INDIAN JOURNAL OF SCIENCE AND TECHNOLOGY

RESEARCH ARTICLE

Effectiveness of Organic Smart Agriculture and Environmental Sustainability in a Post-Pandemic World

C Beulah[1], Paul Sujni[2], R Rajasree[3], S Sanjith[4]*

1 Associate Professor, Digital Sciences, Karunya Institute of Technology and Sciences, Coimbatore, Tamil Nadu, India
2 Faculty, Computer Information Science, Higher Colleges of Technology, Dubai, UAE
3 Research Scholar, Digital Sciences, Karunya Institute of Technology and Sciences, Coimbatore, Tamil Nadu, India
4 Assistant Professor, Digital Sciences, Karunya Institute of Technology and Sciences, Coimbatore, Tamil Nadu, India

OPEN ACCESS

Received: 02-06-2023
Accepted: 30-08-2023
Published: 03-10-2023

Citation: Beulah C, Sujni P, Rajasree R, Sanjith S (2023) Effectiveness of Organic Smart Agriculture and Environmental Sustainability in a Post-Pandemic World. Indian Journal of Science and Technology 16(37): 3090-3099. https://doi.org/10.17485/IJST/v16i37.1352

* **Corresponding author**.

drsanjith@gmail.com

Funding: None

Competing Interests: None

Published By Indian Society for Education and Environment (iSee)

ISSN
Print: 0974-6846
Electronic: 0974-5645

Abstract

Objective: The goal of the proposed work is to create a smart farming methodology that automates crop suggestions, smart irrigation, disease management using machine learning, and pest management utilising the Internet of Things concepts. **Methods:** The proposed approach implements smart farming in four different phases. Crop selection is recommended based on the suitability of the soil using XGBoost machine learning algorithm using Kaggle Crop Recommendation dataset. Smart irrigation has been implemented using LM35 soil temperature sensor and DHT22 humidity sensor. Convolutional neural network models were used for automatic crop disease detection. An IoT-based system is proposed for pest management. **Findings:** This approach uses hybrid strategies to increase agricultural productivity in the best possible circumstances. Ten agricultural fields that cultivate rice and vegetables like tomatoes, lady fingers, and brinjal plants in Southern parts of Tamil Nadu have been used as case studies for the research. Crop selection based on soil type resulted in an increase in crop yield of 62% for tomato crops, 71% for brinjal and 77% for ladies finger. Smart irrigation helped in reducing the consumption of water by 34.38% for rice, 56.17% for brinjal, 60% for ladies finger and 64.45% for tomatoes. Tomato leaf diseases could be automatically identified with an accuracy of 96.24%. **Novelty:** XGBoost algorithm has been implemented to choose crops based on soil type for the first time with an accuracy of 98.62%. Smart irrigation is implemented with temperature and humidity sensors and pH meter. Convolutional neural network model has been improved using transfer learning techniques and hyperparameter tuning to achieve an accuracy of 96.24%.

Keywords: Smart Farming; Convolutional Neural Networks; Extreme Gradient Boosting; Deep Learning

1 Introduction

The primary occupation of our country is agriculture with most of the lands used for farming purposes. Farm management information helps farmers to adapt to smart farming. Various processes in farming such as data acquisition, processing, planning, decision-making, and managing of the operations of a farm are nowadays automated using Sensors and Farm management Information systems. Water scarcity, reduction in yield, crop disease, and pest management are some of the concerns of farmers that need to be addressed. Advancing technologies such as machine learning, deep learning, and IoT-based systems can be efficiently implemented to address these issues and increase agricultural productivity and profitability. Sensor-based smart systems can be used to monitor plant growth and can contribute extensively to crop disease and pest management. Smart systems perform these tasks with enhanced accuracy and efficiency. Different types of advanced network technologies such as Wireless Sensor Networks (WSNs) and cloud computing are widely used in the acquisition and transmission of data from different sensing devices. Cloud services may be used for analyzing and processing remote data from IoT devices and this analysis can help businesses make the best possible decisions [(1)]. Deep learning approaches using convolutional neural networks have been recommended for the automation of agricultural activities with utmost precision. Smart agriculture technologies with remote cameras using computer vision can assist farmers in efficient land preparation and harvesting [(2)]. CNNs have been efficient in various image classification tasks. Mussad et al. have used CNN pre-trained models in classifying malware families and with EfficientNet3 they could achieve an accuracy of 99.93%. They trained different variations of Efficient Net B0 to B7 and evaluated the performance. A dense fully connected classification layer with 25 output units and Softmax activation function was added to EfficientNet3 to achieve better accuracy. However, it has been inferred that the models took more time (up to 261 minutes) to train [(3)]. Gupta and Nahar have proposed an IoT-based hybrid ML model for crop yield prediction. They have used the Adaptive k-nearest Centroid Neighbor Classifier model to classify soil samples based on soil properties. Extreme Machine Learning (ELM) with a modified Butterfly Optimization algorithm has been used to predict crop yield with improved accuracy and minimum error [(4)].

Artificial Intelligence, machine learning, and blockchain are some of the digital technologies that have been increasingly used in the agro-food sector, especially after the pandemic for growth and sustainability. Smart farming techniques are necessary to build a resilient food system in the post-COVID world. According to Sridhar et al. pandemic has led to dietary changes and created a negative impact in the areas of food production, environment, transportation, and the overall supply chain [(5)]. Thus digitization of the agriculture supply chain secured with blockchain can lead to a more sophisticated, socio-technically innovative ecosystem [(6)]. According to Stefano et al., food security has become the most important issue to be addressed especially after the pandemic, and digital technology such as machine learning, artificial intelligence, and blockchain can contribute to building a resilient, eco-friendly agriculture supply chain [(7)]. Crop diseases are also a concern in a secure food ecosystem since they lead to poor yield which can further lead to food adulteration. Various CNN models have successfully been implemented for crop disease detection. Rajasree et al. have discussed the effectiveness of transfer learning CNN algorithms in detecting leaf diseases in tomato plants. Though these algorithms produce a high accuracy, they suffer from overfitting. The authors have also implemented data augmentation techniques in order to minimize overfitting [(8)]. James et al. have used IoT-based systems to enable data analytics-based decision making in various farm operations such as irrigation, application of fertilizers, and pest management [(9)]. In another work, Rajasree et al. have fine-tuned the hyperparameters in RESNET-152 to detect crop diseases with better accuracy [(10)]. Yadhav et al. tracked and diagnosed leaf diseases that affect the growth of paddy and banana crops using satellite images and sensors. This IoT-based smart system makes data analytics based decisions that are communicated to farmers via the web server [(11)]. Altalak et al. have proposed an intelligent agriculture system based on a hybrid model of CNN and SVM, capable of early detection of plant diseases. The model consists of three main parts of CNN with an attention mechanism applied and an SVM classifier that enabled early detection of plant diseases [(12)]. Olive Debnath et al. have also implemented an IoT-based intelligent farming approach using CNN for early detection of diseases in rice paddy. The system used smart sensors for data collection. An accuracy of 97.7% was reported in this approach [(13)].

After an extensive survey of the literature, the following research gaps were identified. Most of the existing systems focus only on one aspect of farming such as smart irrigation or disease detection. Therefore, a comprehensive system addressing multiple issues has been felt as the need of the hour. Only a few systems focus on crop recommendation based on soil type and such systems have less accuracy. The impact of crop selection on productivity is also not studied in many of the approaches. Most of the crop disease detection systems using CNN models suffer from overfitting. The research gaps identified in the literature are identified as the focus of the current study.

2 Methodology

2.1 Crop Selection using Analysis of Soil Type

Extreme gradient boosting also referred to as XGBoost, is a decision tree technique that uses gradient boosting and was created with performance and speed in mind. Both the time complexity and the space complexity of this approach are minimal. It offers the best possible use of memory. Through the use of parallel processing, time complexity is decreased. Compared to other gradient boosting methods, the algorithm operates much more quickly. Comparing this approach to other gradient boosting algorithms, it is also more scalable. Although it is a technique adapted from the gradient boosting framework, extreme gradient boosting is more efficient than gradient boosting. To prevent overfitting and bias, it makes use of high-performance methods including parallel processing, tree pruning, handling missing information, and regularisation. The results show that XGBoost is a superior algorithm, particularly for large training data sets by outperforming other classifiers. In the current method, a machine learning model is built using the XGBoost classification algorithm to choose the crops that are best for the soil based on its nutrient content and the local geological circumstances.

2.2 Smart Irrigation using Moisture Sensors

Watering plants is a mundane task in farming. Feeding plants with the required amount of water is vital on a daily basis. Less water can make the plants dry and excessive water may make the plants rot and also lead to wastage of water. Automating the process of watering using sensors would make this task both easier and more effective. We need data acquisition in the field initially. The parameters like temperature, humidity, ph, and rainfall are collected from the identified field. The water content of the soil can be measured with the soil moisture sensor. This will be a very crucial parameter that will be the backbone to provide other nutrients to the soil. In the present approach, soil moisture is taken as a parameter for the automated watering system also and this has led to significant water conservation. The soil temperature is measured using the LM35 soil temperature sensor. The humidity sensor DHT22 measures air temperature and moisture. The pH level is also constantly maintained and monitored using the pH meter[14]. All of this data is collected from the sensors using an Arduino microcontroller, and it is then stored in a data repository. The IoT-based system design is shown in Figure 1.

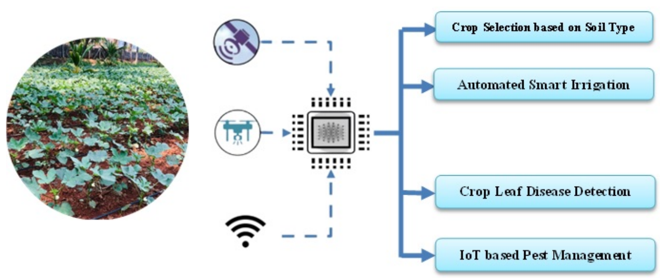


Fig 1. Smart Farming System Design

The smart farming system uses environmental sensors namely, temperature and humidity sensor (DHT22) and soil moisture sensor (LM35) to measure the temperature, humidity, and soil moisture. The input is provided through analog input ports in the range of 5.0 Vdc to the microcontroller. Specific regions of the farm are identified for placing the Wi-Fi modules to transmit the environmental data from the Arduino microcontroller to the cloud server. This data is used to operate the water pumps based on the soil moisture condition, temperature, and humidity. To remotely monitor the connected equipment and manage the farm operations, an Android user interface built on an Arduino platform is employed together with a free cloud service.

2.3 Crop Leaf Disease Identification using Convolutional Neural Networks

Manual detection to identify leaf disease is very tricky. Convolutional neural networks are recently used for image classification techniques since they outperform most of the other techniques. Convolutional neural networks can be used for easily detecting crop diseases using images. Figure 2 shows sample tomato leaves from the dataset.

Convolutional Neural Networks (CNN) models require very little preprocessing and the models prove to be very effective in crop disease detection. Early detection of diseases helps to save crops from infections and prevents the yield of crops from getting affected. In the present approach, we are using convolutional neural networks for detecting 9 types of leaf diseases

Fig 2. Sample Images from Dataset

in tomato plants. We used a plant disease dataset containing tomato leaves affected by 9 diseases. The following diseases are considered for our research purpose: Early Blight, Late Blight, Leaf Mould, Bacterial Spot, Septoria Leaf Spot, Two-spotted Spider Mite, Target Spot, Tomato Mosaic Virus, and Tomato Yellow Leaf Curl Virus. There is a total of 14091 images in the dataset. The images are split into a training set and a validation set. The training set consists of 9838 images and the validation set consists of 4250 images. The images are preprocessed before classifying them using convolutional neural networks. Custom dataset from the fields is used as the test dataset. The data in the dataset were subject to various data augmentation procedures. Data augmentation helps in reducing overfitting and increasing the accuracy of classification. Figure 3 shows the augmented data.

Fig 3. Augmented images from dataset

Convolutional neural networks, commonly known as Convnets or CNN are a type of neural network with multiple layers that are highly suitable for image classification using deep learning models. The CNN takes images as input and classifies them using the labels provided. CNNs function based on the connectivity patterns of neurons in the human brain. Convolutional neural networks extract various spatial and temporal features automatically from the images and classify the images based on those features. A typical CNN gets its input from an input layer. Then it performs a convolution operation using an activation function associated with a set of convolutional layers. The output of the convolution layers is passed to the pooling layers. After max pooling, the results are passed to an activation function in the fully connected layers. The final results are obtained from the output layer. The framework of the proposed approach is depicted in Figure 4.

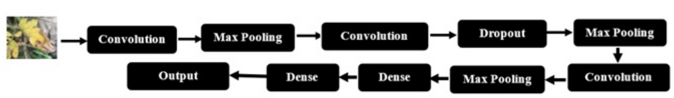


Fig 4. Framework of Crop Disease Detection using CNN

The convolutional neural network uses several layers for feature extraction. The simple features are extracted using the initial layers and the complex ones are extracted by the higher level layers. The mathematical formula for the convolution operation is shown in equations (2) and (3).

$$f(x) \,.\, g(x) = \int f(x).g(x-k)dk \tag{2}$$

$$f(x) * g(x) = \sum_{k=-\infty}^{\infty} f(x).g(x-k) \tag{3}$$

f(x) and g(x) are known as the input and the kernel, respectively, and the convolution operation takes the input and produces a feature map as output [15].

2.4 Pest Management Using IoT

The advanced technologies help in increasing yield and productivity but at the same time, excessive use of pesticides on plants is a major threat to human health and also to the environment. Pesticides can cause adverse effects on health such as memory loss, and mood swings, and are also a source of deadly diseases such as cancer, asthma, and hypersensitivity. Especially after being struck by this terrible pandemic situation, everyone prefers to go with natural healthy foods. The economic loss in agriculture is mainly due to insects and pests. Farmers usually use many pesticides to control weeds and plant diseases. This type of pest usage affects not only human health but also the entire environment around us. In smart farming, the plants are made to receive the necessary vitamins and minerals from the nutrient solution instead of the soil so there is no explicit need for chemical pesticides.

The current research has used some below listed organic pesticides in our home gardening system that are eco-friendly as well as suit all kinds of crops.

• Neem oil is one of the best insecticides that works as a complete pesticide solution. This solution decreases the number of insects coming, stops feeding, and also prevents the larvae from maturing. Neem oil can also make the insects suffocate and die.

• Garlic spray, a "green" solution, that controls ants, beetles, worms, and many more can be applied to parts of plants such as the backside of the leaves where usually insects lay eggs.

• Red Pepper spray prevents plants from flying insects that feed on different parts of the plant.

• Milk spray, especially organic milk, has natural antibiotics. The mix of milk and water is the best fungicide spray that reduces fungal diseases in plants.

3 Results and Discussion

3.1 Effect of Automated Crop Selection Based on Soil Type

A crop recommendation dataset is used for the purpose of classification of crops based on soil composition. The dataset consists of 2500 records with seven features namely Nitrogen, Phosphorus, and Potassium composition, the temperature, humidity, and average rainfall of the place, and the pH of the soil from fields in India.

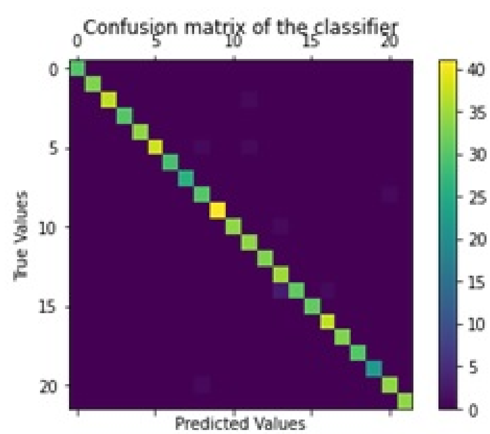


Fig 5. Confusion Matrix of the XGBoost Classifier

The dataset consists of soils growing crops such as rice, maize, chickpeas, brinjal, kidney beans, ladies finger, black gram, lentils, tomato, pomegranate, banana, mango, grapes, watermelons, muskmelon, apple, orange, papaya, coconut, cotton, jute, and coffee. This dataset is mined using the XGBoost algorithm. 67% of the data has been used for training the model and 33% was used as the test set.

The learning rate of the model was fixed as 0.3 and multi: softprob is used as the loss function since the problem is a multi-class problem. The machine learning model has been used for identifying suitable soil for crops such as rice, brinjal, ladies finger, and tomatoes in our approach. The confusion matrix of the classifier is shown in Figure 5 . The prediction accuracy achieved was 98.62%. The classification report of the XGBoost classifier is shown in Figure 6 .

```
Accuracy: 98.62%

Micro Precision   : 0.99
Micro Recall      : 0.99
Micro F1-score    : 0.99
Macro Precision   : 0.99
Macro Recall      : 0.99
Macro F1-score    : 0.99
Weighted Precision: 0.99
Weighted Recall   : 0.99
Weighted F1-score : 0.99
accuracy               0.99      726
macro avg              0.99      0.99      0.99      726
weighted avg           0.99      0.99      0.99      726
```

Fig 6. Classification report of the XG Boost Classifier

Micro-averaged F1-score is used for evaluating the quality of classification problems It is calculated from the confusion matrix of the model. This metric performs a global calculation by considering all classes together.

Table 1. Impact of Soil Classification on the Yield of Crops

Recommended Crop	Percentage of Increase in Yield
Tomato	62%
Ladies Finger	77%
Brinjal	71%

Macro-averaged F1-score calculates the metrics for individual classes and then the unweighted mean of the measures is calculated. Based on the results of the XGBoost classification, a change of crop was recommended for four of the ten fields under study. The increase in yield after the recommendation is recorded in Table 1. On measuring the yield from different fields, the productivity of 80% of the fields is found to be increased by an average of 70% as a result of planting crops that are suitable for the soil types.

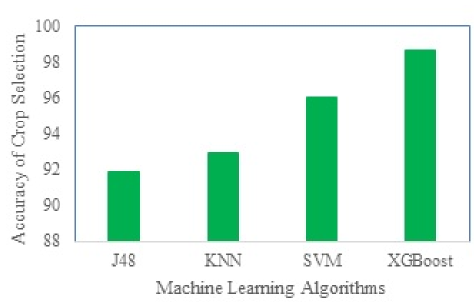


Fig 7. Comparison of XG Boost Classifier with existing systems

Machine learning techniques have been proven to be efficient in soil classification and selection of crops based on soil type. Existing systems use several machine learning algorithms such as SVM, KNN, J48, and decision trees for the classification of soil types and crop selection based on soil type[16,17]. The accuracy of the current system is compared with the above existing systems and the results are depicted in Figure 7.

3.2 Effect of Automated Smart Irrigation

The plants are watered automatically using the Arduino-based drip irrigation system using automatic water sprinklers. Water is a scarce resource in various places where farms are located. Therefore, wastage of water can be avoided if plants are watered with the exact quantity of water that is essential for them. The automated drip irrigation system is used for this purpose. A water level indicator fixed in the sump measures the level of water and automatically pumps the water to the drip irrigation system.

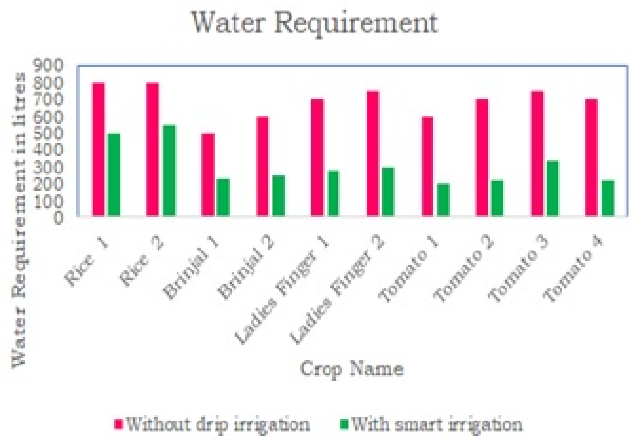


Fig 8. Water Requirement

Based on the soil moisture content, the plants are watered for a maximum of three times a day. A timer is set up in the Arduino microcontroller in order to water the plants at specific times of the day. The drip irrigation system will be turned on only if the soil moisture content is below 60%. This helps to conserve water to a large extent. The average water consumed per day in different fields in a month with and without the automated drip irrigation system is recorded and the results are shown in Figure 8. It is trivial from the graph that the water requirement is reduced to a considerable extent because of the smart drip irrigation system. Based on our measurements, the average consumption of water was reduced by 34.38% for rice, 56.17% for brinjal, 60% for ladies finger, and 64.45% for tomatoes. Thus, the proposed approach has been found to be useful in water conservation.

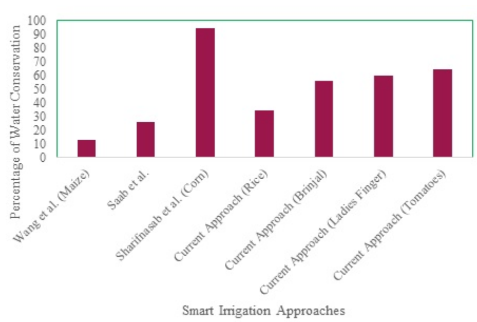
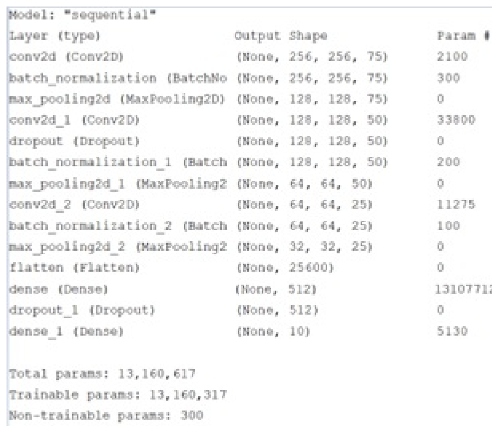


Fig 9. Comparision of Water Conservation using Smart Irrigation

With an increase in population especially in India, water is becoming a scarcity in many places and therefore, the conservation of water is felt as the need of the hour. According to the literature, smart irrigation systems designed with water controllers and IoT can be effectively used for water conservation. However, the amount of water conservation depends on the type of crop and varies from one crop to another. Wang Y et. al. could attain water conservation of 11% to 15% for maize crops using drip irrigation[(18)]. 94.74% of water conservation was recorded for corn crops using intelligent irrigation systems[(19)]. Saab et al. could achieve 25.7% water efficiency using real-time irrigation[(20)]. The existing systems are compared with the proposed approach and the results are shown in Figure 9.

3.3 Effect of Crop Leaf Disease Detection using CNN

Convolutional neural networks were used for crop disease detection in tomato leaves. In the proposed experiment, the input layer, hidden layers, and output layers have been added to the convolutional neural network.



```
Model: "sequential"
Layer (type)                 Output Shape              Param #
conv2d (Conv2D)              (None, 256, 256, 75)      2100
batch_normalization (BatchNo (None, 256, 256, 75)      300
max_pooling2d (MaxPooling2D) (None, 128, 128, 75)      0
conv2d_1 (Conv2D)            (None, 128, 128, 50)      33800
dropout (Dropout)            (None, 128, 128, 50)      0
batch_normalization_1 (Batch (None, 128, 128, 50)      200
max_pooling2d_1 (MaxPooling2 (None, 64, 64, 50)        0
conv2d_2 (Conv2D)            (None, 64, 64, 25)        11275
batch_normalization_2 (Batch (None, 64, 64, 25)        100
max_pooling2d_2 (MaxPooling2 (None, 32, 32, 25)        0
flatten (Flatten)            (None, 25600)             0
dense (Dense)                (None, 512)               13107712
dropout_1 (Dropout)          (None, 512)               0
dense_1 (Dense)              (None, 10)                5130

Total params: 13,160,617
Trainable params: 13,160,317
Non-trainable params: 300
```

Fig 10. Summary of the Convolutional Neural Network Model

The model has been finetuned with the various hyperparameters in the hidden layers such as dropout, batch normalization, and max-pooling. The size of the convolutional layer is set as 256 X 256. The total number of parameters used in the proposed model is 13,160,617. The summary of the model is shown in Figure 10. The training accuracy of the proposed model was 97.3%. The fields were monitored using CCTV cameras and the samples were analyzed using the model. The testing accuracy was found to be 95.28% on the real-time data.

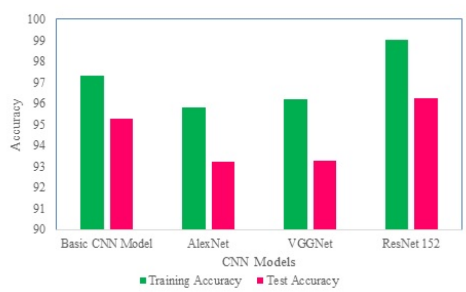


Fig 11. Classification Accuracy of CNN Models

The model could identify 9 diseases from tomato leaves. The model is further improved with transfer learning approaches using AlexNet, VGGNet, and ResNet 152. The highest accuracy obtained on the training set was 99% and on the test set was 96.24% with ResNet 152. The results are shown in Figure 11. A pest management model using IoT is also in progress but not yet implemented.

There has been a variety of literature that uses variations of CNN for effective detection of crop diseases. A few variants of CNN on tomato leaf detection are compared with the current approach and the results are portrayed in Table 2.

Table 2. Comparison of Crop Disease Detection Neural Networks

Name of the Existing System	CNN Architecture Used	Classification Accuracy
Mohit Agarwal et al. [21]	CNN	91.20% [21]
Prajwala T M et al. [22]	LeNet	94.90% [22]
Trivedi N K et al. [23]	CNN	98.49% [23]
Antonio et al. [24]	GAN	99.00% [24]
Current Approach	Basic CNN	95.28%
	AlexNet	93.2%
	VGGNet	93.25%
	ResNet	96.24%

4 Conclusion

This research has contributed to smart agriculture in terms of suggesting suitable crops based on soil composition, smart watering system, disease control, and pest control with organic pesticides. Covid-19 has emphasized the importance of smart organic agriculture for every one of us. As a result, we can see many home farming systems implemented during the period of lockdown. This type of smart farming helps in saving water, increases production, and provides us with a sustainable environment. The present approach has been found to be performing better than the existing approaches. Crop selection based on soil type using XGBoost machine learning algorithm with an improved accuracy of 98.62% helped in boosting the productivity of 80% of the fields by an average of 70%. Sensor-based smart irrigation techniques helped to achieve water conservation to a maximum of 64.45%. Though this is not better than some of the existing systems, most of the results are crop-dependent since the water requirement varies for different crops. The algorithm used for disease detection also helped in automated CCTV surveillance-based crop disease management with a significant accuracy of 96.24% with real-time test data. However, the disease management algorithms were tested only for tomato leaf diseases and would be further extended to other crops.

References

1) Farooq MS, Riaz S, Abid A, Umer T, Zikria YB. Role of IoT Technology in Agriculture: A Systematic Literature Review. *Electronics*. 2020;9(2):319. Available from: http://dx.doi.org/10.3390/electronics9020319.
2) Dhanya VG, Subeesh A, Kushwaha NL, Vishwakarma DK, Kumar TN, Ritika G, et al. Deep learning based computer vision approaches for smart agricultural applications. *Artificial Intelligence in Agriculture*. 2022;6:211–229. Available from: https://doi.org/10.1016/j.aiia.2022.09.007.
3) Algarni MD, Alroobaea R, Almotiri J, Ullah SS, Hussain S, Umar F. An Efficient Convolutional Neural Network with Transfer Learning for Malware Classification. *Wireless Communications and Mobile Computing*. 2022;2022:1–8. Available from: https://doi.org/10.1155/2022/4841741.
4) Gupta A, Nahar P. Classification and yield prediction in smart agriculture system using IoT. *Journal of Ambient Intelligence and Humanized Computing*. 2023;14(8):10235–10244. Available from: https://doi.org/10.1007/s12652-021-03685-w.
5) Sridhar A, Balakrishnan A, Jacob MM, Sillanpää M, Dayanandan N. Global impact of COVID-19 on agriculture: role of sustainable agriculture and digital farming. *Environmental Science and Pollution Research*. 2022;30(15):42509–42525. Available from: https://doi.org/10.1007/s11356-022-19358-w.
6) Thinakaran J, Paul S, Latha CBC, Jacob G. Blockchain in Big Data for Agriculture Supply Chain. *Studies in Big Data*. 2023;p. 257–291. Available from: https://doi.org/10.1007/978-981-19-8730-4_9.
7) Bisoffi S, Ahrné L, Aschemann-Witzel J, Báldi A, Cuhls K, Declerck F, et al. COVID-19 and Sustainable Food Systems: What Should We Learn Before the Next Emergency. *Frontiers in Sustainable Food Systems*. 2021;5. Available from: https://doi.org/10.3389/fsufs.2021.650987.
8) Rajasree CR, Latha SBC, Paul AM. Tomato Leaf Disease Detection using Deep Learning Algorithm. *International Journal of Creative Research Thoughts*. 2022;10(9):104–114. Available from: https://www.ijcrt.org/papers/IJCRT2209017.pdf.
9) James A, Saji A, Nair A, Joseph D. CropSense – A Smart Agricultural System using IoT. 2019. Available from: https://doi.org/10.5281/zenodo.3566563.
10) Rajasree R, Latha CBC, Paul S. Application of Transfer Learning with a Fine-tuned ResNet-152 for Evaluation of Disease Severity in Tomato Plants. *Mobile Computing and Sustainable Informatics*. 2022;p. 695–710. Available from: https://doi.org/10.1007/978-981-19-2069-1_48.
11) Yadhav SY, Senthilkumar T, Jayanthy S, Kovilpillai JJA. Plant Disease Detection and Classification using CNN Model with Optimized Activation Function. *2020 International Conference on Electronics and Sustainable Communication Systems (ICESC)*. 2020;p. 564–569. Available from: https://doi.org/10.1109/ICESC48915.2020.9155815.
12) Altalak M, Uddin MA, Alajmi A, Rizg A. Smart Agriculture Applications Using Deep Learning Technologies: A Survey. *Applied Sciences*. 2022;12(12):5919. Available from: https://doi.org/10.3390/app12125919.
13) Debnath O, Saha HN. An IoT-based intelligent farming using CNN for early disease detection in rice paddy. *Microprocessors and Microsystems*. 2022;94:104631. Available from: https://doi.org/10.1016/j.micpro.2022.104631.
14) Akhter R, Sofi SA. Precision agriculture using IoT data analytics and machine learning. *Journal of King Saud University - Computer and Information Sciences*. 2022;34(8):5602–5618. Available from: https://doi.org/10.1016/j.jksuci.2021.05.013.
15) Bedi P, Gole P. Plant disease detection using hybrid model based on convolutional autoencoder and convolutional neural network. *Artificial Intelligence in Agriculture*. 2021;5:90–101. Available from: https://doi.org/10.1016/j.aiia.2021.05.002.

16) Saranya N, Mythili A. Classification of Soil and Crop Suggestion using Machine Learning Techniques. *International Journal of Engineering Research and*. 2020;9(02). Available from: http://dx.doi.org/10.17577/IJERTV9IS020315.
17) Gaikwad S, Aiwale A, Rekade V, Kalunge V. Soil Classification and Crop Suggestion using Machine Learning Techniques. *International Journal for Research in Applied Science and Engineering Technology*. 2022;10(5):4984–4986. Available from: .https://doi.org/10.22214/ijraset.2022.43524.
18) Wang Y, Li S, Cui Y, Qin S, Guo H, Yang D, et al. Effect of Drip Irrigation on Soil Water Balance and Water Use Efficiency of Maize in Northwest China. *Water*. 2021;13(2):217. Available from: https://doi.org/10.3390/w13020217.
19) Sharifnasab H, Mahrokh A, Dehghanisanij H, Łazuka E, Łagód G, Karami H. Evaluating the Use of Intelligent Irrigation Systems Based on the IoT in Grain Corn Irrigation. *Water*. 2023;15(7):1394. Available from: https://doi.org/10.3390/w15071394.
20) Saab A, Jomaa M, Skaf I, Fahed S, Todorovic S, M. Assessment of a Smartphone Application for Real-Time Irrigation Scheduling in Mediterranean Environments. 2019. Available from: https://doi.org/10.3390/w11020252.
21) Agarwal M, Singh A, Arjaria S, Sinha A, Gupta S. ToLeD: Tomato Leaf Disease Detection using Convolution Neural Network. *Procedia Computer Science*. 2020;167:293–301. Available from: https://doi.org/10.1016/j.procs.2020.03.225.
22) Prajwala TM, Pranathi A, Saiashritha K, Chittaragi NB, Koolagudi SG. Tomato Leaf Disease Detection Using Convolutional Neural Networks. In: 2018 Eleventh International Conference on Contemporary Computing (IC3). IEEE. 2018;p. 1–5. Available from: https://doi.org/10.1109/IC3.2018.8530532.
23) Trivedi NK, Gautam V, Anand A, Aljahdali HM, Villar SG, Anand D, et al. Early Detection and Classification of Tomato Leaf Disease Using High-Performance Deep Neural Network. *Sensors*. 2021;21(23):7987. Available from: https://doi.org/10.3390/s21237987.
24) Guerrero-Ibañez A, Reyes-Muñoz A. Monitoring Tomato Leaf Disease through Convolutional Neural Networks. *Electronics*. 2023;12(1):229. Available from: https://doi.org/10.3390/electronics12010229.