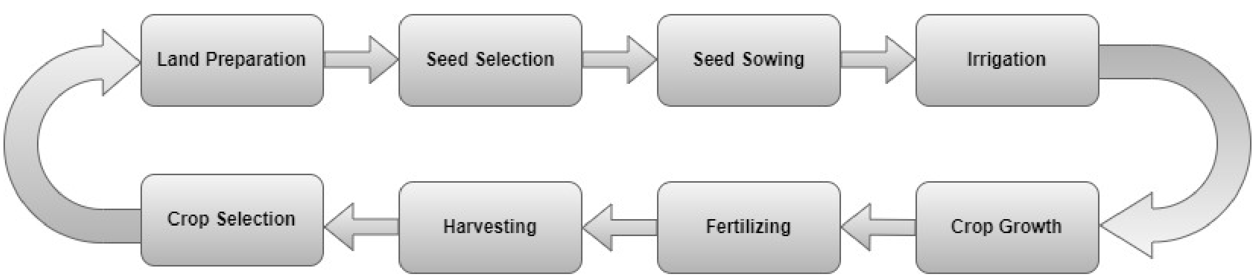

Figure 2. Basic Crop Production Cycle

Plant age, soil, climate, and weather conditions all influence the timing and sequencing of agricultural processes. Sowing methods-broadcast and row-crops, winter or spring crops (harvested products such as grain, hay, and silage), and weather conditions, plant age, soil and climate are all factors that influence the timing and sequencing of agricultural processes [29]. Computer vision applications in agricultural and popular techniques are shown in Table1.1

3.1 Soil health monitoring system

The foremost step involved in improving crop growth is preparing the seedbed. The ideal seedbed is constantly firm, wet to the surface, and weed-free. "Good seed-to-soil Contact essential" according to common comment held on seeding records. When seeds have sufficient soil contact, germination is improved. On the other side, a seedbed that is overly firm makes it harder to get the seed into the ground. [30]. Agriculture-IoT may connect with sensors, communication protocols, and microcontrollers in a current competitive environment to automate process executions and boost production. Deep learning performance yields acceptable findings and addresses a number of real-time challenges associated to agricultural developments. Sumathi et al [28] discussed the design of a soil condition estimation system based on through IoT network communication system. In modern agriculture, soil quality is a critical aspect in increasing production and regulating hydrological cycles. An improved deep learning model for IoT network-based automated evaluation of soil quality keeps track of the various soil properties and climatic elements that contribute to those issues. For soil quality prediction, a deep learning model was created with the capacity to fit huge data. Weight factors are calculated in order to precisely measure soil quality.

3.2. Sorting of Seeds based on Deep Learning

Seed sorting would be a mechanized process that aims to produce a high-purity, high-quality end product. Such processes are extremely difficult to predict and regulate. The 'Mixed cropping seed classifier along with quality tester,' is a deep learning-based system for precise seed classification as well as based on quality tests on structure, color, together with texture. The dataset includes labeled pictures of healthy and damaged pearl millet and maize seeds. Its capacity to distinguish between infected and healthy maize seeds improves its food sector application. Chunlei Li et.al [30] proposed SeedSortNet, a compact CNN associated with visual attention that is quick and efficient. First, a block of light weight feature extraction module with two branches. Shield-block is detailed developed by conducting higher-dimensional spatial transformation, identity mapping, and different receptive field modelling, and as a result, with fewer parameters and reduced computing complexity, it may reduce information loss while correctly defining the multi-scale feature.

3.3. Seed Sowing using Deep Learning

Seed should be planted 1.5 - 2.0 inches deeper after the seedbed has been prepared to ensure enough moisture availability for effective seed germination. The seed requires certain conditions in order to germinate optimal moisture along with temperature conditions, thus constantly check on the soil temperature and moisture requirements at several times [29]. Agriculture access is a starting point toward a better living, and agricultural tool development is the foundation for agricultural progress. RenukaDhavale et al [31] propose employing an agribot to design a system that saves operational costs, minimizes digging time, and improves seed sowing performance. DC motors, moisture sensors, IR Sensors, and ultrasonic sensors are employed inside this machine with the support of a Wi-Fi interface running android application on a field oeuvre robot. The seed-spreading and digging robot will walk through several rows of soil, digging up, sowing seeds, and covering the soil with a cover.

Lukasz Gierz et.al [32] conducted survey at triticale seed samples of varying quality. The seeds were collected during tests that resemble actual planting circumstances. The experiments have been performed on such a specially developed testing facility by the respective authors. The air speed in the pneumatic tube conveying seeds was adjusted for sowing. The air speed in the pneumatic conduit conveying seeds (15, 20, 25 m/s) were varied for sowing. The generated visual database allowed for the classification of six seed classes based on sowing-speed and quality. The database seemed to be constructed in order to build training, validation, along with test sets. The neural models were created using statistical analysis and multi-layer perceptron networks.

3.4. Smart irrigation system using Deep Learning

Water plays a vital resource for crop production, is becoming increasingly limited, even as farmland continues to increase due to global population expansion. Farmers have been found to benefit from proper irrigation schedule in terms of crop quality and productivity, as well as reduced water usage. One of the most essential crop irrigation factors is soil moisture (SM), This represents the total amount of water from the soil. Estimating future soil moisture (forecasting) is a vital job for crop irrigation regarding water consumption optimization along with crop yields. The amount of moisture in the soil varies a lot depending on humidity, weather, and time. As a possible solution, Paweena Suebsombut et al.[35] provide a novel Long-Short Term Memory (LSTM)-based approach to estimate future soil moisture levels based on information collected from multiple sensors. A dataset from the real world, including a collection of factors relevant to weather forecasts, soil moisture, along with other associated smart sensors, was used to gather parameters in a greenhouse in Chiang Mai province, Thailand, in order to train and verify this model.

Thomas Henry Colligan et al [34] present a novel approach for Mapping irrigation, which they apply to Montana from 2000 to 2019. The approach totally depends on raw Landsat surface Reflectance data, and it is built over an ensemble using convolutional neural networks. Without any supervision, the ensemble of networks technique learns to mask clouds and disregard Landsat 7 scan-line failures, avoiding the requirement for data preprocessing or feature engineering. Jessica Kwok et al [35] developed an Irrigation system based on deep learning that can modify water quantities for each type of plant based on plant recognition. Software and hardware are the two primary components of the solutions. The former is linked to cameras for plant identification and utilises a database to estimate the proper amount of water; the latter restricts the amount of water that may flow out.

3.5 Crop Growth recognition using Deep Learning

Plant growth and yield forecasting are critical tasks for greenhouse growers and farmers in overall. Developing models that can accurately estimate growth and yield can aid producers in improving environmental management, matching supply and demand, and lowering prices.

Machine Learning but particularly, Deep Learning, have recently advanced dramatically in which they can anticipate powerful new analytical tool. According to Yi Xie et al., [36] deep learning approaches were used to combine an crop-growth methodology with a time series using remotely sensed data to improve the accuracy for local wheat-yield estimates in China's Henan Province. Models such as the LSTM, one-dimensional Convolutional neural network, as well as random forest were trained and evaluated using the leaf area index along with grain yield time series simulated aside Crop Environment Resource incorporate for wheat model. Finally, the regional LAI was calculated using a model of the exponential connection among field-measured LAI along with MODIS NDVI, which had been then fed and in to trained LSTM, 1-D CNN, along with RF models to predict wheat yields within a certain wheat growing region.

The suggested work by Bashar Alhnaity et al. [37] employs machine learning as well as deep learning approaches to forecast yield and plant growth variance in controlled greenhouse conditions for two separate scenarios: tomato yield forecasting as well as ficus benjamina stem development. While in prediction formulas, a newly developed deep recurrent neural network was used, this utilizes Long Short-Term Memory neuron framework. By integrating different cutting-edge temporal sequence processing networks-temporal convolutional network as well as recurrent neural network. Liyun Gong et al.[38] established a novel greenhouse crop production prediction system. Different datasets acquired from various genuine greenhouse sites whereas tomato growth have been used to evaluate the proposed method in depth. Hafiza Ufaq Rehman et al.[39] provide a viewpoint planning method enabling harvest robots in order to enhance fruit detecting outcomes. Robots can use viewpoint planning to consider active sensing techniques rather than simply one standard viewpoint. The planner uses the current environment for input and produces the optimum viewpoint from a list on pre-defined options: moves right, left, or stay still. The perspective planning problem is formulated as a categorization issue, and it is implemented with a deep neural network. Using a fruit detector, they initially extract local fruit areas as well as nearby regions around the fruit from each current scene. Following fruit-wise segmentation, then employ the classifier's labels in the viewpoint planner to select the best perspective.

3.6 Fertilizer Estimation using Deep Learning

Crop management may include fertilization. Before adding fertilizer to every crop, its soil should be tested for plant nutrients. The use of suitable fertilizers depending on the soil and/or plant analysis helps ensure that the nutritional requirements of the planted crop are met. Rice, wheat, barley, corn, oats, rye, sorghum and millet are all grain crops that are widely farmed all over the world. A crucial responsibility for sustainable agriculture is to monitor the health of grain plants and to detect diseases early. Early detection of various diseases can help with disease control through the adoption of appropriate pest control technologies to boost grain output. Manual diagnosis of grain plant problems might result in erroneous pesticide measurements.

Using Neural Networks, JuhiReshma et al.[40] proposed predicting the quantity of fertilizers needed for a specific banana crop and regression approaches for future plantations. One of the most important variables that affect food production and reduce losses will be plant diseases. Deep learning methods have significantly increased their usefulness in plant disease diagnosis, resulting in a complete tool with exceptionally accurate results. Andre Abadeet.al [41] suggests the current cutting-edge technology on the use of convolutional neural networks (CNN) in the diagnosis and classification of plant diseases, as well as to identify trends and gaps.

3.7 Crop Harvesting using Deep Learning

Abozar Nasirahmadi et al.[37] suggest using a digitized two-dimensional imaging system integrated with convolution approaches to identify apparent sugar beet mechanical damages while harvest using a harvester machine. Hafiza Ufaq Rehman et.al.[39] expresses a point or view design enabling harvest robots in order to increase fruit detecting outcomes. Robots can use viewpoint planning to recommend active sensing techniques rather than just one standard viewpoint. As a result, the difficulties with viewpoint planning are reformulated as a classification issue, which is then implemented making use of a deep neural network. Using a fruit detector, we extract local fruit areas as well as nearby regions surrounding the fruit from each current scenario.

Then the labels supplied through the classifiers are used in the perspective planner to determine the optimum point of view after conducting fruit-wise classification. Tanmay U. Sane et.al[42] Various robotic harvesting systems were examined in his work, including those that have adopted or aim to apply such strategies to recognize a crop, travel to it, and harvest it effectively and reliably. This explores the criteria for selecting an AI/DL approach as well as the challenges and benefits encountered in its field application. Based on its durability and performance, Convoluted Neural Networks are a common choice of DL approach for such applications.

3.8 Crop Recommendation System using Deep Learning

A crop recommendation system can be proposed by a digital farming solution to help farmers determine which crop to sow in their field depending on weather conditions, moisture, and season. Deep learning and machine learning approaches offer a practical foundation for making data-driven decisions. Using the Deep Learning/ ML recommendation engine, this application also assists in identifying the optimal pesticide, seed spacing, and seed as illustrated in figure.3.

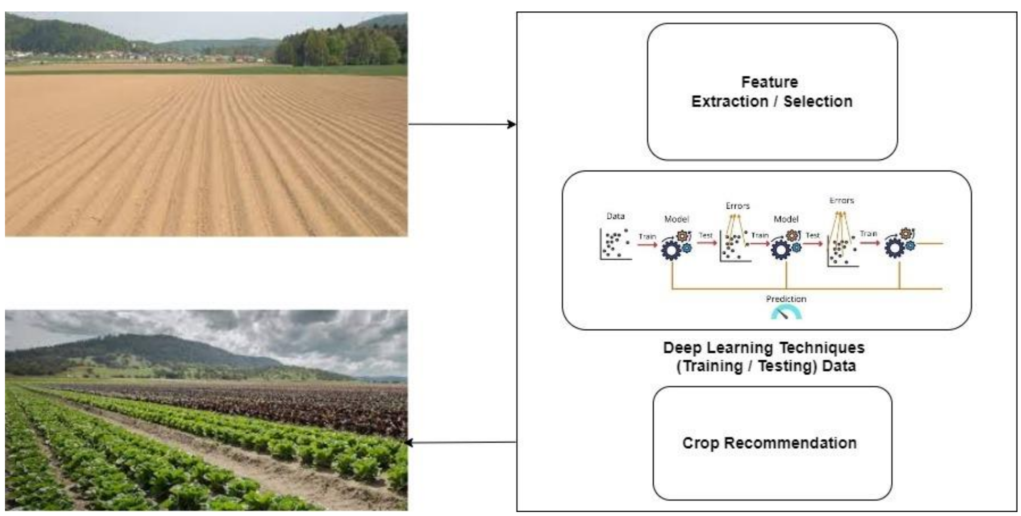

Figure. 3 Crop Recommendation Cycle

In the agricultural sector, seed quality is a crucial element [43].Because certain seeds are naturally tiny, it might be difficult to distinguish and classify changes across species. Experts use the conventional way to classify these changes based on morphological structure, texture, and color. This approach requires an expensive, subjective, and time-consuming classifying procedure, possibly precluding the development of a system that can detect the kind of seed automatically. Using CNN, one of the deep learning algorithms, a smartphone application has been built that accurately recognizes and classifies seed images.

Crop production is an ever-evolving approach to agricultural advancements and farming methods [44].Dealing with climatic changes due to soil erosion and industry emissions are two of the challenges that farmers face. Nutritional deficiencies in the soil, caused by a lack of important minerals like potassium, nitrogen, and phosphorus, can cause crop growth to be delayed. Farmers commit mistakes by farming the same crops every year without trying new types. MadhuriShripathi Rao.et.al recommends that farmers choose the best crop prediction model that can assist them pick what sort of crop to produce depending on the meteorological conditions and nutrients from the soil. To classify two distinct criterion Gini and Entropy, popular approaches including Decision Tree, Forest Classifier, and Random K-Nearest Neighbor are employed. Fuzzy Classifiers used for health care and IoT based system [47]-[48]. Table 1.2. shows the datasets available in pubic related to agriculture.

4. Scope & Challenges of Artificial Intelligence & Deep Learning in Crop Management System

This section presents a complete analysis of sophisticated methods based on Deep Learning as well as Machine Learning that are used within smart farming. We specifically examine the scope, recent application, and opportunities, problems, limits and future research avenues of Machine Learning as well as Deep Learning-based advanced approaches used within smart farming.

4.1 Role of Artificial Intelligence in Smart Farming:

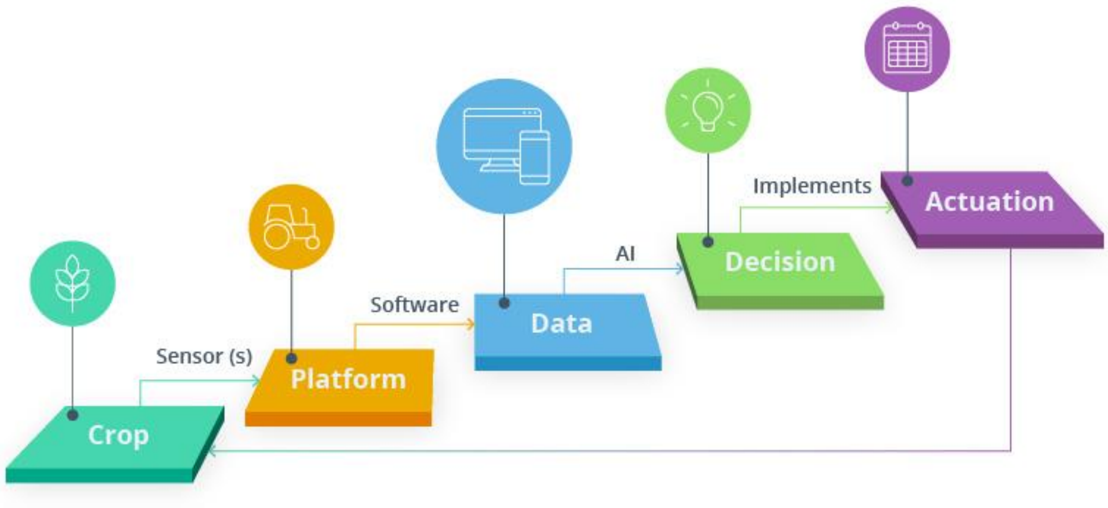

Figure. 4. Source: MDPI – From Smart Farming towards Agriculture 5.0

Over the years, technology has reshaped farming, as well as technological breakthroughs have an influence on the agriculture industry by variety of aspects. Agriculture is a major activity in several countries across the world, and as the world's population grows, so does agriculture, which, according to UN projections, will increase from 7.52 billion to 9.78 billion by 2050, there will also be additional land pressure, because just 4% of land will be farmed by that time [49]. As a result, farmers would have to do more with less. Also according to the survey, food production will need to increase by 60% in order to serve an additional two billion people. Traditional approaches are inadequate to meet this enormous need. This is causing farmers and agribusinesses to look for innovative ways to enhance output while reducing waste. As a result, AI is progressively becoming a part of the agricultural industry's technical growth. Applications of computer vision in agriculture AI-powered solutions may not only help farmers increase efficiency, but they will also boost crop yield, quality, and assure a faster time to market.

4.2 Farmers challenges in adopting new technologies

A number of challenges and factors influence the technology's acceptance and implementation. Farmers are the primary stakeholders in the technology since they will be using it to better the farming system. Due to a lack of resources to build a knowledge exchange platform, as well as farmers' interest in accepting technology as the new normal in their everyday life. The key reason for the lack of interest is a general lack of understanding and information about how technology may bring concrete progress both financially and environmentally to establish sustainable development architecture for all stakeholders. Although many research works are carried out in the research sector, the practicality and application of these research works are sometimes ignored.

Even apart from applicability, there is a significant empty space in field work where qualified professionals can go about explaining the value of technology, which is the major obstacle to adopting the technology. The key difficulty is that security concerns might lead to agricultural harvesting disasters, resulting in food shortages, causing concerned parties to be hesitant to use the technology. Furthermore, issues and scopes are a continual process that must be addressed and altered often through check and balance in order to offer a sustainable development with real outcomes for the whole community [50].

4.3 Challenges in Deep Learning

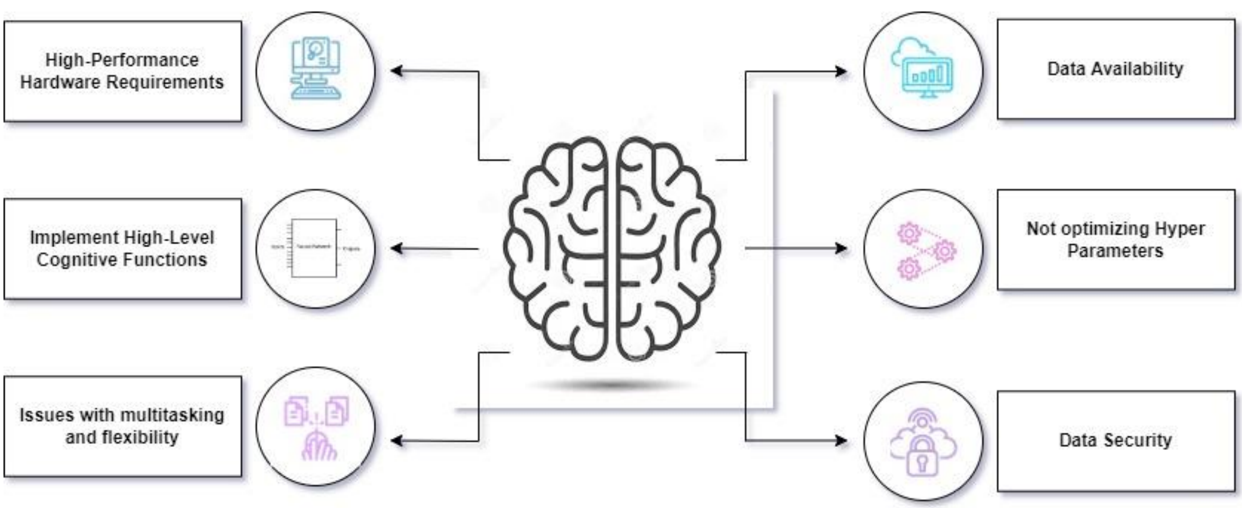

Figure 5. Challenges in Deep learning

Deep Learning had already emerged among the most essential learning topics towards the development of intelligent systems. Deep Learning techniques make use of artificial neural network (ANN) imitate human minds and progressively learn how to deal with a given particular situation. However, there are substantial challenges with Deep Learning systems that we must be aware of as shown in Figure.5.

4.3.1 Massive amount of data

Data is used to train deep learning algorithms to learn in a progressive manner. To ensure that the machine produces the appropriate results, large data sets are required. The equivalent artificial neural network needs a large quantity data, as the human brain need a large amount of experience to learn and interpret information. The greater the abstraction, hence more parameters that must be modified, and much more parameters demand more data.

4.3.2 High-performance hardware is needed

A huge volume of data is required to train data set sufficient for deep learning solution. To tackle problem in the real world, the machine must have sufficient computing power. Data scientists use multi-core high-performance GPUs and equivalent processing units in order to improve efficiency and decrease time consumption. Such processing machines are costly. and may consume more power. Deep Learning systems at the industrial level requires elevated data data centres, whereas drones, robots, and mobile devices are examples of smart technologies that require compact yet effective computational units. As a result, installing a deep learning system in the actual world is both expensive and energy intensive.

4.3.3 Neural network overfitting

There is sometimes a significant discrepancy between the errors encountered in the training data set also the issue identified in the newly declassified data set. It happens in complicated framework when there if there are so many parameters in comparison with volumes of data. The effectiveness a model consists of determined by its capacity to execute effectively for unknown data set, rather than based on its effectiveness on training data provided to it.

Typically, a model is developed by optimizing its efficiency on such a certain training data set. As a result, the model remembers the training instances but it does not understand to generalise current circumstances or data sets.

4.3.4 Hyperparameter Optimization

The value of hyper parameters is determined before the learning process begins. A slight change in the value of such parameters might cause a significant difference which affects the performance of your model. Using its default configuration and without conducting hyperparameter optimization may possess substantial influence in terms of model effectiveness. Holding very few hyper - parameters and adjusting those by manually rather than employing optimization methods is also a type of performance limiting factor.

4.3.5 Implementing High level Cognitive Functions

If we know what our parameters of the model are, how do we feed a known data to neural networks and how are they assembled. However, seldom grasp how they arrive at a certain solution. Researchers struggle to grasp how neural networks draw conclusions since they are basically black boxes. The inability of neural networks to reason abstractly makes high-level cognitive processes challenging to accomplish. Furthermore, their functioning is mostly transparent to humans, making them inappropriate for areas where process verification is critical.

4.3.6 Lacking of Multitasking and Flexibility

Deep Learning methods could provide extremely efficient and precise solutions (once trained) to specific problems. But, in today's world, neural network topologies were extremely customized for a particular purpose fields. The majority of the systems are based on this concept, and they excel at handling a single issue. Even handling a related situation need re-training and reassessment. Deep Learning frameworks that could also multitask without having to redesign the entire architecture are being extensively investigated by researchers.

4.3.7 Data Security

Deep learning has been identified in lot of sectors and has delivered great performance in final outcome due to the advancement of algorithms in vast data and strong computing services. It is important in everyday applications and is gently affecting societal conventions, habits, and behaviors. Data-based learning methodologies, on the other hand, are bound to create possible security and privacy risks, as well as raise public and government concerns regarding their use in the real world. In order to interrupt the training process or cause the model to deliver unexpected results, data security threats try to compromise the integrity or availability of data.

Black-box and white-box attackers are the two categories of attackers regarded in general. A DNN model's internal information, like optimization methods, parameter arrangement, as well as training sets, is not accessible to a black-box attacker. In order to increase access to the search function, the white-box attacker gains a lot of information, such as the structure, DNN model specification as well as certain training data. White-box attackers were undoubtedly superior to black-box attackers in terms of effectiveness.

4.4 Recent Deep Learning Algorithms in Smart Farming

With a flood of anticipation flowing into the DL sector, significant advances have been made in recent years. Image recognition is one of its agricultural applications, and it has overcome several difficulties that have slowed rapid progress with robotics and automation farming and agro-industry. Many parts of agriculture have improved, including weed control, counting of plants as well as plant disease identification. Researchers in agriculture are not necessarily skilled programmers. The researchers commonly use publicly available deep learning software frameworks before carefully analyzing their learning methods. Studying deep learning models will improve the analysis of data as well as agricultural research will be improved. Despite the availability of many software product architectures, Deep learning algorithm has ideas, software restrictions, flow diagrams, as well as sample codes, that could aid agricultural researchers in quickly and efficiently learning important DL approaches.

A variety of techniques are used in deep learning models. Although networks are not perfect, several techniques were more suitable for specific tasks than others. It's critical to understand all of the essential algorithms in selecting the most suitable ones. During current history, deep learning techniques like recurrent neural networks (RNN), convolutional neural networks (CNN), and generative adversarial networks (GAN) had been intensively investigated as well as employed for a variety of industries, including agriculture. Table 1.3 summarizes the various Deep Learning Algorithms. The focus of this research is to give agricultural researchers a comprehensive understanding about DL as well as to improve existing precision agricultural innovation.

5. Conclusion and Future Scope

The wide majority of recent agricultural developments produced through researchers were strongly associated with productivity and all other aspects of agriculture, to improve crop productivity, reduce and prepare for plant diseases, and promote mechanised and automated modernized agriculture and agro-industry. The principles, techniques, restrictions, and algorithms of machine learning as well as deep learning are summarized elaborately in this paper. Deep Learning applications in agriculture were discussed. Deep Learning has been within the scope of smart applications for agriculture, including crop management systems. Crop cultivation, crop disease diagnostics, water along with soil management, crop distribution, weed control, rigorous fruit counting, and yield prediction are all part of the process. The objective of this study is to inspire more scholars in order to explore with deep learning, utilizing it to address a wide range of agricultural issues involves classification or prediction, but also computer vision and image analysis, as well as generalized analysis of data. In the future, researchers may intend to extend the broad ideas and knowledge of deep learning, as described within this study, to other agricultural areas where all this contemporary approach has yet to be adopted. Deep learning’s long term benefits were promising because of its future application in to smarter, extra sustainable farming and then more secure food supply.

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Appendix

Table1.1 Applications utilizing computer vision with agricultural with popular approaches.

S.No	Agriculture Application	Data analysis techniques
1	crop mapping / Soil as well as vegetation	SVM, end-member extraction technique, linear polarizations (HH, VV, HV), image fusion, co-polarized phase differences (PPD), linear mixing models, logistic regression, distance-based classification, decision trees, ANN, NDVI
2	crop canopy as well as the leaf area index	NDVI, linear regression analysis
3	Crop phenology	NDVI, Fourier transformations, and wavelet-based filtering
4	Fertilizers' effect and biomass, crop height, estimation of yields	Vegetation index (NDVI, ICWSI), wavelet-based filtration, linear polarizations (VV), linear and exponential regression analysis.
5	Crop monitoring	Feature extraction using stepwise discriminate analysis (DISCRIM), linear regression, co-polarized phasing differences (PPD), linear polarizations (HH, VV, HV, RR, and RL), classifiers tree analysis
6	Identification of seeds and species rearrangement	Linear regression analysis, principal component analysis, feature extraction
7	Nitrogen content and treatment of soil and leaves, as well as salinity detection	Analysis of linear and exponential regression
8	Irrigation	Image classification methods (density slicing using thresholds, unsupervised clustering), NDVI, and linear regression analysis are all used in decision trees.
9	Pest detection and management	CEM nonlinear signal processing, Analysis of linear and exponential regression, NDVI, image processing using sample imagery, statistical analysis.

10	Weed detection	Wavelet-based classification as well as Gabor filtering, evolutionary computation, pixel classification employing k-means clustering as well as the Bayes classifier, FFT and GLCM feature extraction techniques, Fuzzy approaches, genetic algorithms, as well as artificial neural networks, logistic regression, edge enhancement, colour detection, principal component analysis, segmentation of erosion as well as dilatation
11	Contaminant detection, sickness or defect detection, and bruise detection	Principal component analysis, FFT, SVM, discriminant analysis analysis, classification trees, K-nearest neighbourhood, decision trees, fusion, standard Bayes discriminant analysis, feature investigation, colour, shape, and geometric features utilising discrimination analysis, K-mean clustering, 3-dimensional vision, invariance, pattern classification, and image modality
12	Hail damage to crops	Unsupervised image categorization, linear and exponential regression analysis
13	Expansion and intensification of agriculture	Wavelet-based filtering
14	Greenhouse monitoring	Analysis of linear as well as exponential regression, unsupervised classification, NDVI, including IR thermography

Table 1.2. Agriculture-related datasets those are publicly available.

S.No	Dataset /organization/link	Dataset characteristics
1.	Image-Net Dataset http://image-net.org/explore?wnid=n07707451	Images of various plants (trees, vegetables, flowers)
2.	Image Net Large Scale Visual Recognition Challenge (ILSVRC) http://image-net.org/challenges/LSVRC/2017/#det	Images that allow object localization and detection
3.	University of Arcansas, Plants Dataset https://plants.uaex.edu/herbicide/ http://www.uaex.edu/yard-garden/resource-library/diseases/	Herbicide injury image database

4.	PFL, Plant Village Dataset https://www.plantvillage.org/en/crops	Images of various crops and their diseases
5.	Leafsnap Dataset http://leafsnap.com/dataset/	Leaves from 185 tree species from the Northeastern United States.
6.	LifeCLEF Dataset http://www.imageclef.org/2014/lifeclef/plant	Identity, geographic distribution and uses of plants
7.	PASCAL Visual Object Classes Dataset http://host.robots.ox.ac.uk/pascal/VOC/	Images of various animals (birds, cats, cows, dogs, horses, sheep etc.)
8.	Africa Soil Information Service (AFSIS) dataset http://africasoils.net/services/data/	Continent-wide digital soil maps for sub-Saharan Africa
9.	UC Merced Land Use Dataset http://vision.ucmerced.edu/datasets/landuse.html	A 21 class land use image dataset
10.	MalayaKew Dataset http://web.fsktm.um.edu.my/~cschan/downloads_MKLeaf_dataset.html	Scan-like images of leaves from 44 species classes.
11.	Crop/Weed Field Image Dataset https://github.com/cwfid/dataset https://pdfs.semanticscholar.org/58a0/9b1351ddb447e6abdede7233a4794d538155.pdf	Field images, vegetation segmentation masks and crop/weed plant type annotations.
12.	University of Bonn Photogrammetry, IGG http://www.ipb.uni-bonn.de/data/	Sugar beets dataset for plant classification as well as localization and mapping.
13.	Flavia leaf dataset http://flavia.sourceforge.net/	Leaf images of 32 plants.
14.	Syngenta Crop Challenge 2017 https://www.ideaconnection.com/syngenta-cropchallenge/challenge.php	2,267 of corn hybrids in 2,122 of locations between 2008 and 2016, together with weather and soil conditions
15.	Global Pesticide Grid https://sedac.ciesin.columbia.edu/data/set/ferman-v1-pest-	A global gridded data set of commonly-used for

	chemgrids-v1-01	agricultural pesticides
16.	Effects of Climate Change on Global Food Production from SRES Emissions and Socioeconomic Scenarios, v1 (1970–2080) https://sedac.ciesin.columbia.edu/data/set/crop-climate-effects-climate-global-food-production	To provide an assessment of potential climate change impacts on world crop production.
17.	India Annual Winter Cropped Area, v1 (2001–2016) https://sedac.ciesin.columbia.edu/data/set/india-india-annual-winter-cropped-area-2001-2016	To provide data that can be used in land cover and land use change (LCLUC) studies, agricultural applications, and to assist with policy-making in regards to sustainable agricultural intensification.
18.	Croplands, v1 (2000) https://sedac.ciesin.columbia.edu/data/set/aglands-croplands-2000	To provide data on the extent of croplands for research on human-environment interactions.
19.	Potential Impacts of Climate Change on World Food Supply, v1 (1995–2110) https://sedac.ciesin.columbia.edu/data/set/crop-climate-potential-impacts-world-food-supply	To provide an assessment of potential climate change impacts on world crop production, including quantitative estimates of yield changes of major food.
20.	Fifth Assessment Report (AR5) Observed Climate Change Impacts, v2.01 (2007–2014) https://sedac.ciesin.columbia.edu/data/set/ipcc-ar5-observed-climate-impacts-v2-01	To provide such a database of observable environmental changes for multidisciplinary study.

Table 1.3 Deep Learning algorithms used in agriculture

Type	BP	CNN	RNN	GAN	BP	DBN
Different versions	RBF GRNN	LeNet, AlexNet VggNet	LSTM	DCGAN	MLP	DBM
Network Infrastructure	Input Layer Output Layer Hidden Layer	Input layer Convolution layer Pooling layer	Input layer Hidden layer Output layer	Discrimination model Generation model	Input Layer Hidden Layer Output Layer	Input layer Hidden layer1 Hidden layer2 Hidden layer3 Output layer
Various Application	Fitting data Pattern detection Classification	Image processing Speech signal Natural Language Processing	Analysis of time series Emotional examination Language of Nature Processing	Image creation Video creation	Image Recognition, Object detection, Route Adjustment	Motion-capture Image generation video recognition Image classification