A Comprehensive Study of Application Domains of IoT and AI in Horticulture: A Case Study of Plant Leaf Disease Detection and Classification using CNN

Subramanya S. G[1*], Parkavi A[2], Shwetha R[3], B M Thippeswamy[4], Manjunatha B N[5], Asha PN[6]

[1]Research Scholar, Department of Computer Science and Engineering, Ramaiah Institute of Technology, Bangalore-560064 (Affiliated to Visvesvaraya Technological University, Belagavi, Karnataka, India.)
*Assistant Professor, Department of Computer Science and Engineering, Nitte Meenakshi Institute of Technology, Yelahanka, Bangalore 560064, Karnataka, India.
[2]Associate Professor, Department of Computer Science and Engineering, Ramaiah Institute of Technology, Bangalore-560064, Karnataka, India.
[3]Asistant Professor, School of Computer Science and Engineering, Reva University, Bangalore-560064, Karnataka, India.
[4] Professor, School of Computer Science and Engineering, Reva University, Bangalore-560064, Karnataka, India.
[5] Professor, Department of Computer Science and Engineering (AIML), R L Jalappa Institute of Technology, Doddaballapur-561 203, Karnataka, India.
[6]Assosiate Professor, School of Computer Science and Engineering, Reva University, Bangalore-560064, Karnataka, India.

Abstract - Horticulture is a branch of agriculture that deals with growing fruits, nuts, vegetables, flowers, and ornamental plants. It is one of the fastest-growing economic sectors contributing 30% to India's Gross Domestic Product (GDP), upholding India as the second largest horticulture producer in the world. However, Horticulture crops face many challenges including effective utilization of land, shortage of labor, shortage of water, low soil fertility, early detection and treatment of plant disease, pest control, crop monitoring, timely harvesting, and yield prediction. In this paper, we presented a qualitative survey addressing the mentioned challenges in agriculture and horticulture using technologies like IoT and AI. We discussed the application of IoT at various stages of farming, from irrigation to crop harvesting, and explored the application of AI techniques for disease detection, yield prediction, etc. We also presented a case study of plant leaf disease detection and classification using Convolutional Neural Network (CNN), an application of AI in agriculture. We used transfer learning (TL) based CNN model to train and validate using an enormous dataset of 87,867 labelled images. We were able to achieve training and validation accuracies of 0.69(69%), and 0.86 (86%) respectively, for 10 epochs, 0.0001 learning rate, and 50 % dropout rate. The model demonstrated training and validation losses of 1.05 and 0.53, respectively.

Keywords: IoT and AI in Agriculture; Intelligent Farming; Smart Farming; Transfer Learning; Deep Learning; CNN.

1. INTRODUCTION

India is the land of agriculture, the second largest producer of the world’s most wanted food sources like wheat and rice. Also, it is the second largest producer of horticulture (fruits and flowers) crops. One-third of the Indian population depends on agriculture and allied sectors for their livelihood. According to Financial Express, horticulture production in India was around 146 million tonnes in 2001-02. In 2018-19, it rose to approximately 314 million tonnes. Also, the land used for horticulture crops has been increasing each year. In 2018-19, the entire horticulture land increased to 25.5 million hectares, occupying one-fifth of the total agricultural land. But the total agriculture production area has been decreasing every year. In 2016-17, the entire land used for agriculture was 129 million hectares, which has come down to 124 million hectares in the year 2018-19. The increased demand for agriculture/horticultural crops in the world has created better export opportunities, with a promise to fetch high profits for our farmers in the coming days. The above statistics indicate that technology-driven horticulture with a vision of better yield will be a new success mantra for the governments to achieve food security, escalate GDP through exports, and secure our farmers financially. However, the farmers face many difficulties at various stages of traditional farming. Some of them are ineffective land utilization, land fragmentation, labor shortage, water scarcity, low soil fertility, early detection and treatment of plant disease, pest or weed control, crop monitoring, timely harvesting and yield prediction, etc.

The emergence of technologies like the Internet of Things (IoT) and Artificial Intelligence (AI) has changed our lives, revolutionized businesses and business models, and improved healthcare and supply chains. The revolution in IoT, AI, and their blended adoption in horticulture at various stages of farming provides smarter and better solutions to many problems and increases production with limited resources (Alreshidi, 2019) (Hussein, 2019) (Madushanki, 2019). In this paper, we discussed the various application domains of IoT and AI for smart, sustainable horticulture. Also, we presented a case study of plant leaf disease detection and classification using Convolutional Neural Network (CNN) by subjecting a large plant leaf dataset. The case study gives insights into how we can use an AI model in disease detection, classification and prediction. This case study is included to show case an application of AI model in agriculture domain.

2. RELATED WORKS

Eissa Alreshidi (Alreshidi, 2019) illustrated how IoT and AI technologies are used for Smart Sustainable Agriculture (SSA) and developed a technical architecture using IoT/AI to enhance SSA platforms. The architecture supports current agricultural practices resulting in high productivity and better quality. Also, Eissa stated that the unified architecture helps in resolving too much fragmentation of the agriculture process.

Abdel Rahman H. Hussein (Hussein, 2019) discusses upcoming applications, various research challenges, and the latest advancements in IoT technologies. Further, Abdel narrates the potential domains of IoT such as smart cities, healthcare, smart agriculture and water management, retail and logistics, and the research challenges in each domain like privacy and security, monitoring and sensing, M2M communication protocols, interoperability issues, the blockchain of things, processing and management, etc.

A. A. Raneesha Madushanki et al. (Madushanki, 2019) reviewed 60 research publications between 2016 and 2018. Their study was to showcase which IoT sub-vertical is the most researched area and what type of sensor data is measured/collected the highest number of times. They found water management as the most researched sub-vertical. The next most researched sub-vertical is crop management, followed by smart farming. The least researched sub-verticals are irrigation management and livestock management. Of the entire critical sensor data collected, environmental temperature is the highest, and the next highest is environmental humidity followed by soil moisture and soil pH. Further, of all IoT communication technologies, Wi-Fi is more frequently used compared to mobile technology. They conclude that the agricultural sector is the most researched sector and hence, IoT should be improved or developed to increase productivity.

Tanmay Anand et al. (Anand, 2021) created an AgriSegNet, a Deep Learning model for precision agriculture. The model uses Unmanned Aerial Vehicle (UAV) - remote sensing based on IoT, which captures images of the farm. These captured images are then analyzed based on visual data analytics (multi-scale attention semantic segmentation) to detect farm anomalies, which helps to monitor crops and hence, increases the efficiency of precision agriculture.

Lalbihari Barik (Barik, 2019) designed an IoT device using a combination of Arduino UNO with Raspberry Pi (to process and control), HTU-211D sensor (to collect environmental data), and ESP8266 Wi-Fi module (to communicate). The environmental temperature and humidity are sensed using an HTU-211D sensor. The collected data is then uploaded to the ThingSpeak cloud and sent to farmers' mobile using the GSM module. The graphical analytics of the data can be visaulized through user interface. The farmer can monitor and control irrigation by controlling the DC motor (on/off) for further action.

Neda Fatima et al. (Fatima, 2021) designed a Smart Greenhouse system using IoT and deep learning for monitoring, alerting, cloud storage, automation, and disease prediction for Greenhouse. This system monitors and controls environmental factors like temperature, humidity, and soil moisture conditions for better crop yield and immediate actions against abnormal conditions. Further, they state that the system employs automatic irrigation control and disease identification using a deep-learning model from leaf images. The system can be used for small and large greenhouses.

Muhammad Amir Nawaz et al. (Nawaz, 2020) proposed a system developed using sensors to identify whether the leaf is natural or infected. The infected leaf identification is based on the parameters like moistness, temperature, the shade of the leaf, and stickiness. Moistness and temperature were measured using the DHT11 sensor; leaf shade was measured using the TCS3200 color sensor. The collected data were processed using Arduino UNO, then sent to the ThingSpeak cloud, and analyzed. The system helped to identify the nature of the leaves (infected or natural), and if the plant was infected further spread could be controlled with proper measures.

Kohei Arai et al. (Arai, 2018) present AI-based fertilizer control to enhance the rice crop quality and crop harvest. Also, the research included rice field monitoring using drone technology. In this system, the quality and amount of rice harvest can be controlled by suitably changing fertilizer type, and the amount of fertilizer supplied which further reduced its wastage and also, requirements. The authors stated that based on the early stage of leaf growth, crop yield and quality can be predicted.

Marizel B. Villanueva et al. (Villanueva, 2018) proposed a crop yield prediction system to determine the yield of bitter gourd. For this, images of bitter melon plant leaves were collected (sampling) and classified into good or bad based on leaf description, and then a test model was designed. The system made use of a Convolutional Neural Network and Machine Learning Algorithm. Training and testing of data were conducted using MATLAB and Keras. The research concludes that training with 293 images can create an ML model to classify bitter gourd plants as good or bad.

A.M. Kassim et al. (Kassim, 2020) developed a robotic pesticide sprayer for the chili farm. They proposed to design and implement a robotic navigation system with a flexible robotic sprayer that can navigate itself and spray pesticides without human intervention. It consisted of two modules: the Navigation system and the Sprayer system. The navigation system included ultrasonic sensors, a microcontroller, and a direct current (DC) motor. But the sprayer system was built using a pesticide pump and a microcontroller. It's an unmanned pesticide sprayer powered by IoT for chili crops.

Ahmad Alfian Ruslan et al. (Ruslan, 2021) present a prototype that collects data like pH, and soil moisture from the palm oil field, processes and transmits them to the cloud using LoRa technology. The prototype was developed using hardware such as a pH sensor, moisture sensor, and TTGO LoRa SX1278 ESP32 OLED. The sensor data (pH, moisture level in soil) are sent to the micro-controller for further processing and then sent to ThingSpeak (cloud) using the LoRa Wi-Fi module, and the same is sent to the OLED display as well. They stated that the prototype enables workers in the palm oil industry to monitor soil conditions.

N.N. Misra et al. (Misra, 2020) discussed several technologies like IoT, AI, and Big Data and their roles in farming. The combined use of big data, AI, and IoT has improved the present food Industry and agriculture domains making complex tasks possible successes. They conclude that the research in technologies AI, big data, and IoT will impact industries, agriculture, and the food supply chain.

M. Biswas et al. (Biswas, 2021) proposed a futuristic model which combines IoT, AI, and Blockchain to create a smart agricultural system. This model provides an effective, secure, and open decision support system for rich and larger agriculture productivity. Thus it helps farmers to fetch more profits through the combined assistance of the said technologies.

Harikumar Pallathadka et al. (Pallathadka, 2021) discussed ML, Deep Learning (DL), and AI applications in agriculture, healthcare, social studies, and management. These include yield improvement, prediction of plant disease, water & irrigation optimization, etc. They highlighted popular techniques of ML and DL that addressed several issues related to health care, agriculture, etc.

Table 1: Comparative Study of Application Domains of IoT and AI in Horticulture

Sl. No.	Domain	Challenges	Technologies Discussed	Outcome	Author	Year
1	SSA (Intelligent machines, fertilization human resources, irrigation/water, crops, soil, pests, agriculture products, weather, livestock, machines and fields.)	Operation and control of AI & IoT machines, inter-operability, data acquisition, sharing, management, analysis & storage	IoT and AI	Blended IoT-AI architecture to create a Smart, Sustainable Agriculture (SSA)	Eissa Alreshidi (Alreshidi, 2019)	2019
2	Application Domains of IoT (smart cities, healthcare, smart agriculture, water management, retail, and logistics)	Energy-efficient monitoring & sensing, processing, analysis, management of big data in the heterogeneous platform, implementing privacy and security, M2M communication protocols, Blockchain of Things, interoperability issues	IoT, Big data, Blockchain	Application domains of IoT and their research challenges	Abdel Rahman H. Hussein (Hussein, 2019)	2019
3	Agriculture and smart farming (management of crops, water, livestock, and irrigation)	Sensor Data Collection & Analysis	IoT, Big data	Less Human interaction, reduced labor cost, water saving measures, energy saving measures	A. A. Raneesha Madushanki et. al. (Madushanki, 2019)	2019
4	Precision Agriculture	Visual data analytics (multi-scale attention semantic	IoT, Deep Learning	Farm and crop monitoring, increased efficiency of	Tanmay Anand et. al. (Anand, 2021)	2021

		segmentation) from UAV images		precision agriculture		
5	Irrigation	Data Collection, Processing, and Control	IoT (Raspberry Pi, sensors, & Wi-Fi)	Temperature and Humidity Control, Automated Irrigation	Lalbihari Barik (Barik, 2019)	2019
6	Smart Greenhouse system	Monitoring, alerting, cloud storage, automation, and disease prediction	IoT and Deep Learning	Automatic irrigation control and disease identification	Neda Fatima et. al. (Fatima, 2021)	2021
7	Plant disease identification and control	Data collection, storage, and processing	IoT	Disease identification and control	Muhammad Amir Nawaz et. al. (Nawaz, 2020)	2020
8.	Fertilization and control, crop monitoring	Creating a knowledge base based on data from SPAD, Quality analysis, Harvest estimation	AI	Improved quality and volume of harvest	Kohei Arai et. al. (Arai, 2018)	2018
9.	Crop yield prediction	Data acquisition, Analysis	Computer Vision, Machine Learning with CNN	Yield Prediction of bitter gourd	Marizel B. Villanueva et. al. (Villanueva, 2018)	2018
10.	Pest Management (Automated Pesticide Sprayer Robot)	Robotic Navigation, Robotic sprayer	IoT, Robotics	Unmanned robotic sprayer	A.M. Kassim et. al. (Kassim, 2020)	2020
11.	Soil Monitoring	Data collection, Storage and processing	IoT	Efficiency and productivity will be increased	Ahmad Alfian Ruslan et. al. (Ruslan, 2021)	2021
12.	Agriculture and Food Industry	Data collection, processing, data analytics, controlling	IoT, ML, Big Data	Applications in the agriculture and food industry, challenges in implementing IoT, ML in handling big data	N.N. Misra et. al. (Misra, 2020)	2020
13.	Smart Agricultural System	Integration of blockchain	AI, IoT, and Blockchain	Effective, secure, and open decision	M. Biswas et. al. (Biswas, 2021)	2021

		along with IoT and AI		support system for rich and larger agricultural productivity		
14.	AI (ML & DL) in healthcare, agriculture, social studies & management	Implementation of ML, DL algorithms for various domains	Artificial intelligence (machine learning & deep learning)	control, operation & implementation of AI for yield improvement, prediction of plant disease, water & irrigation optimization, management, etc	Harikumar Pallathadka et. al. (Pallathadka, 2021)	2021

3. STAGES OF AGRICULTURE USING IOT AND AI SYSTEMS

There are several stages of agriculture that can be automated by using IoT and AI. Fig. 1 depicts the different areas of agriculture that can be automated. Agriculture methods are grouped into four important domains namely Monitoring, Control, Prediction, and Logistics.

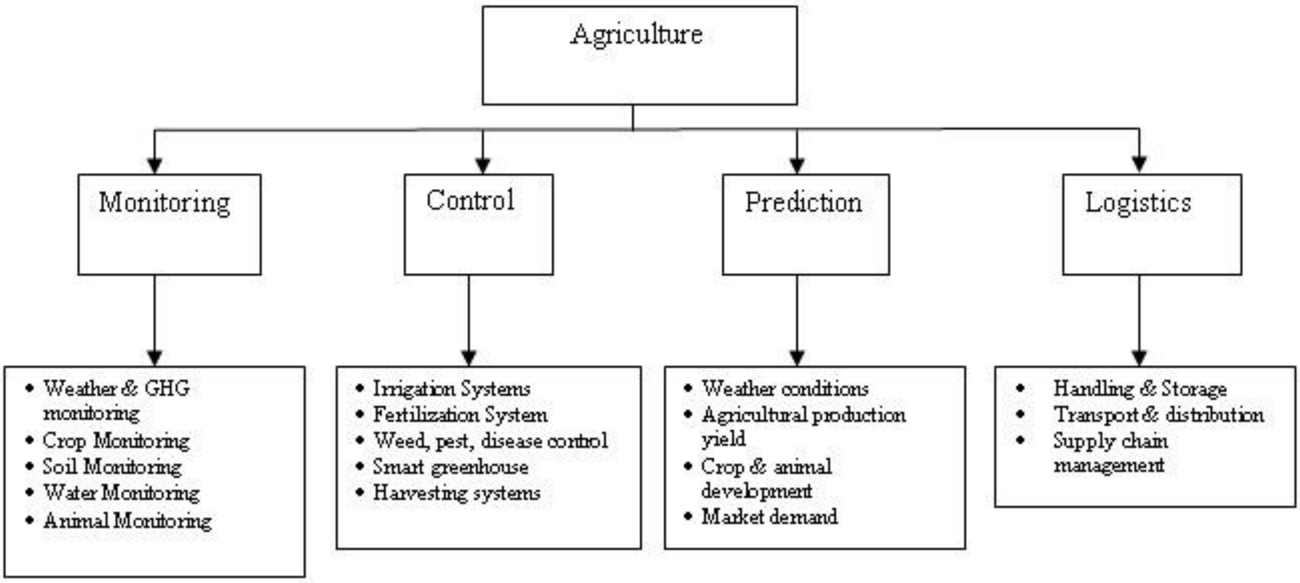

Figure 1: Agricultural System involving IoT and AI Modules

3.1 IoT in Agriculture

IoT is a large cluster of various electronic devices (things) like sensors, controllers, and actuators connected to the Internet (Hussein, 2019). These devices (usually sensors) collect data from the surrounding environment, transmit them to the cloud, and analyze and perform specified actions on them. The IoT echo system integrates data collection, communication, processing, and applying analytics to share the most valuable information with applications to address specific needs (Anand, 2021) as shown in Fig. 2.

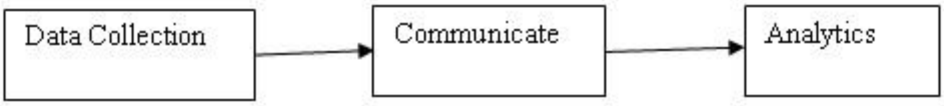

Figure 2: IoT Echo System

IoT can be used in Monitoring and Control systems as depicted in Fig. 1. The sensors collect environmental data like weather moisture, soil moisture, humidity, and temperature. The collected data are either processed locally (Edge Computing/Fog computing) or may be sent to the cloud to process further and store (Cloud computing). The processed data are then analyzed using AI algorithms. Based on the analysis results, control actions (irrigation control, fertilization control, weed/pest control, etc.) are applied at various stages of farming.

3.2 AI in Agriculture

Artificial Intelligence is an imitation of human intelligence by machines. With the overwhelming advancement of AI techniques, machines have become smarter. AI technology has infiltrated our daily lives. Automation has a significant role in almost all sectors like business, healthcare, retail, finance, automobiles, etc. IoT blended with AI provides smarter, precise solutions to complex problems. This combination of IoT and AI has to be explored in the field of agriculture and allied sectors as there is more scope for automation in every stage starting from sowing to harvesting (Misra, 2020). Besides, when agriculture is automated with the least human intervention, it can solve major problems such as shortage of water, shortage of labor, effective utilization of land, etc.

AI plays a crucial role in precision irrigation, soil monitoring, plant disease/weed control (Kassim, 2020) (Biswas, 2021), crop recommendation, fertilizer recommendation, weather forecasting, market/yield prediction, etc.

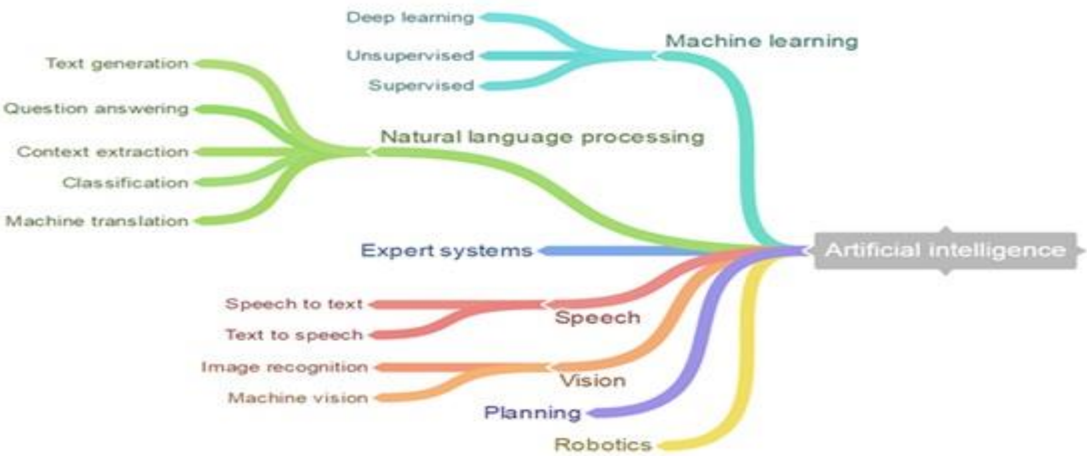

Figure 3: Artificial Intelligence

Based on the soil type suitable crop can be recommended using predictive analytics (Anand, 2021) (Ruslan, 2021), irrigation can be done more precisely by measuring moisture content in the soil and in the atmosphere (Barik, 2019) (Pallathadka, 2021), soil fertility can be improved by knowing the exact mineral deficiencies and providing only necessary manures (Arai, 2018) (Ruslan, 2021) which saves unnecessary expenditure, crop diseases can be identified at the early stages by using Deep Learning algorithms (Fatima, 2021) (Nawaz, 2020) and can be treated intelligently (Kassim, 2020), crop yield can be predicted (Villanueva, 2018) along with its current market value to fetch better profits, weather forecasting can alert farmers and prevent the cause of potential damage to the crop. Likewise, many smart solutions can be provided at various farming stages using AI. In the following section, we present a case study of plant leaf disease detection using CNN to demonstrate how we can employ AI in agriculture domain.

4. CASE STUDY: PLANT DISEASE DETECTION USING CNN MODEL

The early and accurate detection of plant diseases is crucial for ensuring agricultural productivity and reducing economic losses. This section presents a comprehensive study on the application of Convolutional Neural Networks (CNNs) for the detection and classification of plant diseases (Srivastava, 2014). Leveraging the power of AI, CNN models can automatically identify patterns and features in plant images, offering a significant improvement over traditional manual inspection methods. In this case study, we trained CNN model on a diverse dataset comprising thousands of labelled images of healthy and diseased leaf images of different plant types. The diverse dataset provides a better foundation for the model to learn and generalize. The CNN model is designed meticulously and optimized through hyper-parameter tuning, data augmentation, and transfer learning techniques to enhance its performance.

4.1 Objective of the Case Study

1. To develop a CNN-based model for the detection and classification of plant leaf diseases from image dataset.
2. To evaluate the performance of the CNN model using a vast, diverse plant leaf image dataset including both healthy and diseased leaf images.
3. To optimize the CNN model performance through hyper-parameter tuning, data augmentation, and transfer learning.

4.3 Materials and Methods

The success of a Convolutional Neural Network (CNN) model for plant disease detection heavily relies on the quality and diversity of the dataset used for training and evaluation. This section provides an overview of the dataset employed in this study, highlighting its composition, sources, and pre-processing steps.

a) Dataset

The dataset used in this study comprises huge number of labeled images of various plant leaves, categorized into two main classes: healthy and diseased. Each diseased class corresponds to a specific type of plant disease. The dataset is sourced from New Plant Leaf Disease datasets available in Kaggle (https://www.kaggle.com/datasets/vipoooool/new-plant-diseases-dataset/), which provides 87,867 labelled images belonging to 38 classes of various plant species including apples, cherry, corn, orange, grape, potato, strawberry, raspberry, pepper, soybean etc. and various diseases.

The key components of the dataset are:

- Healthy Leaves: Images of leaves that exhibit no signs of disease or abnormalities, representing the healthy class.
- Diseased Leaves: Images of leaves affected by various diseases, with each disease type forming a separate class.

Common diseases included in the dataset are Bacterial Blight, Powdery Mildew, Downy Mildew, Leaf Rust, Late Blight, Mosaic Virus, and Anthracnose etc. The dataset is split into three subsets to facilitate training, validation, and testing of the CNN model:

- *Training Set:* Comprising 80% of the dataset that is 70,295 images belonging to 38 classes are used to train the CNN model and update its weights.
- *Validation Set:* Comprising 20% of the dataset that is 17,572 images belonging to 38 classes, used to tune hyper-parameters and monitor the model's performance during training.

Figure 4: Plant Leaf Disease Dataset

b) CNN Model

CNN is an artificial neural network with convolution layers, pooling layers and fully connected layers. The convolution layers use kernel/filters on the input image to detect image features like edges, patterns or color. The pooling layers reduce the spatial dimension. The deep layers capture more complex features like shape and texture. The fully connected layer combines all the neurons to create a feature vector to classify. The final layer also called as output layer outputs class probabilities. The table 2 summarizes complete CNN Architecture used in the case study.

Table 2: CNN Model Summary

Layer (type)	Output Shape	Parameters
conv2d (Conv2D)	(None, 128, 128, 32)	896
conv2d_1 (Conv2D)	(None, 126, 126, 32)	9,248
max_pooling2d (MaxPooling2D)	(None, 63, 63, 32)	0
conv2d_2 (Conv2D)	(None, 63, 63, 32)	9,248
conv2d_3 (Conv2D)	(None, 61, 61, 32)	9,248
max_pooling2d_1 (MaxPooling2D)	(None, 30, 30, 32)	0
conv2d_4 (Conv2D)	(None, 30, 30, 64)	18,496
conv2d_5 (Conv2D)	(None, 28, 28, 64)	36,928
max_pooling2d_2 (MaxPooling2D)	(None, 14, 14, 64)	0
conv2d_6 (Conv2D)	(None, 14, 14, 128)	73,856
conv2d_7 (Conv2D)	(None, 12, 12, 128)	147,584
max_pooling2d_3 (MaxPooling2D)	(None, 6, 6, 128)	0
conv2d_8 (Conv2D)	(None, 6, 6, 256)	295,168
conv2d_9 (Conv2D)	(None, 4, 4, 256)	590,080
max_pooling2d_4 (MaxPooling2D)	(None, 2, 2, 256)	0
conv2d_10 (Conv2D)	(None, 2, 2, 512)	1,180,160
conv2d_11 (Conv2D)	(None, 0, 0, 512)	2,359,808
max_pooling2d_5 (MaxPooling2D)	(None, 0, 0, 512)	0
dropout (Dropout)	(None, 0, 0, 512)	0
flatten (Flatten)	(None, 0)	0
dense (Dense)	(None, 1500)	1,500
dropout_1 (Dropout)	(None, 1500)	0
dense_1 (Dense)	(None, 38)	57,038

The model has total parameters of 4,789,258 (18.27 MB) of which trainable parameters are 4,789,258 (18.27 MB) and non-trainable parameters are 0 (0.00 B).

c) Classification using CNN

To prepare the dataset for training the CNN model, several pre-processing steps are undertaken to enhance image quality and consistency:

1. *Image Resizing:* All images are resized to a uniform dimension, typically 128x128 pixels, to match the input size expected by the CNN model.
2. *Normalization:* Pixel values are normalized to a standard range (e.g., 0 to 1) to ensure consistent input data and improve model convergence.
3. *Data Augmentation:* Techniques such as *rotation*, *flipping*, *zooming*, and *color* adjustments are applied to artificially increase the size of the dataset and introduce variability, helping the model generalize better.
4. *Label Encoding:* Each image is labelled according to its class (healthy or specific disease type), and these labels are encoded in a format suitable for training the CNN model.
5. *Over fitting and Multi-class classification:* To avoid overfitting we used a dropout rate of 40% in the dense layer and the output layer consists of 38 neurons for classifying the plant disease into 38 different classes.

d) Hyper-parameter optimization

We used an initial input image shape 128×128×3 (Height ×Width × RGB channels). The training and validation set is split into 2,197 and 550 batches respectively. Each batch consists of 32 images (batch size) approximately. We trained the model with 10 epochs with a learning rate of 0.0001. Further, Adam optimizer used in the model adjusts the learning rate of each parameter based on the mean and variance of the gradients. We used 50% dropout rate at the fully connected layer to avoid overfitting and 'softmax' as the activation function at the output layer for classifying plant diseases into 38 classes. The tables 3 summarize the hyper-parameters used in the model.

Table 3: Hyper-parameters

Hyper-parameter	**Values**
Input shape	128 ×128×3
Learning Rate	0.0001
Batch Size	32
Number of Epochs	10
Optimizer	Adam
Dropout Rate	50%
Number of Filters	32
Kernel Size	3×3
Stride	2
Padding	same
Activation Function	Softmax

e) Results and Discussions

We have evaluated the CNN model for accuracy and loss. The results show training and validation metrics used for plant disease detection. The metrics include accuracy and loss values for both the training and validation sets across multiple epochs. The table shows the obtained results.

Table 4: Results

Epoch	Training Accuracy	Validation Accuracy	Training Loss	Validation Loss
1	0.12825948	0.406157523	3.24043	2.276834
2	0.296521813	0.610118389	2.527699	1.612108
3	0.397652745	0.72228545	2.096276	1.23528
4	0.477900267	0.753129959	1.794448	1.025949
5	0.5358845	0.81373775	1.580863	0.806118
6	0.579457998	0.838151634	1.427752	0.662713
7	0.613244176	0.850273132	1.306638	0.643784
8	0.643445492	0.876052797	1.20064	0.517925
9	0.670118809	0.886182547	1.107101	0.458299
10	0.687104344	0.864727974	1.049247	0.527407

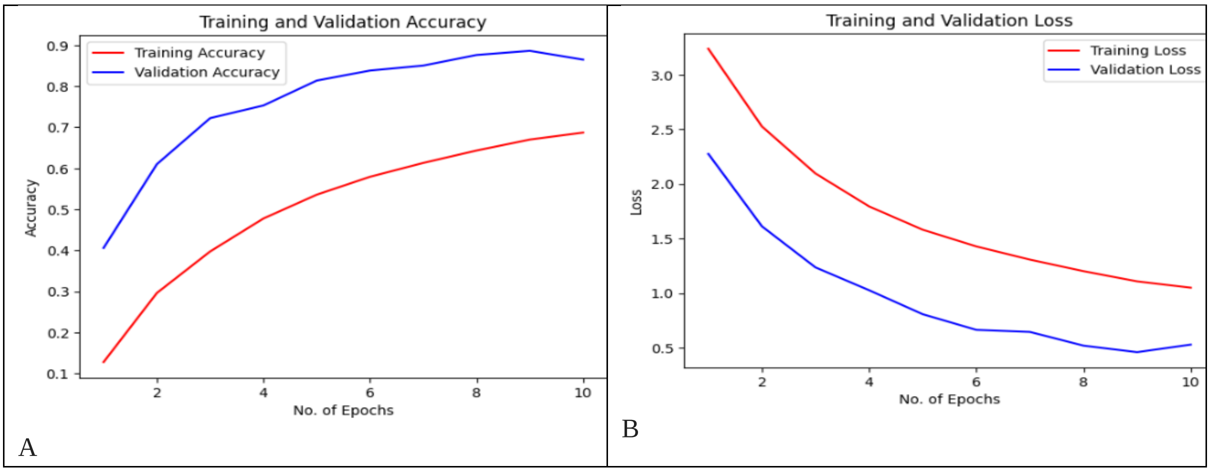

Figure 5: (A) Accuracy v/s No. of epochs. (B) Loss v/s No. of epochs

In table 4 and figure 5, we observe that the accuracy increases steadily over the epochs whereas the loss decreases consistently over the epochs. The model achieves training accuracy of 0.687104. The steady increase in training accuracy over the epochs indicates that the model is learning and improving its classification ability. The model achieved training loss of 1.049247. A decreasing loss indicates that the model is becoming better at making predictions, as the error in its predictions is reducing. The validation accuracy follows a similar trend to the training accuracy, achieving maximum value at 9^{th} epoch with 0.886182547, suggesting that the model is generalizing well to unseen data. Similarly, the lowest validation loss of 0.458299 is recorded at 9^{th} epoch showing that the model is not overfitting and is improving its performance on the validation set. The figure 4 shows the summary of these results.

IV. CONCLUSION AND FUTURE WORK

We presented a qualitative survey referring to peer-reviewed research articles between 2019 and 2021. We have highlighted the importance of IoT and AI in the automation of agriculture/horticulture as a solution to many challenges that our farmers face at various stages. The survey showcases critical challenges that need to be addressed in agriculture domains and processes, from irrigation to crop harvesting. Hence, IoT and AI blended adoption results in better yield using optimal resources. In the latter part of the work we presented a case study of plant leaf disease detection and classification using CNN model. The model is trained and validated using an enormous dataset of 87,867 labelled images having dimension 128 ×128×3. We used training and validation split ratio of 80:20, batch size as 32, 10 epochs and a learning rate of 0.0001 with Adam optimizer. The dropout rate of 50% avoids overfitting and the use of 'softmax' activation function converges the model better for multiclass classification. The model recorded highest training and validation accuracies of 0.69(69%), and 0.86 (86%) respectively and least training and validation losses of 1.05 and 0.53 respectively.

Due to the limitation of available resources like computing power, GPUs and RAM, we restricted the model training to 10 epochs only. The model may perform better when trained using more number of epochs (like 15, 20, 25, and 30 etc.) as the dataset considered in the our case study is relatively large as well as diverse having 38 classes. Therefore, we suggest that the model should be trained for more number of epochs so that the model could learn more complex features pertaining to various plant leaf diseases. In the future work, we would like to conduct a detailed comparative study of state-of-the-art CNN models for plant leaf disease detection and classification using relevant case studies, and also the implication of IoT/AI technologies in various domains of agriculture/horticulture.

Declaration of Interests

We declare that we have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

REFERENCES

1. Alreshidi, E. (2019). Smart Sustainable Agriculture (SSA) Solution Underpinned by Internet of Things (IoT) and Artificial Intelligence (AI). *International Journal of Advanced Computer Science and Applications,, 10*(5), 93-102.
2. Anand, T. (2021, August 15). AgriSegNet: Deep Aerial Semantic Segmentation Framework for IoT-Assisted Precision Agriculture. *IEEE Sensors Journal*, *21*(16), 17581-17590.
3. Arai, K. (2018). Artificial Intelligence based Fertilizer Control for Improvement of Rice Quality and Harvest Amount. *International Journal of Advanced Computer Science and Applications, 9*(10), 61 - 67.
4. Barik, L. (2019). IoT based Temperature and Humidity Controlling using Arduino and Raspberry Pi. *International Journal of Advanced Computer Science and Applications*, *10*(9), 494-502.
5. Biswas, M. (2021). BIoT: Blockchain based Smart Agriculture with Internet of Thing. *2021 Fifth World Conference on Smart Trends in Systems Security and Sustainability (WorldS4)*, (pp. 75 - 80).
6. Fatima, N. (2021). IoT-based Smart Greenhouse with Disease Prediction using Deep Learning. *International Journal of Advanced Computer Science and Applications*, 113 - 121.
7. Hussein, A. R. (2019). Internet of Things (IOT): Research Challenges and Future Applications. *International Journal of Advanced Computer Science and Applications*, *10*(6), 72-82.
8. Kassim, A. (2020). Design and Development of Autonomous Pesticide Sprayer Robot for Fertigation Farm. *International Journal of Advanced Computer Science and Applications, 11*(2), 545 – 551.
9. Madushanki, A. A. (2019). Adoption of the Internet of Things (IoT) in Agriculture and Smart Farming towards Urban Greening: A Review. *International Journal of Advanced Computer Science and Applications, 10*(4), 11-28.
10. Misra, N. N. (2020). IoT, big data and artificial intelligence in agriculture and food industry. *IEEE Internet of Things Journal*.
11. Nawaz, M. A. (2020). Plant Disease Detection using Internet of Thing (IoT). *International Journal of Advanced Computer Science and Applications*, *11*(1), 505 – 509.
12. Pallathadka, H. (2021). IMPACT OF MACHINE learning ON Management, healthcare AND AGRICULTURE. *Materials Today: Proceedings*.
13. Ruslan, A. A. (2021). IoT Soil Monitoring based on LoRa Module for Oil Palm Plantation. *International Journal of Advanced Computer Science and Applications*, *12*(5), 215 – 220.
14. Srivastava, N. a. (2014). Dropout: a simple way to prevent neural networks from overfitting. *The journal of machine learning research*, 1929--1958.
15. Villanueva, M. B. (2018). Bitter Melon Crop Yield Prediction using Machine Learning Algorithm. *International Journal of Advanced Computer Science and Applications*, *9*(3), 1- 6.