

## Short Research Article

### Multimodal remote sensing and Machine Learning for Precision Agriculture

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#### Abstract:

This study proposed various machine learning and deep learning techniques to integrate and analyze varieties of data in precision agriculture systems. Agricultural systems have undergone a digital transformation, which has resulted in the evolution of many management components into artificially intelligent systems to better value the ever-increasing amounts of data. In the process of putting in place farming systems that are based on knowledge, several obstacles can be overcome using machine learning. The data obtained are transmitted to on-site storage, where extraction, loading, and transformation are performed. The data is preprocessed and transferred to the AWS (Amazon Web Services) cloud (Amazon S3 Bucket). The best model is deployed such that new data can be fit into the model to make adequate prediction or classification. Such a solution can be adapted by building an algorithm to simulate the AWS machine learning technique. A small-scale pilot project can be executed, and the output of the prediction or classification model can be displayed using a web-based software or mobile app.

**Keywords:** Data fusion, deep learning, intelligent system, machine learning, remote sensing

#### Introduction

IoT-based devices are used in the discipline of precision agriculture, which aims to boost profitability and make farming more intelligent (Kumar et al., 2021). In most cases, Internet of Things (IoT)-based irrigation helps to keep the field's water level in equilibrium and prevents the excessive use of groundwater in a comprehensive system. The system is responsible for water management and will irrigate the crops when it is necessary to do so. The productivity of crops and the quality of groundwater can both suffer when fertilizers are used in excess. One may monitor previous fertilizer application sequences using an internet-of-things-based fertilizer doze

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suggestion system and then use that information to make predictions about the actual dose of fertilizer that will be administered in the future.

Agricultural systems have undergone a digital transformation, which has resulted in the evolution of many management components into artificially intelligent systems to better value the ever-increasing amounts of data. In the process of putting in place farming systems that are based on knowledge, several obstacles can be overcome using machine learning (Benos et al., 2021). As crop picture databases continue to expand, the application of deep learning will assist in identifying irregularities that may be present in them (van Klompenburg et al., 2020). Image classification is more straightforward using pre-trained Convolutional Neural Network (CNN) models like VGG16, VGG19, InceptionV3, and ResNet50. The models can either automatically foretell or detect the earliest stages of the onset of plant illnesses or damage. Also, input-level feature fusion based Deep Neural Networks (DNN-F1), intermediate-level feature fusion based Deep Neural Networks (DNN-F2), Partial Least Squares Regression (PLSR), Random Forest Regression (RFR), and Support Vector Regression (SVR) help to predict crop yield based on multimodal information such as thermal and texture features, canopy spectra, and structure. This is accomplished by fusing the elements at diverse levels of the network (Muruganantham et al., 2022).

In agriculture, incontrovertible progress advancements have been made to the convergence of sensor networking, machine learning, and deep learning. Khelifi (2020) conducted an experiment on an agricultural area by utilizing a wireless sensor network to collect data on the soil and air parameters. A cross-level fusion method was used by Kong et al. (2021) to increase the overall performance of a multi-stream hybrid architecture when it came to grain recognition. Dasika et al. (2019) evaluated the accuracy and precision of two widely utilized technologies (LiDAR and Photogrammetry) in remote sensing to simulate the physical quality of alfalfa. Then they connected the outcome with the quality of feed.

Similarly, Maimaitijiang et al. (2020) utilized a low-cost multi-sensor unmanned aerial vehicle (UAV) to gather hyperspectral photos of soybean plants to predict the yield, contribute to plant phenotyping, and improve precision agriculture. They discovered that using multimodal data to fuse together can accurately estimate crop yield regardless of genotype. According to the findings of these types of studies, using sensor networks, drones, and satellite photos to analyze

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the physical and biological aspects of crops optimizes agricultural processes in terms of the management of labor, cost, and time. This study proposed various machine learning and deep learning techniques to integrate and analyze varieties of data in precision agriculture systems.

## Methodology

### Data collection

Before the development of models, data will be collected from all available systems. Figure 1 shows the innovative irrigation system, which comprises soil moisture sensors, a satellite, and a drone that gathers information on soil moisture levels, soil type, canopy cover, crop diseases, and other useful information. Also, the fertilizer system, which has n-p-k sensors, collects information on the Nitrogen, Phosphorus, and Potassium content of the soil. The crop disease detection and damage prediction system use contents from drones, Geographic Information Systems (GIS), Global Positioning Systems (GPS), and Variable Rate Technologies (VRT).

The data obtained are transmitted to on-site storage, where extraction, loading, and transformation are performed. The data is preprocessed and transferred to the AWS (Amazon Web Services) cloud (Amazon S3 Bucket). The data will be processed further by AWS Sagemaker, and the clean data will be subjected to a machine learning algorithm. The output of the analyzed data is then sent to the farmer's mobile device, and analytics monitor for decision making or the automatic control system senses the change and sends timely information to the irrigation system to activate or stop irrigation.

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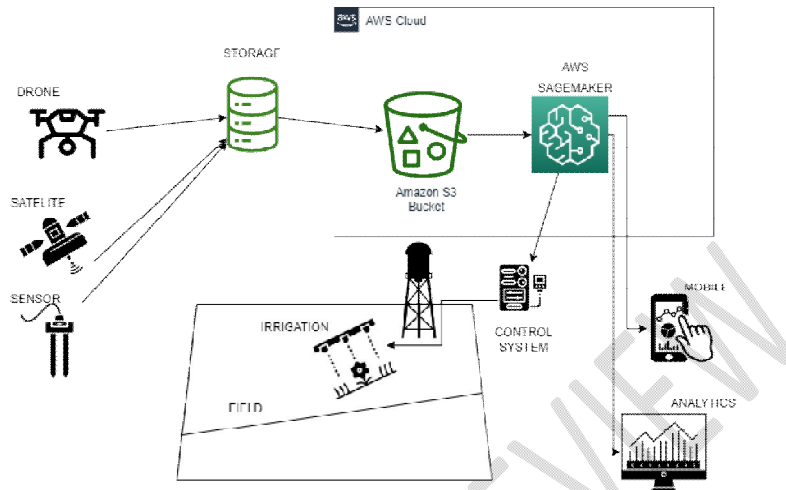


Fig 1: On-site and Cloud-based pipeline for precision irrigation using multimodal remote sensing.

### Data analysis

The data obtained from all the systems are pre-processed to ensure the raw data are suitable for use in a machine learning and deep learning algorithm. After that, the extraction or selection of features is made to create the most informative subsets of the learning model during the training phase. In the testing phase, split data that is not part of the training data is fit into the model. The models can be validated using a new data set before making decisions. However, to actualize the research objectives, there is a need to design a pipeline for feature generation, modification, and output, as Benos *et al.* (2021) described. The separation of the primary features will be done by calibrating a pre-trained Convolutional Neural Network model with data streams obtained from the field.

In the modification phase, the concatenation of the elements of three layers will be incorporated with a dropout layer. The output phase takes the output generated from the modification phase into the dense layer. Benos *et al.* (2021) used sigmoid for the activation function and trained the model with 30 epochs for similar research. The number of epochs (a hyperparameter representing the number of times the learning algorithm will work through the training dataset) can be adjusted to improve the model's performance on non-training data. For crop damage

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prediction, classification models such as Decision Tree (DT), Random Forest (RF), Light Gradient Boosting Machine (LGBM), Extreme Gradient Boost (XGB), and K Nearest Neighbor (KNN) can be used.

### Evaluation of the models

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The models will be evaluated based on precision, recall, accuracy, and F1 score as expressed in the Equations (1-4).

$$Precision = \frac{t_p}{t_p + f_p} \quad (1)$$

$$Recall = \frac{t_p}{t_p + f_n} \quad (3)$$

$$Accuracy = \frac{t_p + t_n}{t_p + f_p + t_n + f_n} \quad (2)$$

$$F_1 \text{ score} = 2 \times \frac{Precision \times Recall}{Precision + Recall} = \frac{t_p}{t_p + \frac{1}{2}(f_p + f_n)} \quad (4)$$

Where  $t_p$  = true positive,  $t_n$  = true negative,  $f_p$  = false positive, and  $f_n$  = false negative.

### How does the research create a solution?

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Integrating all the data obtained from the entire intelligent systems into a smart solution for end-users (farmers) requires detailed data collection and analysis phase observation. Once data are obtained, pre-processed, and used to train a model, the model can be deployed for use in the cloud. For instance, when raw data are stored in an on-site data store and the AWS S3 bucket, data integration is done with AWS Glue Databrew, and models are trained with AWS SageMaker, then deployed. The best model is deployed such that new data can be fit into the model to make adequate prediction or classification. Such a solution can be adapted by building an algorithm to simulate the AWS machine learning technique. A small-scale pilot project can be executed, and the output of the prediction or classification model can be displayed using a web-based software or mobile app.

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