Journal of Engineering Research and Reports

23(8): 30-34, 2022; Article no.JERR.92508
ISSN: 2582-2926

Multimodal Remote Sensing and Machine Learning for Precision Agriculture: A Review

O. B. Falana [a*] and O. I. Durodola [a]

[a] *Department of Biosystems Engineering, Auburn University, Alabama, United States.*

Authors' contributions

This work was carried out in collaboration between both authors. Both authors read and approved the final manuscript.

Article Information

DOI: 10.9734/JERR/2022/v23i8740

Open Peer Review History:
This journal follows the Advanced Open Peer Review policy. Identity of the Reviewers, Editor(s) and additional Reviewers, peer review comments, different versions of the manuscript, comments of the editors, etc are available here: https://www.sdiarticle5.com/review-history/92508

Short Research Article

Received 05 August 2022
Accepted 10 October 2022
Published 15 October 2022

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.

1. INTRODUCTION

IoT-based devices are used in the discipline of precision agriculture, which aims to boost profitability and make farming more intelligent [1]. 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

Corresponding author: Email: obf0005@auburn.edu;

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 [2]. One may monitor previous fertilizer application sequences using an internet-of-things-based fertilizer doze 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 [3]. As crop picture databases continue to expand, the application of deep learning will assist in identifying irregularities that may be present in them [4]. Image classification is more straightforward using pre-trained Convolutional Neural Network (CNN) models like VGG16, VGG19, InceptionV3, and ResNet50 [5]. 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 [6].

In agriculture, incontrovertible progress advancements have been made to the convergence of sensor networking, machine learning, and deep learning. Khelifi [7] 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.* [8] to increase the overall performance of a multi-steam hybrid architecture when it came to grain recognition. Dasika et al. [9] 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. [10] 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 the physical and biological aspects of crops optimizes agricultural processes in terms of the management of labor, cost, and time [11]. This study proposed various machine learning and deep learning techniques to integrate and analyze varieties of data in precision agriculture systems.

2. METHODOLOGY

2.1 Data Collection

Before the development of models, data will be collected from all available systems. Fig. 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.

2.2 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. [3] 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. [3] 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 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.

2.3 Evaluation of the Models

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

$$Precision = \frac{t_p}{t_p + f_p} \tag{1}$$

$$Accuracy = \frac{t_p + t_n}{t_p + f_p + t_n + f_n} \tag{2}$$

$$Recall = \frac{t_p}{t_p + f_n} \tag{3}$$

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

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

2.4 How does the Research Create a Solution?

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

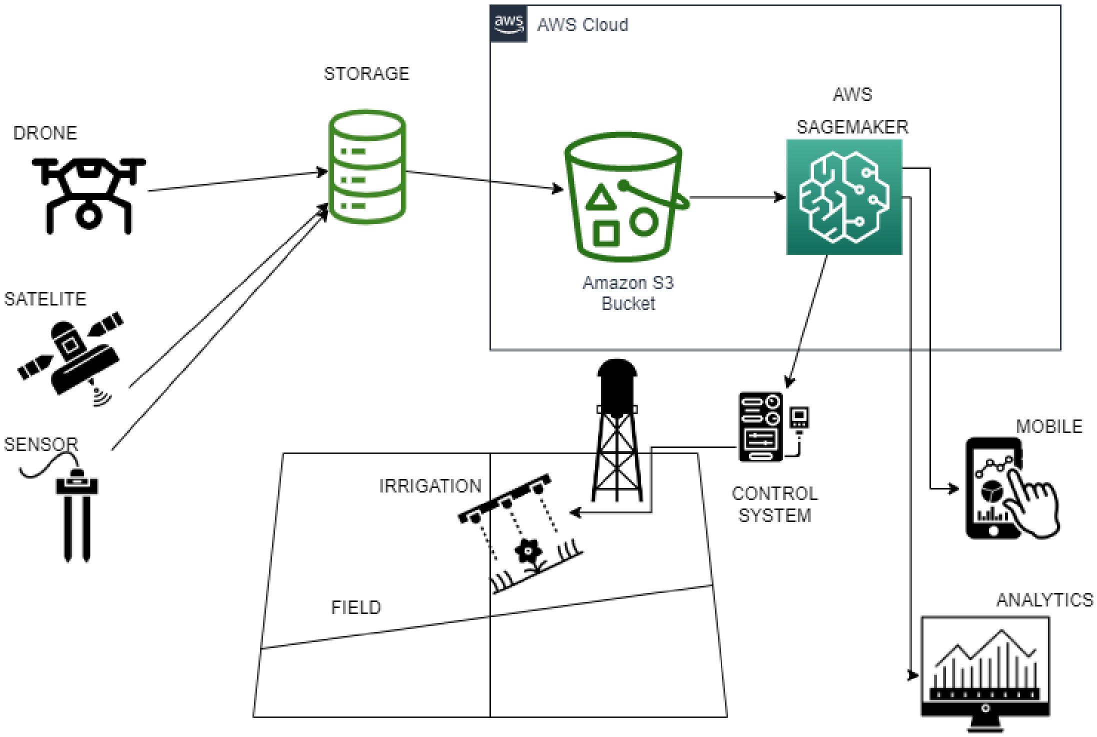

Fig. 1. On-site and cloud-based pipeline for precision irrigation using multimodal remote sensing

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.

3. CONCLUSION

The implementation of an on-site and cloud-based pipeline for precision irrigation that makes use of multimodal remote sensing and a variety of machine learning and deep learning techniques to integrate and analyze the many different types of data collected would make irrigation, crop production, and farming system more productive and profitable.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

REFERENCES

1. Kumar1 L, Ahlawat P, Rajput P, Navsare RI, Kumar Singh P. Internet of things (Iot) for smart precision farming and agricultural systems productivity: a review. International Journal of Engineering Applied Sciences and Technology. 2021; 5(9).
   Available:https://doi.org/10.33564/IJEAST.2021.v05i09.022
2. Innes R. Economics of agricultural residuals and overfertilization: Chemical fertilizer use, livestock waste, manure management, and environmental impacts. In Encyclopedia of Energy, Natural Resource, and Environmental Economics Elsevier. 2013;50–57.
   Available: https://doi.org/10.1016/B978-0-12-375067-9.00118-2
3. Benos L, Tagarakis AC, Dolias G, Berruto R, Kateris D, Bochtis D. Machine learning in agriculture: a comprehensive updated review. Sensors. 2021;21:3758.
   Available:https://doi.org/10.3390/s21113758
4. van Klompenburg T, Kassahun A, Catal C. Crop yield prediction using machine learning: a systematic literature review. Computers and Electronics in Agriculture. 2020;177:105709.
   Available:https://doi.org/10.1016/j.compag.2020.105709
5. Dhaka VS, Meena SV, Rani G, Sinwar D, Kavita K, Ijaz MF, Woźniak M. A survey of deep convolutional neural networks applied for prediction of plant leaf diseases. Sensors. 2021;21(14):4749.
   Available:https://doi.org/10.3390/s21144749
6. Muruganantham P, Wibowo S, Grandhi S, Samrat NH, Islam N. A systematic literature review on crop yield prediction with deep learning and remote sensing. Remote Sensing. 2022;14(9):1990.
   Available:https://doi.org/10.3390/rs14091990
7. Khelifi F. Monitoring system based in wireless sensor network for precision agriculture. In: Alam M, Shakil K, Khan S. (eds) Internet of Things (IoT). Springer, Cham; 2020.
   Available: https://doi.org/10.1007/978-3-030-37468-6_24
8. Kong J, Wang H, Wang X, Jin X, Fang X, Lin S. Multi-stream hybrid architecture based on cross-level fusion strategy for fine-grained crop species recognition in precision agriculture. (Multi-stream hybrid architecture based on cross-level fusion strategy) Computers and Electronics in Agriculture. 2021;185:106134.
   Available:https://doi.org/10.1016/j.compag.2021.106134.
9. Dasika S, Sama M, Pampolini L, Good C. Performance validation of a multi-channel LiDAR sensor: assessing the effects of target height and sensor velocity on measurement error. Transactions of the ASABE. 2019;62(1):231-244.
10. Maimaitijiang M, Sagan V, Sidike P, Hartling S, Esposito F, Fritschi F. Soybean yield prediction from UAV using multimodal data fusion and deep learning. Remote Sensing of Environment. 2020;237: 111599.
    (Maitiniyazi Maimaitijiang - Google Scholar)
    Available:https://doi.org/10.1016/j.rse.2019.111599.

11. Khan N, Ray R L, Sargani GR, Ihtisham M, Khayyam M, Ismail S. Current progress and future prospects of agriculture technology: Gateway to sustainable agriculture. Sustainability. 2021;13(9): 4883.
Available:https://doi.org/10.3390/su13094883

Peer-review history:
The peer review history for this paper can be accessed here:
https://www.sdiarticle5.com/review-history/92508