International Journal of Research Publication and Reviews, Vol 4, no 7, pp 382-387 July 2023

International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Assessment of Crop Quality Using Machine Learning Techniques for Smart Farming.

Richard Essah[1], Jonathan Kwabena Boam[2], Anagrolia Faustino[3] and Abraham Tetteh[4]

[1] Chandigarh University, Department of Computer Science. 140413, India
[2] Chandigarh University, Department of Computer Science. 140413, India
[3] Chandigarh University, Department of Computer Science. 140413, India
[4]Bia Lamplighter College of Education, Mathematics and ICT Department, Ghana
[1]Richardeessah84@gmail.com ,[2] anagrolia.r31@cumail.in , [3]abrahamtetteh@blce.edu.gh

ABSTRACT:

Farms and agricultural fields are now being automated. Many of these facilities automate procedures and boost productivity by using Internet of Things technologies. Additionally, using machine learning and deep learning to make decisions continuously based on data analysis. In this paper, we close a knowledge gap and provide a novel architecture for the continuous evaluation of crop quality in agriculture based on IoT and machine learning/deep learning technologies. Three layers make up this design, which cooperate to collect, process, and analyse data from various sources in order to assess crop quality. The trials show that the suggested method, which relies on data aggregation from multiple sources, achieves a smaller percentage error than using only one source. In the studies, the suggested method based on combining data from various sources achieves a smaller percentage error than using only one source. specifically, the percentage inaccuracy attained.

Keywords: Machine learning, Smart farming, IoT, deep learning, CNN, Crop.

I. INTRODUCTION

All facets of our society have been impacted by automation, and farms and agriculture are no exception. In this environment, farms and agricultural fields are becoming increasingly automated to improve the efficiency of their production[2]. This rise in automation will make it possible to connect millions of devices with high bandwidth and low latency thanks to the introduction of mobile next-generation networks (5G) and Internet of Things (IoT) technology. Additionally, the combination of Big Data technologies with Machine Learning (ML) and Deep Learning (DL) methods will accelerate the analysis and extraction of information from data. IoT has had a significant impact on agriculture among all of these technologies because it has made it possible to integrate communication capabilities with sensors and actuators. As a result, it is theoretically possible to use hardware devices in the final installations to transmit data about the production environment, such as the pH of the water[4], the amount of fertiliser, or the level of brightness. A local server or a server in the cloud receives this data from the sensors. In general, a portion of data processing is carried out in compute nodes adjacent to the sensors using the Edge Computing (EC) paradigm in order to obtain low latency replies. The remaining data, in contrast, is kept in cloud databases[1] for future analysis. IoT technology also enable actuators to receive commands to make system corrections after the analysis is complete.

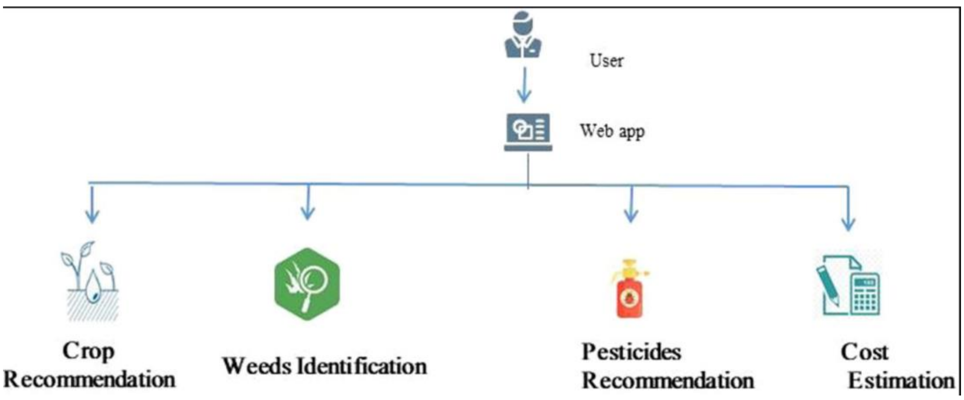

Fig 1: Smart Farming

When calculating the cost of a crop, several factors must be taken into account. It gives calculations for each of the five categories that it splits agricultural costs into. It also provides examples of how to calculate the cost of a crop[4]. It is a theoretical paper that serves as a constant guide for implementing cost-of-cultivation estimation. The proposed model's cost of cultivation calculation was based on the results of this theoretical investigation. It was quite useful because it gave simple explanations that could be used to estimate agricultural costs. The suggested system used the calculations from this study to forecast expenditures through the year 2028.

II. LITERATURE REWIEW

A local server or a server in the cloud receives this data from the sensors. In general, a portion of data processing is carried out in compute nodes adjacent to the sensors using the Edge Computing (EC) paradigm in order to obtain low latency replies[6]. The remaining data, in contrast, is kept in cloud databases for future analysis. IoT technology also enable actuators to receive commands to make system corrections after the analysis is complete. Typically, wireless channels are used for this communication, and IoT devices frequently create Wireless Sensor Networks (WSN) utilising open standards.

In the context of predicting crop quality, ML/DL technologies have risen to prominence recently. Typically, wireless channels are used for this communication, and IoT devices frequently create Wireless Sensor Networks (WSN) utilising open standards.

In the context of predicting crop quality, ML/DL technologies have risen to prominence recently[7]. These methods are centred on creating models that can continuously forecast the quality of the end result and extract information from the input data. These models often go through two distinct stages of development. The model learns the knowledge underlying the data in the first stage, which is referred to as training. The models are evaluated for performance in the second stage, known as the test, using data that has never been seen before. ML/DL can therefore analyse data from agricultural sensors and enhance decision-making processes.

Despite the widespread usage of IoT designs in the field of precision agriculture and on farms, many of these systems are designed for changeable monitoring. Integrating IoT systems with ML/DL models that enable us to extract precise information and make the best decisions is one of the main issues facing us today[9]. Farm production can be increased in this way. The only purpose of the present solutions is to monitor crops and gather data for future plantation improvement. However, some unforeseen circumstances that arise during the growth of the crop may lower the plantation's output. The impact of these unforeseen events will be reduced by combining monitoring and corrective measures, hence increasing production. The evaluation of crop quality in particular is another important challenge.

Table 1: literature Review

Author & Year	**Findings**	**Journal**
Ahoa et al. [88] (2021)	The Ghanaian cocoa industry's supply chain has been found to be constrained. Information isn't readily available enough to the agricultural community. It has been demonstrated that implementing information technology (IT) systems improves both the manufacturing and supply chain processes.	Sustainability (MDPI)
Hati et al. [89] (2021)	The project's main emphasis is on the application of sophisticated indoor farming techniques. An app-based mobile device is used to collect and analyse data in order to optimise the agricultural process in order to accomplish this goal. Various performance measures were used to examine a number of ML algorithms.	Agri Engineering (MDPI)
Adhitya et al. [65] (2020)	Digital pictures of cocoa beans were subjected to a textual feature analysis. The use of IoTs (IoT) has been suggested as a way to improve supply chain security.	Agronomy (MDPI)
Elijah et al. [90] (2018)	It was looked at how data analytics and IoTs (IoT) fit into the framework of smart farming. Smart farming's business breakthroughs and hopes for the future were covered.	IEEE IoTs Journal
Goyal et al. [91] (2021)	It was shown how to analyse different methods for spotting food adulteration. In order to categorise food classes, many ML techniques were considered. Several datasets were looked at in order to analyse food.	Archives of Computational Methods in Engineering (Springer)
Sharma et al. [92] (2020)	Multiple research publications on the use of ML in the context of smart farming were examined as part of the study. The significance of ML in the agriculture supply chain was clarified in the paper.	Computers and Operations Research (Elesvier)
Ahoa et al. [93] (2020)	The Ghanaian cocoa supply chain's modern operations and technological foundation were revealed.	NJAS - Wageningen Journal of Life Sciences (Elsevier)

	It has been demonstrated that there are several handoffs throughout the supply chain, which could necessitate a substantial amount of time. IoTs (Internet of Things) systems are used to lessen this danger.	
Oluyisola et al. [94] (2022)	It was recommended to use an approach for managing the supply chain using IoT technologies. Case studies on food businesses, particularly those that specialise in snacks and sweets, were evaluated while taking into account a number of factors. This essay analyses the problems and difficulties that come up when IoT (Internet of Things) technology is applied to smart farming applications.	Journal of Intelligent Manufacturing (Springer)
Ouhami et al. [85] (2021)	To identify plant diseases, many ML approaches were investigated. Compare the effectiveness of several data fusion approaches using different factors for the goal of identifying plant diseases. An overview of the most pressing problems and emerging trends in the study of plant diseases is provided in this article.	Remote Sensing (MDPI)
Balakrishna et al. [95] (2021)	The focus of the study was on problems with food security. A paradigm that makes use of both ML and IoT has been proposed. Different ML platforms were contrasted.	Global Transitions Proceedings (Elsevier)
Isaac [96] (2021)	A strategy for predicting coffee yield in Tamil Nadu's Eastern Ghats was put forth, with a focus on the farmer's point of view. While the ML (ML) module is used to forecast coffee yield, the IoTs (IoT) module is responsible for collecting environmental data.	Annals of R.S.C.B
Senthilmurugan and Chinnaiyan [97] (2021)	The implementation of a distributed strategy based on blockchain would make it possible for farmers and retailers to work together more effectively in the supply chain and field experiments. The goal was to keep the product's current pricing point. The detection of illnesses in the produce was given priority.	International Conference on Computer Communication and Informatics (ICCCI -2021) (IEEE)
Thakur and Mittal [98] (2020)	Utilising the IoT and ML in a cloud setting can help with the identification of agricultural illnesses. This study outlines a system for identifying and diagnosing agricultural illnesses using Raspberry Pi technology. Apply the clustering and classification algorithm K-means.	International Journal of Innovative Science and Modern Engineering

Machine learning and deep learning to evaluate crop quality

Numerous studies have been conducted on the application of ML/DL methods in agriculture [19]. The most significant applications of ML/DL are in agricultural management, animal management, water management, and soil management[10]. We are particularly interested in crop management, where the following activities can be found: yield prediction, disease and weed detection, crop quality assessment, and species identification.

In this context, crop quality, a subfield that is closely tied to disease detection, is in charge of estimating the final quality of crops. Since the price and competitiveness of businesses depend on the quality of their products, this subject is extremely important. In this regard, the authors of presented a study centred on the identification and categorization of prevalent categories. A short wave near-infrared hyperspectral imaging equipment was employed during the study. To distinguish between persistent-calyx pear (PCF) and deciduous-calyx pear (DCF), the authors of presented a study. An approach called non-destructive hyperspectral imaging was adopted, following the lead of earlier writers. According to the authors, the proposed model, which is based on Support Vector Machines (SVM), can distinguish between PCF and DCF. For DCF and PCF, respectively, the final accuracy was 93.3% and 96.7%. The authors of [26] suggested another project to assess quality. According to the writers, the country of origin affects the rice's quality. To ascertain the origin of the rice, they carried out experiments. It was specifically discovered by using inductively coupled plasma mass spectrometry (ICP-MS). The authors of introduced a novel image processing method to identify thrips (Thysanoptera) on strawberry plants in order to predict illnesses. SVM was employed in the thrips detection process as well as the categorization of parasites[11]. The SVM used images captured by a mobile agricultural robot as input data. The photographs were taken at an 80 cm distance with good natural lighting. The photos also required conversion from RGB to HSV colour format. In [12], the detection of the yellow rust wheat disease is examined. The authors provided a method for early yellow rust illness identification. At various stages of yellow rust development, the authors utilised a classification algorithm and a reflectance spectrum for this. The top 5% important spectral characteristics were chosen as the An 86% true positive rate was attained by the authors. In order to identify plant illness, a CNN method that solely looked at photos of plant leaves was used in the study. There were several CNN architectures examined, with the VGG-based architecture having the best success rate (99.53%). 87 848 photos were used to train the model, while 17 548 images were used to test it.

Finally, an ML algorithm-based IoT architecture for smart farming was proposed. The agricultural productivity and drought can be predicted using a machine learning (ML) algorithm built into the architecture that is based on the PART classification technique. More and more farms and agricultural fields are automating their processes to improve their productivity[13]. This automation, in most cases, is achieved by means of sensors that measure different variables and actuators that perform actions in the physical world, and therefore allow us to correct deviations in the system.

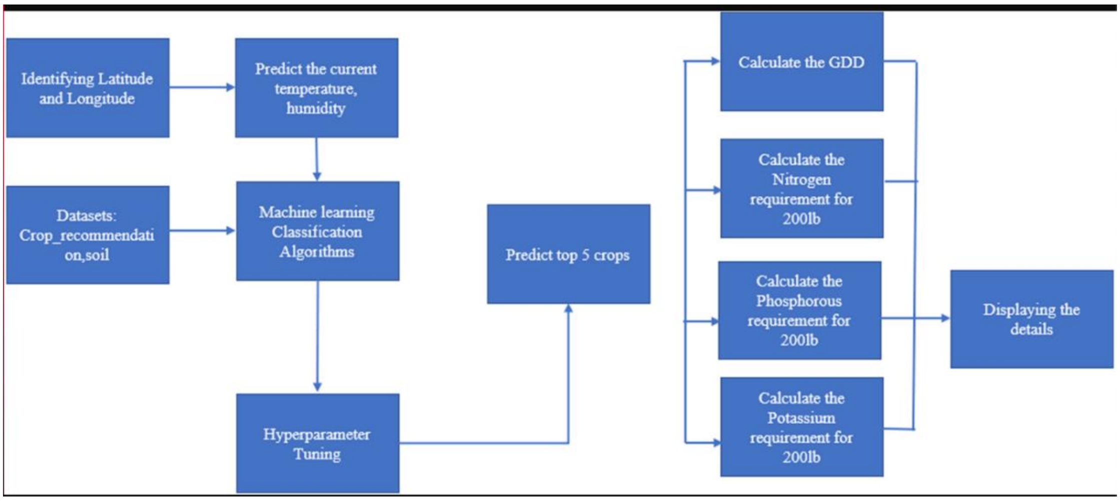

Fig:2 Crop recommendation system architecture.

This paper proposes four modules, including crop recommendation, weed identification, pesticide advice, and crop cost estimation[14]. A Web application using the Django framework is what is being proposed. The User Login page opens the Web Interface. Users must register first by providing their basic information, including their name, address, country, state, pin code, phone number, username, and password. Once the account has been created, the user is forwarded to the login page, where they must log in with their credentials. The modules are described in de pth in the sections that follow.

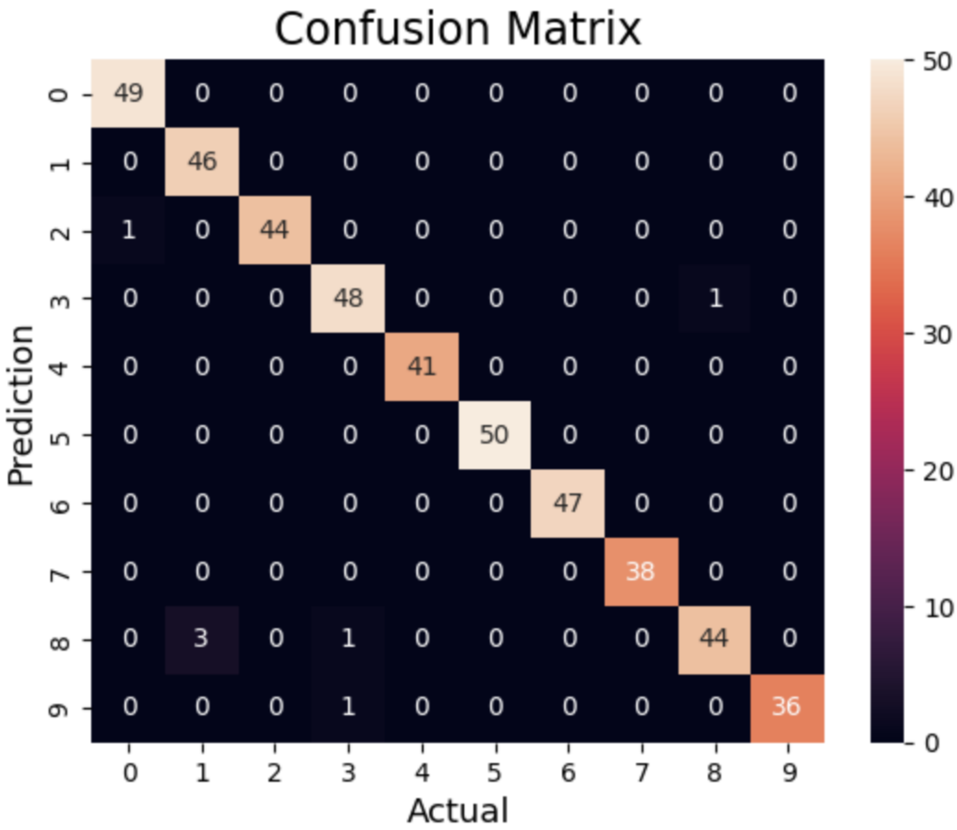

Fig 3: Confusion Matrix

Data visualisation is used to analyse the dataset in a visual style once the fundamental information about it has been gathered. A correlation matrix is just a table with the correlation coefficients between attributes specified as a relationship lattice[15]. The first line and the first column of this text concern the qualities.

III. ANALYSIS OF RESULT

Artificial neural networks are based upon the pattern of neuron connection of the brain. These networks try to learn the things like brain. Neuron nodes in artificial neural networks are linked together like a web, just like in the brain. There are millions of neurons in the human brain[16]. A cell body, which is the component of each neuron, oversees processing information by transporting it into and out of the brain. The neural network tries to seek pattern from the data supplied to produce desired output from the input information, which receive a variety of information based on an internal weighting system. This study compares various deep learning architectures for detecting plant leaf disease using the PlantVillage dataset to determine the suitable hyper-parameters. Using the PlantVillage dataset and the GoogleNet architecture, it is discovered that 30 epochs and a 0.0001 learning rate are appropriate for the investigation of plant leaf disease detection. The findings of the experiment indicate that 30 epochs are enough because training takes less time without significantly degrading accuracy. Better outcomes are obtained with a 104 learning rate without the modals being overfit. The Adam optimizer is found to perform better than the Sgdm optimizer. Eight distinct architectures—GoogleNet, ResNet18, ResNet50, ResNet101, MobileNetv2, ShuffleNet, AlexNet, and SqueezNet—are examined using these hyperparameters, and it is discovered that ResNet50 & ResNet101 perform best[16].

IV. Conclusion

In this work, we proposed a novel three-layer architec- ture called FARMIT that uses both IoT and ML/DL tech- nologies to carry out a continuous assessment of the crop quality using data from different sources. The architecture provides necessary mechanisms to analyze aggregated data, extract information from it and recommend actions to correct quality deficiencies. For this purpose, operators can define corrective policies that trigger actions when a certain parameter is outside its range. Additionally, we have deployed the architecture in a tomato plantation with both sensors that obtain visual information (RGB cameras) and non-visual information, i.e., temperature, wind direction, or pH[17]. From these data, together with the data on pests, defects and tasks carried out on the crop, an evaluation of the tomato quality was performed. For this, a Random Forest model was used to assess the crop quality, obtaining results very close to those determined by a professional taster. Besides, we conducted another experiment to com- pare the performance of our proposal that considers data from different sources and a traditional solutions that only consider data from sensors. In this sense, our proposal achieved a lower percentage error (6.59%) than a tradi- tional solution (6.71%). As future work, we consider the inclusion of new types of information sources, such as aerial images taken from drones[18]. This will allow us to obtain graphical information on the entire plantation without installing a large number of cameras. Additionally, we plan to test DL models that improve the results we have obtained in this work.

V. Reference

1. Essah, R., Anand, D., & Singh, S. (2022). An intelligent cocoa quality testing framework based on deep learning techniques. *Measurement: Sensors*, *24*, 100466.

2. Essah, R., & Anand, D. (2021). Proposal on automatic cocoa quality testing and procurement in Ghana. *Asian Journal of Research in Computer Science*, *12*(4), 132-146.

3. Gyane, S. O. J., Essah, R., Senior, I. A. A., & Tetteh, A. (2021). Reliability and efficiency of computerized systems for admission into colleges of education affiliated with the university of cape coast. *Asian Journal of Research in Computer Science*, *12*(4), 84-96.

4. Essah, R., Anand, D., & Singh, S. (2023). Empirical Analysis of Existing Procurement and Crop Testing Process for Cocoa Beans in Ghana. In *Mobile Radio Communications and 5G Networks: Proceedings of Third MRCN 2022* (pp. 229-244). Singapore: Springer Nature Singapore.

5. Essah, R., Atta Senior, I. A., & Anand, D. (2021). Assessing the Performance Analysis of OSPFV3 and EIGRP in Applications in IPV6 Analysis for Articles Published in Scopus between 2016 and 2021. *Asian Journal of Research in Computer Science*, *12*(2), 40-56.

6. Essah, R., Anand, D., & Singh, S. (2022, October). Assessment on Crop testing based on IOT and Machine Learning. In *2022 10th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions)(ICRITO)* (pp. 1-6). IEEE.

7. Essah, R., Kaur, A., & Agbeko, M. (2022). A bibliometric review and future directions in Cloud Architecture and Security in Web of Science from 2008 to 2022. *Computer Integrated Manufacturing Systems*, *28*(12), 2184-2210.

8. Tetteh, A., Essah, R., Badhon, A. J., Asante, Y. A., & Patrick, A. B. (2021). A Statistical Study into Network Security Issues of IT Companies in Accra. *Asian Journal of Research in Computer Science*, *12*(3), 1-13.

9. Asante, Y. A., & Essah, R. (2021). Comparative analysis of OSPFv3/IS-IS and RIPng/IS-IS mixed protocols for real-time applications in ipv6 communication networks. *Asian Journal of Research in Computer Science*, *12*(4), 111-131.

10. Essah, R., Tetteh, A., Baidoo, P. K., Duah, B., & Teye, E. Q. (2021). Information Processing in IoT Based Manufacturing Monitoring System. *International Journal of Research in Engineering, Science and Management*, *4*(8), 168-177.

11. Jain, S., & Essah, R. (2022, November). Movie Recommendation using Collaborative Filtering to Make Accurate Predictions. In *2022 International Conference on Advances in Computing, Communication and Materials (ICACCM)* (pp. 1-5). IEEE.

12. Essah, R., & Ampofo, I. A. S. (2023). A Bibliometric Overview of IoT-Based Digital Voting. *Asian Journal of Research in Computer Science*, *15*(3), 10-23.

13. Essah, R. (2021). The Role of Cloud Computing Fashionable the Strategic Growth of Business Enterprises in India. *Asian Journal of Research in Computer Science*, *12*(1), 37-48.
14. Essah, R., & Anand, D. (2021). Performance Comparison of OSPFV3 and EIGRP with IPv6 Network. *Asian Journal of Research in Computer Science*, *12*(4), 31-51.
15. Tetteh, A., Essah, R., Opoku, G., & Serwaa, M. A. (2021). Computer Security Practices in Senior High Schools in the Keta Municipality. *Current Journal of Applied Science and Technology*, *40*(14), 10-19.
16. Mahajan, R., Joshi, M. M., Qureshi, A. R. K., Pal, H., Essah, R., Jain, A., & Srivastava, A. P. Implementation of Smart Home Security and Automation System based on IoT Technology.
17. OYEBODE, O. J., Singh, N., Prasanth, T., LAKSHMI, T. V., Singla, M., & Essah, R. Blockchain and Machine Learning Based Healthcare Management Systems.