JOURNAL PUNJAB ACADEMY OF SCIENCES (Peer Reviewed Open Access Journal)
JPAS, 24: 33-37 (January-December 2024)
Available online at www.jpas.in
ISSN 2229-7014 (P)

PRECISION AGRICULTURE USING ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING

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ABSTRACT
Agriculture has seen a drastic evolution in the past few years. The usage of artificial intelligence technologies has made a significant impact on the respective field. Precision Agriculture (PA) practices have become very popular nowadays; these are the techniques which are focused on sensing and analyzing specific areas of the crops only such that the productivity of the entire crop field can increase. This article reviews the recent research done in the field of PA based on various machine learning and deep learning techniques. The usage of IoT technologies in supporting these techniques is also crucial. The research gaps in the current scenario of PA have also been discussed.

KEYWORDS: Precision Agriculture, Artificial Intelligence, IoT.

INTRODUCTION
Agriculture has evolved drastically in recent years. The novel Artificial Intelligence (AI) driven technologies have replaced the traditional methods of cultivating soil and growing crops. There have been several types of smart machines designed which are based on Internet of Things (IoT) (Kashyap et al., 2021). These smart technologies not only help the agriculture related tasks performed by humans a lot easier but also quicker. One of such technique is the Precision Agriculture (PA). PA is also referred to as site-specific agriculture or target farming. As the name suggests, precision agriculture is used for focusing the attention to a specific area of the crop in order to optimize the crop yield. PA also aims to minimize the negative impact produced by agriculture practices on the environment and helps in resource conservation. It is made possible by using advanced technologies to keep a check on variability of the soil, crops and other factors to optimize the yields. Since precision agriculture uses advanced techniques to improvise the crop production, it cannot be implemented alone. There are several components that are involved. One of these components is remote sensing and satellite imagery as a bird eye view is must to monitor the growth and health of the crops.

Another significant part is the Global Positioning System (GPS)-based machinery and farm equipment's to reduce the wastage of resources and locate targeted areas of the crop only. Several sensors such as soil moisture sensors and nutrient sensors are also utilized to monitor the levels of moisture and nutrients in soil for managing the soil health efficiently. AI and machine learning (ML) models help to perform predictive analytics and generate decision support systems (DSS) to guide the farmers. Last but not the least, IoT-enabled devices like sensors and smart machinery helps in real-time monitoring and management.

The recent trend in agriculture practices is mainly focused on precision agriculture. This is mainly because of the economic, cultural and other benefits that such techniques provide. These methods reduce the environmental impact through sustainable farming practices. Wastage of resources such as water and fertilizers are minimized leading to profits and savings. The most significant advantage that PA offers is the increase in crop productivity.

This article aims in reviewing the recent research done in the respective field of precision agriculture. The techniques used to implement PA combine AI, ML, and IoT at a great level. The field of robotics has also been explored. The article gives a review about how

AI, ML, deep learning (DL) and image processing techniques are used to perform site-specific farming. The gaps in existing research and potential challenges for the future are also discussed.

RELATED WORK

This section gives a detailed review about the existing techniques and methods used for implementing precision agriculture practices.

Based on Deep Learning

Nguyen-Tan & Le-Trung, 2024presented a novel smart agriculture system based on 5G Private Mobile Network (PMN). Initially, the data collection about the surroundings was done through distributed node sensors. This data was then transferred to LoRa gateway which transmits it to the MEC server. Drones were also used to record high resolution videos of the crops which were again sent to the MEC server through 5G connection. Three YOLOv8 models were combined to create a lightweight model that predicts the stage of development of the crop, its health and nutrition. The simulation of the system was done with UERANSIM and Free5GC combined with Quantum Key Distribution Function (QKDF). The system performed exceptionally well with 93.8% accuracy in the developmental stage, 87% with health status model, and 83% with nutrition model.

Barburiceanu et al., 2021 proposed a CNN-based method for feature extraction to identify leaf diseases and species of the plants. The system takes an imput image, resizes it. Extraction of features performed through CNN models such as ResNet18, AlexNet, Vgg16, and, ResNet50 pre-trained on ImageNet object-based dataset. Further, classification of images done using a Support Vector Machine (SVM) classifier based on which decision making was done. The concept of transfer learning was implemented to pre-train the CNN models. Experiments were conducted on PlantVillage dataset. The system based on pre-trained AlexNet and relu3 layer as the descriptor with SVM outperformed others both in performance and processing time.

Bah et al., 2020exploited the usage of deep learning for detection of weeds and the rows in which crops are planted for a better targeted farming practice. The system was named as CRowNet and it used Unmanned Aerial Vehicles (UAV) to capture images and implemented a Hough transform for crop detection in rows. The input images were fed to a S-SegNet which is a deep CNN for semantic segmentation to find the crop strips or rows. The output of S-SegNet was further fed to CNN-based HoughCNet that was used to search the main lines that indicated rows of the crops. Tests were performed in the beet and the maize field. The results proved that CNN can be used to detect the targeted area even in high weed presence. 93.58% rate of crop row detection was observed and an IoU score per crop was measured to be above seventy percent.

Based on Machine Learning

Seireg et al., 2022 designed a yield detection system for wild blueberries through the implementation of Ensemble ML techniques. A stacking regression (SR) was used that is a two-layer structure with level 0 comprising of gradient boosting regression (GBR), light gradient boosting machine (LGBM), and extreme gradient boosting (XGBoost) while a Ridge was implemented at level-1 for predicting the outputs. Another framework used was the cascading regression (CR) which is very similar to the ML algorithms used in SR but in the form of a succession of algorithms where every output of one algorithm is the input to the next algorithm while erasing the predictions made at each stage. The dataset chosen for testing was produced by a simulation program and data collected by meteorological department over past thirty year from the Maine, USA. The results were measured with root mean square (RMSE) and coefficient of determination (R^2). SR proved to be a better option than CR with RMSE value of 179.898 and 0.984 R^2 value.

Liu et al., 2022proposed an IoT and ML based plant disease detection system that made use of information and communication technologies (ICT) for PA. The life cycle of a disease in plants is directly related to the surrounding conditions of the plants. These conditions can be sensed to predict the presence of disease. This concept was used in the proposed system for early prediction of diseases. The algorithm began with inputs such as amount of rainfall, humidity, and temperature on a daily basis that were captured using IoT based hardware with DHT-22 sensor. The daily conditions were than used to calculate the average conditions on a monthly basis. The ML model made predictions and these were validated by comparing against the observations of the field. These validations were provided as a feedback mechanism to the model. The blister blight and tea plants were chosen for disease prediction. The predictions of the model were recorded for years and it was observed that disease prediction reached 91%. Table 1 depicts analysis of other studies done in the related field of precision agriculture.

Table 1. Related Work

Author (s)	Year	Technique Used	Targeted Area/Purpose	Methodology Used	Results
Gulec et al., 2020	2020	Wireless Sensor Networks	Solar energy harvester nodes	Distributed Connecting Dominating Set (CDS) algorithm for extending the battery life	Increased lifetime upto six times
An et al., 2022	2022	Deep Learning	Strawberry fruit	SDNet (Strawberry Detect Net) based on YOLOX; replaces CSP block with self-designed C3HB block for feature extraction	Precision-94.26%, Accuracy-93.15%, Recall-90.72%
Singh & Sharma, 2022	2022	Wireless Sensor Networks	Crop monitoring and spraying tasks	WSN-UAV integration: Four processing layers 1. Ground level- data collection and filteration through sensor network 2. Edge Intelligence- path planning, UAV, cluster heads 3. Cloud Intelligence- Central controller and processing 4. Analytics- decision making	Coverage efficiency-96.3%
Patel et al., 2020	2020	Deep Learning	Nitrogen presence in soil	DL network for spectral unmixing (DASU): Multilayer perceptron Spectral derivative features acquired, Continuum Removal (CR) applied, fed to spectral derivative linear mixing model	At 1899.2nm: Urea mixed with loamy soil- R^2=0.954 Urea mixed with silt clay oil- R^2=0.945 At 2195.1nm: R^2=0.953 for urea mixed salt clay, R^2=0.944 for urea mixed loamy soil

GENERAL METHODOLOGY

Precision agriculture is a technology that is implemented in several ways and the execution depends on the type of crop, area to be targeted and problem to be optimized. Figure 1 depicts a general framework which needs to be followed for executing PA. The steps are described below:

Data Collection

The first step is the collection of required data of the specific zones. The data acquisition can be collected through remote sensing, local weather data, on-farm sensors, and IoT devices.

Data Analysis & Mapping

The second step is the analysis of collected data which is done through data processing by using software's such as Geographic Information System (GIS). Other methods involve zone segmentation which is dividing the area into small segment for a better understanding as each specific zone may require different treatment. This data from multiple sources is then integrated and analyzed to get an overall understanding of the conditions.

Decision Making

The next step is to make certain decisions based on the analysis done for the collected data. The decisions may comprise of what quantity of seeds, fertilizers to be used, where must these resources be planted, how much water is required by the crop, timing of irrigating the fields, etc. Such decisions can again be made with the help of techniques like DSS and prescription maps.

Implementation

The decision-making step is then followed by implementation of the technique which involves the usage of automated processes such as automated irrigation systems (Boursianis et al., 2021)and GPS-guided machinery.

Monitoring & Evaluation

These PA techniques must be then evaluated and continuously monitor to improve the crop yields. Real-time monitoring is done to perform the required adjustments. Health of the crop is also monitored regularly using remote sensors.

Feedback

The final step involves the feedback mechanism which is necessary for continuous improvement and provide details about what must be changed next time to increase the production. This involves analysis of post-season, change in the zones based on feedback, etc.

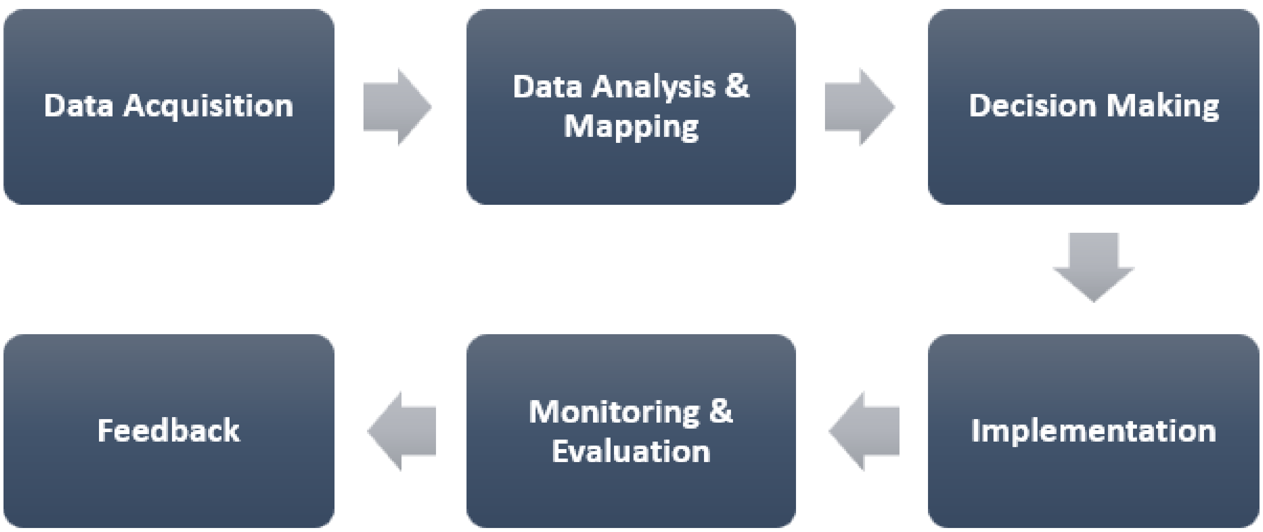

Figure 1. General Methodology

DISCUSSION

There still are certain areas where these smart farming practices need to improve. Some of them are listed below:

- **Quality of the dataset-** PA techniques depend greatly on the data collected through sensors and other IoT machinery such as UAV's, etc. But there is a lack of quality data. Effective methods to handle noise and low-quality data must be generated.
- **Excessive computation-** Learning done by existing models can be transferred to novel systems through Transfer Learning (Mohyuddin et al., 2024) for enhancing the site-specific farming. This saves time and resource consumption also.
- **Food supply chain traceability-** The major problem of today's agriculture practices lies in the food supply chain. New high-speed technologies (Mohyuddin et al., 2024) such as NB-IoT and 5G can be integrated.

CONCLUSION AND FUTURE SCOPE

Precision agriculture also known as site-specific farming or target farming, is a type of agriculture practice which uses various techniques and methods for implementing smart farming to improve crop yields for higher productivity. This article presents a review about the recent articles proposed for the execution of PA. PA involves usage of smart IoT based sensors for detecting the soil moisture content, environmental factors, growth of the crop, etc. The data collected through these sensors is then transmitted to the predictions models for making decisions such as how much pesticides be sprayed on the crop, what fertilizers can be used, how much water is required. The use of machine learning, deep learning and IoT has gradually increased as highlighted in the article. The future of PA is the integration of these technologies.

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