



Machine Learning Applications in Smart Agricultural Farming, Opportunities, Challenges and Future Trends

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Abstract

The purpose of the smart agricultural farming is to enhance the optimization of the scarce lands and other agricultural resources to improve food security. Smart agricultural farming employs Internet of Things (AI) technologies/devices to create automated and sustainable farming. The AI devices such as sensors, actuators and other smart agricultural devices generate huge amount of data. Therefore, the huge amounts of the data generate in the smart agricultural farming, are subjected to analytics, for new knowledge discovery and gain insight, for decision making. Recently, application of the machine learning for smart agricultural farming has gained special attention from research community. However, despite the popularity, special attention gained and achievements made by the machine learning in solving problems in smart agricultural farming, no review or survey has been dedicated mainly on the application of machine learning in smart agricultural farming, to show the opportunities, challenges and future trends. Therefore, in order to bridge this gap, this study conducted a dedicated on survey study on the machine learning applications in smart agricultural farming. In this study, opportunities, challenges and future trends on the applications of machine learning in smart agricultural farming have been unveiled. They study provides opportunities to research community and other experts to propose novel approaches and framework for developing research areas on the machine learning applications in smart agricultural farming. Moreover, new researchers interested in the machine learning applications in smart agricultural farming, can use this study as an entry point.

Keywords: Machine Learning, Artificial Intelligence, Internet of Things, Smart farming, Algorithm

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Introduction

Agriculture is one of the main profitable jobs in Nigeria. It plays a vital role in the money-making boost of Nigeria. Around 70-80 % employment is dependent on agriculture. With the increase of population, everyday changes in climatic conditions and limited resources; it becomes a demanding task to accomplish the food condition of the present populace. Smart farming has emerged as an inventive device to deal with modern challenges in agricultural sustainability. The system that drives this technology is the machine learning (ML). It

gives the machine capacity to learn without being unambiguously programmed. Machine Learning together with AI (Internet of Things) enabled farm machinery the key mechanisms of the next agriculture change.

The main spotlight of Smart Agriculture is to lessen the production rate and environmental effects to boost the farm's profitability. Digital technologies such as AI Artificial Intelligence, Data Analytics, Cloud Computing, and Block-Chain Technology play a key role in Smart Farming (Cambra, *et al.*, 2017).

In Smart farming, AI based smart sensors are deployed in the agriculture land for collecting data related to soil nutrients, fertilizers, and water requirements as well as for analyzing the crop growth. Autonomous and semi-autonomous devices such as an unmanned aerial vehicle (UAV) and robots are used for identifying weed and disease in the plants using computer vision techniques (Changguang *et al.*, 2022).

Satellite images are as well used in smart farming for monitoring the field and identifying the diseases in the plants. The data gotten from the deployed sensors are processed and analyzed using ML algorithms to make farming practice additionally restricted and optimized. In addition, Machine Learning algorithms are used for weather and rainfall prediction based on the data obtained from sensors, climatic records, and satellite images. This could save the lives of millions of farmers who will commit suicide for the reason of crop loss due to uncertainty in weather conditions.

Smart livestock administration is also a significant constituent of smart farming. It helps in monitoring the physical condition, wellbeing, output, and reproduction of animals all through their life cycle. Sensors and cameras monitor animal's wellbeing and computer vision techniques assist in making intellectual decisions such as stopping the common spread of diseases. Autonomous tractors and automated irrigation systems provide contemporary farming solutions to farmers. The prevalent utilization of smart farming across the world is due to the presence of innovative machine Learning (ML) algorithms, high-speed internet access, and efficient computational devices.

In (Damar *et al.*, 2022) the authors have discussed applications of Machine Learning for sustainable Agriculture Supply Chain (ASC) performance. The field data obtained by the deployed sensors is in the form of multimedia which helps in disease discovery in stems, leaves fruits and roots, quality, health of fruits (Dinkins and Jones 2019). This article will offer an insight into the research community about the embracing of digital practices in the farming administration

structure. It is predictable that government agencies will outline policies to encourage smart farming across Nigeria and the world. The main contribution of the article is outlined as follows: Literature Survey, Impact of Artificial Intelligence and AI in Agricultural Farming, Application of AI in Smart Agricultural Farming, Machine Learning Algorithms, Machine Learning applications in Smart Agricultural Farming, Opportunities and Challenges of Machine Learning Applications in Smart Agricultural Farming, Future trends of Agricultural Intelligence in Smart Agricultural Farming and Conclusion.

Impact of Artificial Intelligence and IoT in Agricultural Farming

World's population is growing at a rapid pace and is estimated to reach 10 billion by 2050. This puts an immense responsibility on the agriculture sector to enhance crop production and increase yield per hectare (FAO, 2017). Several pain points for farmers such as small land holdings, labor shortage, climate change, extreme weather conditions, reduction in soil fertility, etc. are making agriculture less profitable. For the last few years, agriculture is continuously challenged by climate change and other environmental problems and they create a huge hurdle in achieving enhanced productivity.

Considering the case of developing countries with highly populated areas where increasing the land area is merely impossible, the only way is to go smarter with the help of cutting edge technologies like the internet of things (AI) and allied technologies like Artificial Intelligence (AI). The recent advancement in ICT (Information and Communication Technology) and associated researchers have identified the 'Internet of things' and 'Artificial Intelligence' as key technologies for revolutionizing modern agriculture practices. By incorporating the use of digital technologies like artificial intelligence and internet of things, better insights can be formed effectively from data gathered from the field and allowing farming practices to be planned systematically with minimal manual labor.

Artificial Intelligence (AI) algorithms have the capability to handle and derive meaningful

insights from the data which can lead to high-quality decision-making. Problem solving and automation have been made quite simple by the introduction of new logic and methods such as Machine Learning, Natural Language Processing, Machine Vision, Artificial Neural Network (ANN) etc. Out of all these, Machine learning and ANN are the most widely applied methods in researches related to automation in agriculture (Gupta *et al.*, 2020).

Machine learning algorithms can work with labeled (supervised learning) as well as unlabeled data (unsupervised learning). Most of the data driven automation and related operations follow the supervised learning algorithms. The current agriculture automation systems highly rely on the Artificial Neural Network (ANN) which performs well on complex classification tasks. ANN is inspired by the biological neurons and its architecture in a layer fashion. The architecture enables them to learn complex non-linear relationships. Deep learning based computer vision techniques that are widely used in agriculture automation are generally built based on Convolution Neural Network (CNN).

CNN has made tremendous progress and has shown exemplary performance in image segmentation, classification, detection, and retrieval related tasks, thus reviving the interest of scientific community in ANNs (Hamna *et al.*, 2022).

The powerful learning ability of CNN is mainly due to the multiple feature extraction stages using a set of layers and convolution operations (Figure 1). For a CNN model to classify an image, it has to go through a series of layers that are convolutional (with kernels/filters), pooling and fully connected

layers. Convolution layer is responsible for extracting the features from the images using kernels. A 2D kernel is a matrix of weights that slides over the input image data and performs element wise multiplication with the part of the input that it is currently on, and then it sums the results to a single pixel. This repetitive sliding operation generates a feature map of the image. Convolution operations with different kernels are helpful in operations such as edge detection, sharpening, blurring, etc. This output of the convolutional kernels is assigned to the activation units, where the non-linearity is added to the model (Yang, 2020). Tanh, Sigmoid and ReLU are the most commonly used activation functions. Pooling operation is performed in the next stage of the CNN in which a significant reduction in number of parameters is performed especially when the images are too large. Max pooling, average pooling, min pooling and sum pooling are the important pooling operations applied over the feature map. Max pooling identifies the largest element from the output of previous layer. Average pooling identifies the average of each patch from the feature map. In the next step, the matrix of values is flattened to vector form and fed to a fully connected neural network. With all these features, a neural network model is constructed and activation functions such as softmax or sigmoid are used to classify the outputs into the various classes based on the identified probability. Over the years, there were modifications in-depth and structure of CNN and this resulted in improved performance and learning capacity. The workflow operations in image classification using CNN is given in Figure 2.

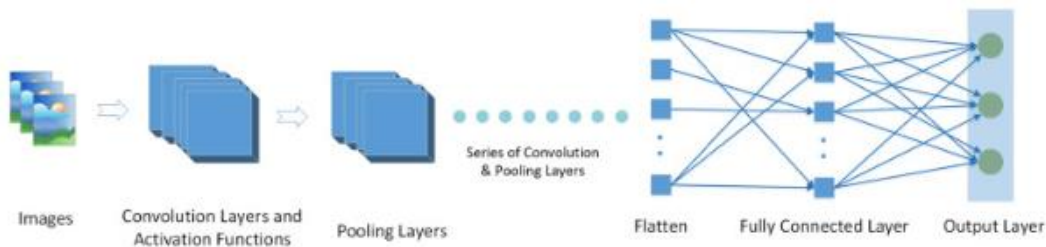


Figure. 1: Architecture of convolution Neural Network (Indolia *et al.*, 2018).

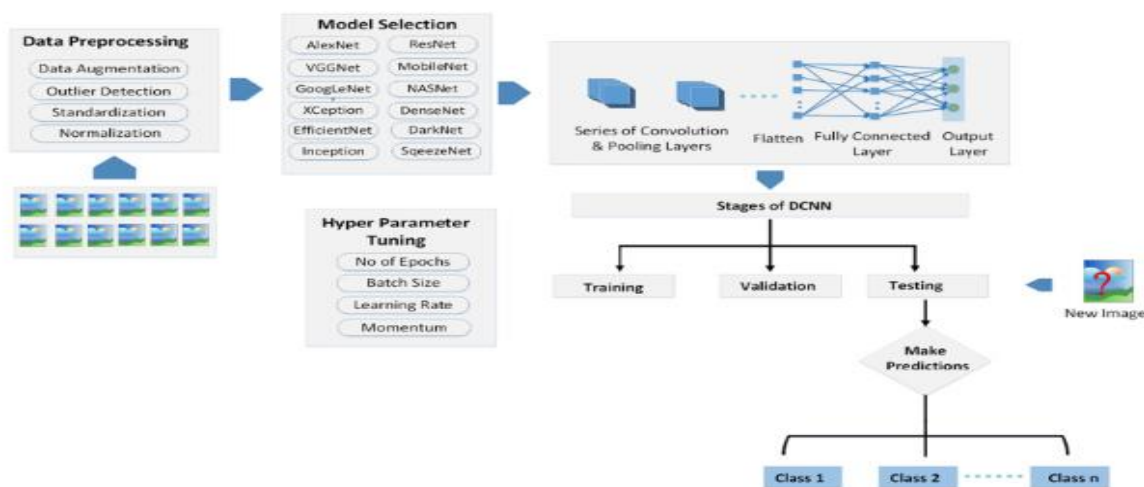


Figure 2: Pre-trained CNN model based image classification pipeline (Indolia *et al.*, 2018).

The Internet of things has a huge potential to become a game-changer in agriculture automation and it is already doing wonders in the field. It is referred to as a network of physical objects called ‘things’ with network connectivity that can enable these objects to collect and exchange data and interact with the environment (Javeria *et al.*, 2022).

The application of the internet of things backed up with an efficient intelligent decision-making system can lead to a significant reduction in human intervention in various agricultural tasks. This intelligent decision-making is the brain of the system, which decides the success, and failure of automated activities. The amalgamation of the internet of things with artificial intelligence results in powerful systems that can even beat human decisions in terms of accuracy. Artificial Intelligence enabled systems are computer systems that can able to perform operations that generally require human intelligence such as speech recognition, visual perception, decision making, and language translations (Jha *et al.*, 2019).

The IoT and AI are considered two sides of the same coin when it comes to the automation of agriculture tasks. Over the decades, the agriculture sector has realized the importance of precision farming. Precision farming is a sustainable alternative that will enhance production by providing a precise amount of inputs reducing the overuse of potential environmentally damaging pesticides and

other inputs. Despite the challenges due to climate change and other factors, the digital technology driven agriculture provides a plethora of methodologies for automating and enhancing agriculture production and productivity. Digitization in agriculture enables real-time analysis that helps in more effective spraying, land management, water management, and even land surveillance (Yang, 2020)

The use of emerging digital technology will allow the agriculture industry to achieve several other benefits such as reducing input costs and wastage, achieving sustainable practices along with enhancing productivity to meet the growing food demand. Digital technology driven agriculture is gaining more and more global attention due to the incredibly easy field management capability and powerful real-time monitoring systems. All these were a few main reasons for moving towards mechanization along with reducing the drudgery (Kastur *et al.*, 2023).

Machine learning Algorithms and Applications in Smart Farming

Machine learning technologies have contributed to boosting agricultural gains. Machine learning is a recent technology that is assisting farmers in reducing farming losses by offering detailed crop suggestions and insights. Machine learning is becoming more efficient and accurate because of deep learning algorithms. Using automated machine learning, one may reduce the need for ML

expertise while also automating the ML workflow with greater precision (Lillo-Saavedra *et al.*, 2022).

It is observed that in previous years research on agriculture using machine learning techniques was limited to predicate crop yield, identification of plant species, and automatic object detection, but in the last two decades, machine learning shows its usefulness in other areas of agriculture like processing, production, marketing, and distribution of crops and livestock production and cost estimation. Now it is clear that agricultural activities serve as the basic source of income, expand GDP, providing raw materials for production in industries so overall continuous contribution to GDP. Machine learning with big data and high-performance computing are used for data-intensive processing in agriculture. In the past machine learning algorithm like Artificial Neural Networks. K-means, support vector machines, decision trees, etc. are commonly used algorithms. In this section, some recent work done in 2022 is highlighted. In this section work done in various areas of agriculture is also reviewed. Agricultural productivity can be increased using the machine learning (ML) in a smartest way. The Food and Agriculture Organization report indicates that the productivity of the crop is getting increased. Smart agriculture is one of the best ways to check the productivity of crops. The applications of ML identify and eliminate issues, which occur in the growth of agricultural crops (Matta and Pant, 2019).

A ML technique is used in the decision making to meet specific requirements. In the modern era, smart agriculture plays a vital role in identifying the decision making and prediction over the crop yield. Due to the lack of farmers, the productivity of the crop gets decreased. To improve the productivity of the crop, the monitoring of the crop and agricultural pests had to be controlled using the smart agriculture. Using the ML techniques, the crop productivity in the agriculture can be improvised. By using the sensor data, the accurate data are predicted by evolving the artificial intelligence, which allows a smart way in farmer decision making. These techniques identify the fast

development in the artificial intelligence in the agricultural field (Matta and Pant, 2019).

The smart farming concept monitors all the procedures, disease prediction, and agricultural pests. To extract the useful type of information from large datasets, ML is used. These applications are used in different sectors, such as biomedical informatics, malware intrusion system, and retrieval of information. The complex structural characteristics are analyzed and other meteorological climatic factors are analyzed using deep learning. These techniques are feasible and cost-effective in predicting the diseases in the crop. To sense the image classification of agriculture, the ML methods develop the ability of agricultural research. Precision agriculture can be able to drive crop management (Matta and Pant, 2019).

Literature Surveys based on Machine Learning

A lot of Research has previous been accomplished in the area of smart farming using diverse technologies like AI, machine learning for building Decision Support System, Data Analytics, etc. in this work we tried to preset different fields in the literature at length as can be seen in the subsections below:

Machine learning are used in diverse agronomic applications, for example remotely observing environmental and soil conditions in order to predict the healthfulness of crops. Watering schedule of agricultural fields is forecasted by employing WSN as observant of environmental conditions like pressure, humidity, temperature, soil moisture, soil salinity and soil conductivity. A lot of work has been done in the literature; and main contributions by various researchers are discussed.

In Matta *et al.*, 2019, AI and machine learning technologies were combined and system was integrated with three primary agricultural operations, which includes crop selection, autonomous watering, and fertilizer suggestion. The following crops Apple, Rice, Maize, Grape, Banana, Orange, Cotton, and Coffee were considered in the study. Three systems are covered in the paper: The crop recommendation system employs machine

learning to examine factors including nitrogen (N), phosphorous (P), potassium (K), pH, and weather before recommending a crop. The crop type and the current levels of soil nutrients are the two main determinants on which the fertilizer recommendation method bases its recommendation. When employing an automatic irrigation system, the crop is irrigated automatically while taking current soil moisture levels and weather forecasts into consideration. The work attempted to

implement the mentioned systems and discusses the successes of the crop recommendation system, the automatic watering system, and the fertilizer recommendation system. They also report the results of simulations of the mentioned systems. To improve crop yield, a final system that is capable of performing several functions needs to be created. For this, three subsystems are combined into one primary system, as illustrated in figure 3.

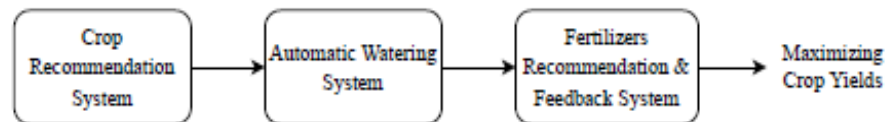


Figure 3: the proposed methodology (Matta *et al.*, 2019).

The recommender system checks the temperature, humidity, and rainfall of the chosen location before checking the NPK and pH of the soil. While the pH data is gathered using a pH sensor, the NPK values are gathered using an NPK sensor. Then, using a

cloud platform open weather api, the values of temperature, humidity, and rainfall are gathered. To suggest the optimum crops, the collected values are then run through a machine learning model, as illustrated in figure 4.

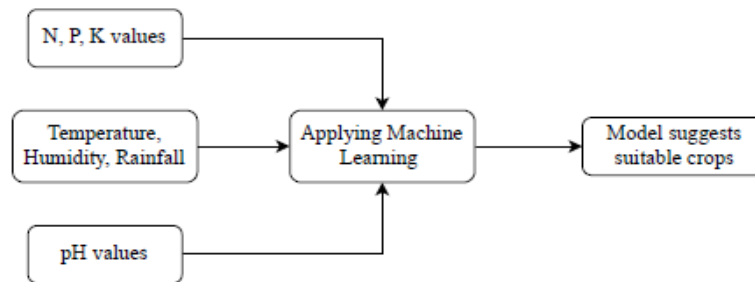


Figure 4: Crop Recommendation System (Matta *et al.*, 2019).

The diverse data values are first clustered using K-Means clustering. The accuracy of 5 distinct machine learning models RFC, GBC, DT, XGB, and KNN would then be compared. Values gathered from the sensor and cloud

will then be transmitted via whichever one is most appropriate. The best crop that could grow in that place would then be suggested by this system as illustrated in figures 5 and 6.

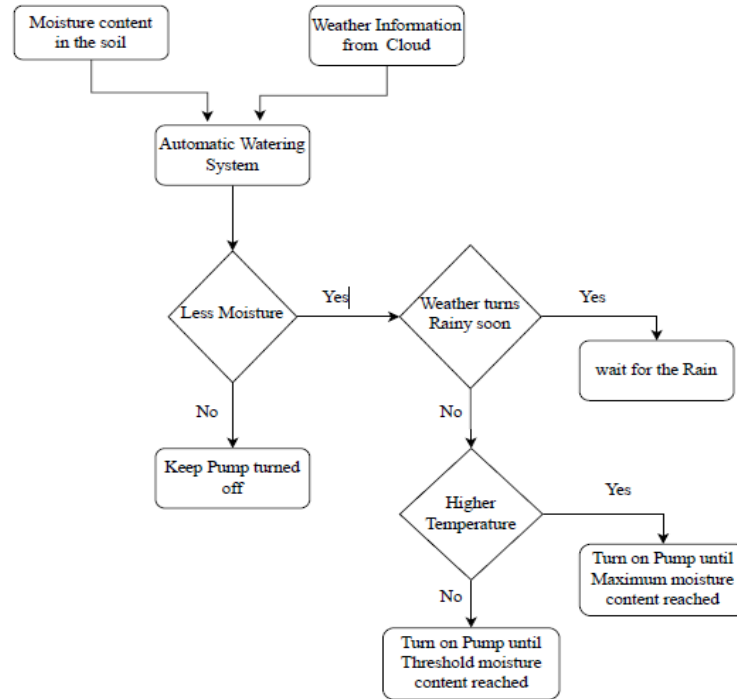


Figure 5: Automatic Watering System (Matta *et al.*, 2019).

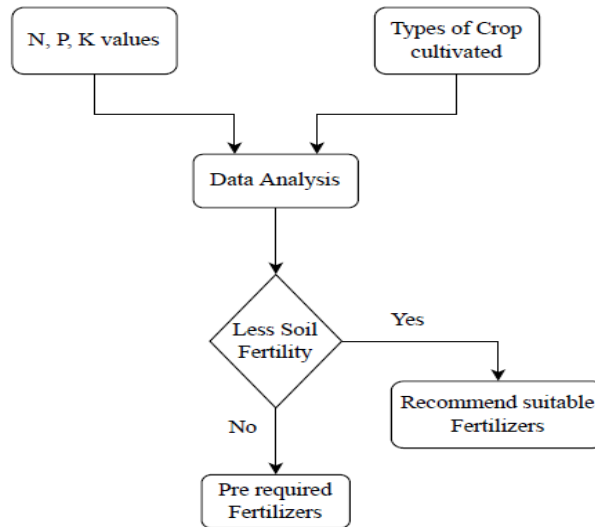


Figure 6: Fertilizer Recommendation System (Matta *et al.*, 2019).

This technology could be used by farmers as an effective decision-making tool to help them reduce manual labor, conserve energy, and increase output. For the future scope of this work, a disease prediction system can be added to the suggested system to predict crop diseases based on image classification.

Mehta *et al.*, (2014) proposed a system for classification of apple diseases using the

machine learning classification algorithms. The two diseases which they classify are apple scab and *Marsonina coronaria* by using the images of leaves of the apple trees as input. Classification algorithms Support Vector Machine, K Nearest Neighbour, Decision Tree and Naïve Bayes were used on the same data. Matlab (2016) was used for the simulation proposed system. They showed it is the K

nearest neighbor which classified the diseases with the 99.4% accuracy. The system was developed in the state of Himachal Pradesh, Uttarakhand.

Mezan *et al.*, (2021) indicates that nodes have the capability to make the system more practical by collecting the real time data from the crop fields to make the agriculture system precise. By incorporating data analytics and machine learning the agriculture system becomes more workable. All these technologies have tremendous applications in other fields. In precision agriculture various applications for farmers are developed to inform them about the status of crops on time. The architecture for precision agriculture is usually composed of three main phases.

The first phase it consists of the number of sensors/AI nodes to monitor physical or environmental conditions, soil conditions, plant conditions, e.g the soil moisture sensor records soil wetting reading, or soil nutrient sensor will check the fertility of the soil. In the second phase we need to collect this precise data, we can either store the data locally to the nearest fog node or we can send it on the cloud for higher computation and remote monitoring it depends upon the need. In third phase of the architecture the analytics methods are applied to know the status of the crop fields. This information is then communicated to the end users (farmers) that help them to identify that if the reading is below or above threshold. Accordingly they initiate communication to the actuator that would switch on (or off) the watering system to pour water to the soil or farmer (end user) may need to spray some fertilizers potassium, nitrogen and phosphorous to balance the fertility of soil. Using analytics and actuators a response mechanism is activated upon recognition (sensing/predicting) of any critical scenario. There are number of applications of AI and WSN in the precision agriculture, some of them are mentioned here. A soil testing toolkit, Lab-in-a-Box, developed by Agrocres is considered to be the complete laboratory test toolkit (Nex and Remondino, 2014).

Ranganathan *et al.* (2023) work on cotton crop in their paper “Explainable Neural Network

for Classification of Cotton Leaf Diseases.” In this, they concluded that various diseases that affect cotton crop yield occur on the leaf for example powdery mildew, leaf curl, leaf spot, target spot, bacterial blight, and nutrient deficiencies. It is observed that if were detected at early-stage crops can be protected from harm. Various computerized methods play a very important role in cotton leaf disease detection at an early stage. The method given by authors in this work consists of two core steps i.e., feature extraction and classification. The author proposed a method, in which data augmentation is applied to balance the input data then features are extracted from a pre-trained VGG-16 model and passed to 11 fully convolutional layers, which freeze the majority and randomly initialize convolutional features to subsequently generate a score of the anomaly map, which defines the probability of the lesion region. This work proposed a model which was trained on the selected hyper parameters that produce great classification results. The proposed model performance is evaluated on two publicly available Kaggle datasets, Cotton Leaf and Disease. The proposed method provides 99.99% accuracy. Reduanul and Ferdous (2022) also worked for the early identification of disease, to find pest patterns, and if there is any deficiency in nutrition present in the ginger plant. For this purpose, the authors used deep artificial neural networks and deep learning-based methods. A real-field dataset was used in this work which consists of both healthy and affected leaves of the ginger plant. They concluded from this work that for disease detection convolutional neural network (CNN) was best having accuracy of 99%, Pest pattern leaves can be identified by VGG-16 with an accuracy of 96% and ANN was considered best for the identification of nutritional deficiency-affected leaves but results obtained in this work was completed for the dataset used in this work and if a dataset is changed may be different results will be obtained.

Sharma *et al.*, (2020) proposed a system that automatically detects disease in eggplant crop leaves. In this work, authors used two-stream deep fusion architecture of CNN-SVM and

CNN-Softmax pipelines, with an inference model to conclude the nine diseases of an eggplant crop. The authors used a dataset that consist of 2284 images of nine disease classes of which 1842 images were taken from various sites in Bangladesh and the source of 442 images was the internet. In this work all images collected were infectious and they are categorized into the following classes aphids (class 0), bacterial wilt (class 1), *Cercospora melongenae* (class 2), collar rot (class 3), eggplant–Colorado potato beetle (class 4), little leaf disease (class 5), spider mites (class 6), Phomopsis blight (class 7), and tobacco mosaic virus (class 8). In this work, it was concluded that the proposed methods had achieved better accuracy and fewer false-positive results compared to VGG16, Inception V3, VGG 19, MobileNet, NasNetMobile, and ResNet50.

Singh and Gupta (2018) worked on rice crops to identify rice blast disease which is the most destructive disease. The size of the area occupied by the disease spot on leaves showed the severity of the disease and traditionally it was checked manually which was time-consuming so correct and fast segmentation of rice blast is of much beneficial for improving the rice yield. It was found that most of the research had been done for the identification of rice disease types only a few works had been done on disease segmentation. In this work, authors proposed a real-time semantic segmentation method called DFFANet network which consists of modules like feature extraction module, feature fusion module, and attention mechanism module. The authors used the following evaluation criteria for evaluating the segmentation model: the average intersection rate (abbreviated as MioU), inference speed (abbreviated as FPS), and several parameters (abbreviated as Params), and IoU is the ratio of the intersection and union of the prediction result. They concluded that the proposed method gains 96.15% MioU, a speed of 188 FPS, and the number of parameters is only 1.4 M, which results in a better balance between accuracy and speed hence decreasing the requirement for hardware and giving support for real-time fast detection of rice diseases.

Sri *et al.* (2019) had done a research study intending to identify the four main types of disease phoma, miner, rust, and *Cercospora* present on coffee leaves using deep learning. In their proposed method, they were able to find out the deep characteristics of coffee plant leaves by using transfer learning and various pre-trained CNN networks. To determine the results authors, choose the best three models and concatenated them for building an ensemble architecture along it with increasing the quality and data sample quantity data pre-processing and augmentation methods were also applied. The outcome of this study was that when compared with other DL models this proposed ensemble architecture achieved 97.31% validation.

Subeech and Mehta (2021) worked for insect detection on a tomato crop field, in this work authors showed the use of the YOLOv5 object detection model on images collected from a tomato crop field for insect detection in yellow sticky traps. For finding the insect population, assigning management, and evaluating the effectiveness of treatment in projects Insect traps were used. The sliding window approach was used in the insect detection process to minimize the duplicate detection on yellow sticky card IT images. The YOLOv5 is doing well in differing element exposure conditions. The work done in this paper focused on insect detection and monitoring as well as it also helped to identify diseases and pests. The authors proposed a method that shows good results compared to related works, 94.4% for mAP_{0.5}, with a precision and recall of 88% and 91%, respectively, using YOLOv5x.

Sundaresan *et al.* (2022) also worked on insect detection. For this work, they used three Deep Convolution Neural Networks Models Faster-RCNN, Mask-RCNN, and Yolov5, along it authors also used two coco datasets based on the Baidu AI insect detection dataset and IP102 dataset and compared these three deep learning models on the two coco datasets. The classification of datasets was done based on the sizes and categories of insect pests. It was observed that in the Baidu AI insect detection dataset, the pest size was significantly different and based on pest size; farmers can use pesticides more accurately on the insect

for pest control. The IP102 dataset consists of ten specific types: armyworm, Asiatic rice borer, brown plant hopper, corn borer, English grain aphid, rice gall midge, rice leaf roller, rice leafhopper, wheat blossom midge, and white-backed plant hopper. The authors choose these insects because these insects are found in common crops like rice, wheat, and corn. They concluded from this work that Yolov5 was best for the Baidu AI insect detection dataset has accuracy above 99% while Faster-RCNNs and Mask-RCNNs reach above 98%. And it was also found that Yolov5 had a faster computational speed than Faster-RCNN and Mask-RCNN. For the IP102 dataset which consists of so many categories, Faster-RCNN and Mask-RCNN show higher accuracy, i.e., 99%, than Yolov5 having an accuracy of 97%.

Tiago *et al.* (2022) had done work for rice growth stages. In their work, they highlighted the issue related to the complete growth of rice crop, which must pass through various stages like a vegetative stage, reproductive stage, and ripening stage, it is very difficult for a new cultivator to observe the conversion from one stage to other and along it aging and labor cost also increase the overall cost of agriculture, to solve this problem authors proposed a random forest (RF)-based machine learning (ML) classification model for rice growth stages. To conduct the experiment a setup was installed in the experiment fields which consisted of an HD smart camera (Speed-dome) to collect the image and video data, along with Internet of Things (AI) devices such as 7-in-1 soil sensors, a weather monitoring station, flow meter, and milometer connected with LoRa base station for numerical data. After that various image processing techniques like object detection, object classification, instance segmentation, excess green index (EGI), and modified excess green index (EGI) were used to calculate the paddy height and canopy cover (CC) or green coverage (GC). These values are used as input in the proposed ML model and, to develop a model various growth-related factors such as height, CC, accumulative temperature, and DAT were considered the result obtained from this optimal model has an accuracy of 0.98772,

and a macro F1-score of 0.98653, so authors concluded that this developed model can be used in real-world scenarios.

Lillo-Saavedra *et al.* (2022) presented a work in which a methodology was proposed for the early prediction of tomato yield by decision tree ensembles, vegetation spectral indices, and shape factors from images since early yield prediction helps a farmer to take a decision and do required planning. For this task images were captured by multispectral sensors board on an unmanned aerial vehicle (UAV) during different phenological stages of crop development. In this work, the predictive model was developed and the tomato yield was estimated for a 0.4 ha plot, having an error rate of 9.28%. The estimation was done based on training characteristics for 6 weeks before harvesting. The authors used a DTE algorithm for forecasting tomato yields. The approach behind generating this model using DTE was obtaining a set of individual decision trees (DT), each of which is trained with a sample slightly different from the training data. The prediction of a new observation is obtained by adding the predictions of all individual trees that form the model and creating ensembles bagging and boosting techniques were used Bagging and boosting are common ways to create ensembles of DTs. Bagging is a technique used to reduce the variation of predictions via a combination of results from various classifiers, each modeled with different subsets taken from the same population and boosting consists of changing the results from various weak classifiers to obtain a robust classifier.

Gubbi *et al.* (2013) have looked at the naive bayes and KNN classification algorithms for precision agriculture. They have analyzed the data and determined the optimal classification method for use in precision agriculture by taking into account a wide range of factors. The Naive Bayes and K-Nearest Neighbour methods are the first and second, respectively. Using these two strategies, they can be able to achieve a precise performance. A java programme is developed to estimate agricultural output.

It can be used by any farmer to test the soil of their fields without going without going any

agriculture laboratory. According to this toolkit it is said that around 100 samples per day can be tested by any farmer without having any lab experience. It means around 36000 samples per year can be tested without visiting any lab.

The application process consists of three stages. Data management comes first, followed by data testing, and finally data analysis. By organizing datasets, we may get datasets from prior years and transform them into a usable format. Because of the use of the Weka tool, all of the datasets included in this undertaking have been transformed into

attribute relation files. In the testing phase, the can conduct tests independently. Two machine learning techniques have been discussed. Naive Bayes and the K-Nearest Neighbour Method are two examples. Any one of several methods was used to evaluate a dataset, with findings similar to those obtained from selecting a single crop, a single location, and a single growing season. In the analysis section, they load an entire dataset file to compare the two approaches' precision. This aids in foreseeing which approach will prove effective as illustrated in figure 7.

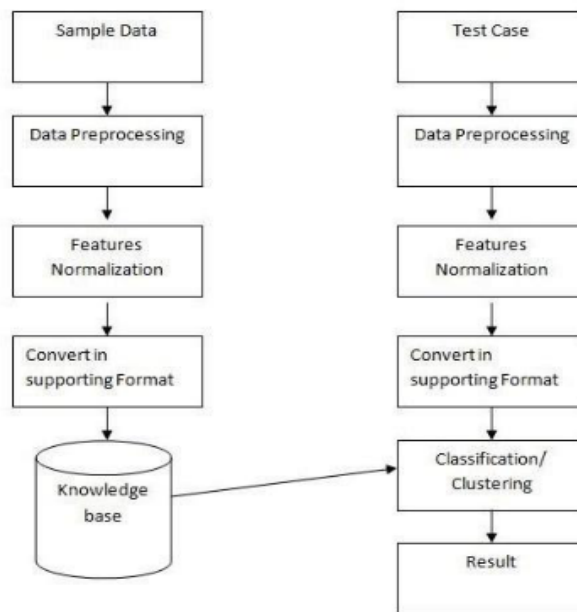


Figure 7: Proposed system (Yang,2020)

Opportunities, and Challenges of Machine Learning Applications in Smart Agricultural Farming

In recent years, machine learning has become one of the most promising technologies. And while it's often associated with consumer applications like Smartphone personal assistants and social media recommendations, its potential extends far beyond that.

Agriculture is a great example of the sector where machine learning and AI are beginning to make a real impact, helping farmers increase yields, reduce costs, and improve decision-making. But like with any new technology, there are challenges that need to be addressed before **the use of machine learning in agriculture** can truly take off. In

this work, we'll explore some of those challenges and their possible solutions.

Opportunities of Machine Learning Application in Smart Agriculture Farming

Machine learning has massive potential to disrupt every part of the agriculture industry in the next 100 years. It is showing up in everything from drones learning how to navigate apple orchards to farm management software. At the end of the day, these technologies increase profits by automating repetitive tasks and using the computer to compute massive data sets.

Artificial Intelligence help will farmers focus on the important things at their farm. They do not have to try to figure out details and remember loads of information at a later date.

An AI tool does not guess or react to intuition based on years of experience like an experienced farmer does. But it can incorporate knowledge from the farm to do a task that growers need done.

There is another significant advantage over traditional methods. Nothing is forgotten by the computer's memory unless you tell it to. There is no need to search for lost papers. Managers and bosses do not have to ask a worker who knows the information to try and remember an important detail that wasn't important months earlier.

Machine learning can help farmers make informed management decisions on what to grow towards matching the crop to the existing market's demands. Smart farming is a concept that has been developing for many years. Crop management is still at the center of all the capital investment and research attention going into AI and machine learning in agriculture.

New types of remote sensors, satellites, drones, tractors, water management tools, and soil monitoring systems are currently being developed to allow growers to benefit from the technology.

An important thing to note is that machine learning is only as good as it is taught, and programmers work hard to teach these machines. Programmers can be informed by growers and packers to make the perfect AI tool. With this information and a finished product AI can help customers time and save money.

There are many opportunities of using machine learning applications in smart Agricultural farming. Given below are some of the most important ones:

i. Analyze Market Demand

Machine learning in agriculture can be used to analyze the market demand of the crops. Sometimes farmers are unable to produce the crop which is in high demand because they did not know about it. Forecasting the demand will help them produce what will sell more and this way they can get better returns for their produce. If the crop lies unsold then farmers are forced to sell it at a minimum support price. In this case, they have to settle for less money and suffer losses. Machine learning

can help prevent all such situations related to market demand.

ii. Risk Management

Risk management is another area in which machine learning can help in agriculture. Risks can arise due to many factors- external related to environment, government rules and weather changes. Therefore, by using machine learning we can estimate the possibility of risks and mitigate it as quickly as we find it out. It is better to control the risk factors than having the whole crop produce go to waste.

iii. Breeding Seeds

Farmers have to check the quality of seeds before sowing them. Breeding seeds means mixing different types of seeds to produce something unique or a different species of crop. To decide which seed can be bred with which depends on proper selection. Machine learning can help in determining which seed will mix with and give the best results. Breeding wrong seeds can lead to disastrous results and the produced crop can even be harmful for consumption. Rightly bred seeds will always help in giving the best outcome. Machine learning can gather the relevant data and predict the results.

iv. Crop Protection

Crops need to be protected from so many things. Bad environment, diseases, fertilizers and even climate can damage the crops. Farmers can take insurance for their crops or they can also resort to machine learning techniques that can help farmers get daily reports about the crop health and what can damage it. Farmers can get a 360 degree view of the crops. They can find out how much fertilizer is needed for the crop and the maximum limit above which the crop will be damaged. Machine learning can be a great source to protect the crop from any sort of attack.

v. Soil Health Monitoring

Soil has to be prepared before crops are sown. Not every kind of soil is suitable for every crop type. Due to soil pollution the soil becomes acidic and it creates fertility issues. Therefore, finding the perfect soil so that soil is fit for growing crops is important. Machine learning

can help us test the soil type and the contents in the soil.

vi. Harvesting

During the harvesting season there is lots of work that farmers have to do. Right from hiring skilled workforce to cutting the crops and sending them to the next process. Machine learning can assist the farmers in a variety of ways and reduce their workload. It can gather data from multiple sources and from past crop seasons can prepare a plan of action for the farmers. Agricultural productivity can be enhanced using machine learning and along with it any harmful impact of it on the environment can be reduced. By relying on forecasting and data a lot of agricultural problems can be eliminated (Wei *et al.*, 2022). There are many platforms on which you can find relevant information related to machine learning and how it can be implemented in agriculture.

Challenges of Machine Learning Application in Smart Agriculture Farming

Despite all the benefits and opportunities of ML in agriculture, it isn't widely used just yet. The main obstacles are lack of knowledge (many farmers are used to traditional farming and are not ready to use machine learning or are unaware of the existing technologies), lack of skills to use ML, lack of access to the solutions, and cost. To change the situation, it's important to raise awareness, educate and train farmers, and continue the development of this sector to make advanced technologies a standard for the industry.

Another barrier is that most machine learning algorithms in agriculture are used on and can be effective only for specific crops in limited regions. With time, the solutions will become more efficient and comprehensive, allowing farmers in different regions to apply them for different crops.

Other challenges of machine learning application in smart agricultural farming include:

- i. **Lack of Internet.** To implement smart Ag technologies, you need a stable Internet connection. Unfortunately, it

is not available in all regions of the world.

- ii. **Low awareness.** Modern systems require fine-tuning and knowing the features of their operation. Some farmers do not fully understand the benefits of using smart farming technologies or do not know how to work effectively with them.
- iii. **Lack of unification.** Many suppliers and machinery manufacturers make it difficult to arrange a single system since their equipment may not be compatible. Smooth integration of equipment and software requires standardization of the technologies used.
- iv. **Lack of scalability.** Both small farmers and large corporations should be able to use the same technologies, just at different scales. Easily scalable solutions would mean easier and faster production expansion.

When implementing intelligent systems, farmers and service providers should take into account the described challenges for smart farming and do everything possible to minimize their impact on production.

The Future Trends of Artificial Intelligence in Smart Agricultural Farming

AI is sure to play an increasingly large role in agriculture and food sustainability over the coming years. Technology has always been at the forefront of agriculture, from primitive tools to irrigation to tractors to AI. Each development has increased efficiency while reducing the challenges of farming.

More importantly, the benefits of AI in agriculture are undeniable. Smart farming tools, intelligent automation, and AI-powered products perform repetitive time-consuming tasks so workers can use their time for more strategic operations that require human judgment. Increasingly affordable computer vision alongside agricultural robotics has the potential to accelerate AI advancement in farming.

AI has the tools to address the challenges posed by climate change, environmental concerns, and an increasing demand for food. It will revolutionize modern agriculture by

improving efficiency, sustainability, resource allocation on top of real-time monitoring for healthier and higher-quality produce.

However, you can't just buy AI and start using it. AI is not something tangible it's a set of technologies that are automated through programming. In essence, an AI algorithm mimics way people think it learns first, and then solves problems based on data. AI-driven transformation of agriculture will require changes in the industry. Farmers need to be educated and trained in how to use AI-powered solutions.

What does this mean for workers in the agricultural industry? AI is likely to change the role of farmers from manual workers to the planners and overseers of smart agricultural systems. An understanding of IT solutions and agribusiness intelligence will potentially become more useful than the ability to use conventional tools or carry out physical labor. Despite AI and machine learning having the potential to radically transform farming, they need other technologies to work in sync. To reap all the benefits of AI, farmers first need a technology infrastructure. It could take years to develop that infrastructure, but doing so could result in a robust, future proof technology ecosystem. Understanding how AI works and how best to integrate technical knowledge into real-life processes is vital for maximizing its benefits. That's why partnering with an expert software development team is an excellent first step. Providers of AgTech solutions have an important role to play. Each must consider how they can improve their tools, address challenges, and clearly convey the measurable benefits of AI and machine learning. If this can be achieved, the future of AI in agriculture is bound to be fruitful. The success of human society is essentially dependent on the optimization of its agricultural systems. Traditional farming methods are becoming outdated, need for advanced technological solutions. Worldwide, the impact of automation on industries has always been considerable. Digital technology is now playing a huge role in transforming agriculture, and the impact of artificial intelligence in agriculture is set to be vast.

Conclusion

The paper has given an extensive literature survey on the smart agriculture farming using machine learning. Furthermore, the applications of these technologies in smart agricultural farming are highlighted.

This paper also highlighted the recent contribution of machine learning in agriculture and concluded that along with disease and insect detection, machine learning plays a vital role in the determination of various growth stages of the crop so that new cultivators can easily determine the transmission of the crop from one stage to another.

Therefore, after conducting this review, it has been determined that agriculture is crucial for the development of any country. In recent years, many new, advanced techniques have been adopted to boost productivity, but because this field requires a lot of labor and time is a crucial consideration, we must use advanced techniques to boost crop growth and quality. This is especially true if we use new technology to track plant development from the seedling stage to harvest. The following conclusions can be drawn from the study:

- i. Artificial Intelligence and Internet of Things are contributing significantly in the area of modern agriculture by controlling and automating farming activities.
- ii. Data generated by various sensors are of paramount importance and require to be managed and analyzed using machine learning based approaches to foresee upcoming challenges in farming practices.
- iii. IoT and AI-enabled products are becoming cost-effective and robust; their widespread adoption in the agricultural field is inevitable.

The most recent information and analysis of machine learning models presented in the work can enrich the future of researchers, agriculture entrepreneurs and other stakeholders for selecting the best models and techniques for the implementation of a specific task.

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