Artificial Intelligence in Plant Pathology: A Prototype Application for Plant Diseases Identification Using Convolution Neural Networks

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1. Introduction: AI for Social Good and the UN SDGs Addressed

1.1. Introduction to Plant Pathology

Plant pathology is the scientific study of plant diseases and pathogenic agents across a diverse range of environments such as agricultural crops, forest trees, and natural plants (Jeger et al., 2021). With emphasis on the interactions between the plant, the disease-causing agent, and the environment, plant pathology aims to understand the nature, causes, and control of plant diseases.

Jeger et al. (2021) indicated that in general, plant diseases are caused by environmental and social factors. It is evident that climate warming leads to increase of diseases in temperate areas as the environmental conditions are more favourable for the pathogen infection cycle. Besides, the increase of pollutants changes the composition of the atmosphere instead of merely carbon dioxide is found to impact pathogen. In the social aspect, labour and water shortages contribute to change of crop cultivation methods and poor management of crops. These factors give arise to the emergence of new plant pathogens and the spread of pathogens to new locations, which is a burgeoning challenge across the globe.

Statistics shows more than 10,000 fungal species have been found to be associated with plant diseases (Nazarov et al., 2020). The pathogens cause harm to global crop production that up to 40% of annual crop losses are attributed to plant diseases, in which around US$220 billion are costed (United Nations International Computing Centre, 2020).

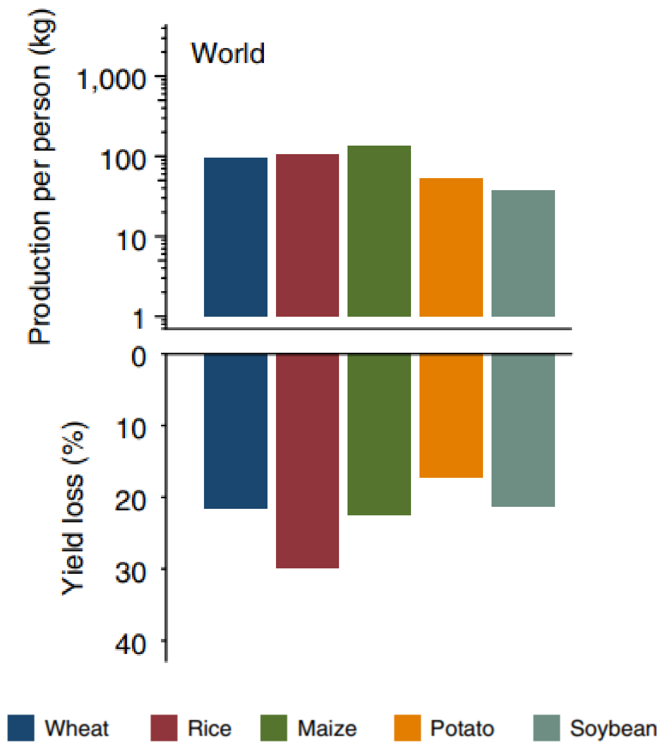

Fig. 1. Global Burden of Pathogens and Pests on Major Food Crops (Savary et al., 2019)

1.2. Plant Pathology and SDGs

Plant pathology is closely related to Sustainable Development Goals (SDGs). It is evident that plant pathology has direct impact on the goal of zero hunger (SDG 2)

(Sharrock & Jackson, 2019). If pests and plant diseases could not be promptly identified, crops may be destroyed, leading to food insecurity and food shortage. Not only will the problem of hunger be more serious, plant diseases also put people's livelihood at risk, which may increase poverty and does harm to the goal of end poverty (SDG 1). As plant pathology may be a direct threat to human and plant health, it is related to the attainment of good health and well-being (SDG 3). In addition to the health issues of plant, plant diseases are also a hazard to other life species on land (SDG 15). Due to the destruction and damage of forests and plants, biodiversity will be hugely reduced, which negatively affects ecosystems.

Moreover, plant pathology is connected to achieving decent work and economic growth (SDG 8). In some countries, farmers may not have sufficient resources to manage plant diseases. In this case, crop reduction, which is caused by plant diseases, is likely to significantly decrease farmers' income and affect trade in international market. The large-scale of crop destruction also cause the failure in efficient use and sustainable management of natural resources, showing the obstacle in pursing responsible consumption and production (SDG 12).

With a view to addressing the pressing global challenge of plant pathology, it is proposed that the utilization of AI technology could effectively identify the infected plants and enable appropriate management of plant diseases. This paper will first explain the AI techniques ideas, followed by demonstrating the proposed prototype. Then, this paper will evaluate the potential pros and cons of the AI application to society.

2. The Idea and the AI Techniques Used

2.1. Detection of Plant Pathology by Leaves

Leaves play a pivotal role in the identification of plant diseases. When plants are infected by microorganisms such as bacteria and fungi, plants respond to the stress by undergoing biochemical changes, including lowering the amount of chlorophyll in leaves and alternating leaf cells structure. This causes radical impairment of the leaves' ability to absorb light. Consequently, the difference in light absorption patterns of leaves would indicate plant disease infection (Kuswidiyanto et al., 2022).

The proposed prototype mainly focuses on rust and scab diseases. Rust diseases destroy many economically essential crops, in which cereal crops such as wheat is a typical example (Figueroa et al., 2017). Orange, yellow, brown, or red spore masses will emerge on leaves infected by rust diseases. On the other hand, scab is a fungal disease that acutely infects fruits, results in inadequate quality and heavy wastage of fruits (Ali et al., 2023). Infected leaves would appear to have sooty, dark spots, or green-gray, water-soaked wounds.

The existing method for plant disease detection is naked eye observation (Singh & Misra, 2017). This traditional identification by visual way requires a large team of specialists and constant monitoring of plants, which is costly and time-consuming. As it is a laborious duty, low accuracy and limited operating scopes are the major concerns. Besides, farmers in developing countries may not have proper facilities and access to the professionals, showing that naked eye observation by experts may not be a suitable approach to deal with the global challenge of plant pathology. Therefore, AI technology may be a possible solution.

2.2. Data Collection

To develop a computer-vision based model for automated plant disease classification, we utilized the publicly available "Plant Pathology Challenge" dataset on Kaggle. The dataset, funded by Cornell Initiative for Digital Agriculture (CIDA), contains high-quality images of apple leaves with expert annotations of healthy, rust, scab, and multiple diseases (Thapa et al., 2020). The dataset comprises 3651 images of apple foliar diseases, captured manually in real-life conditions with varying illumination, angles, surfaces, and noise.

The below are examples of different types of leaves:

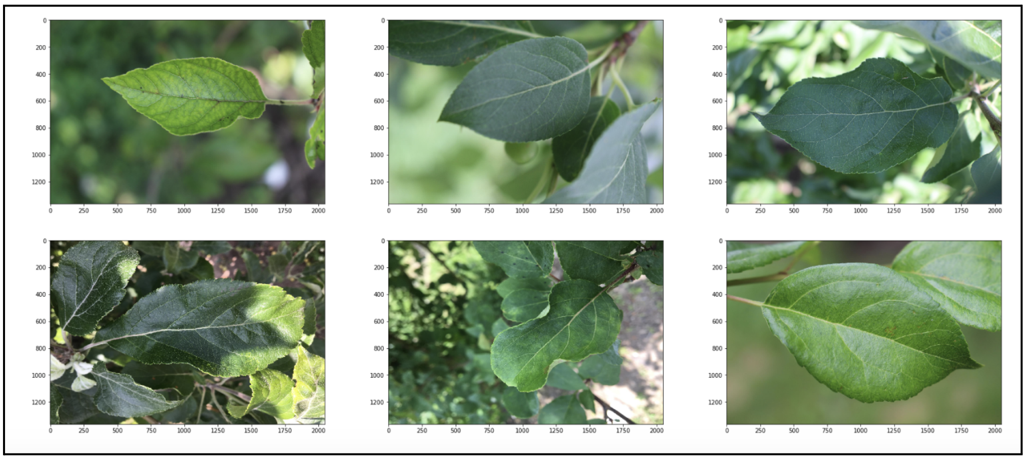

Fig. 2. Example of healthy leaves.

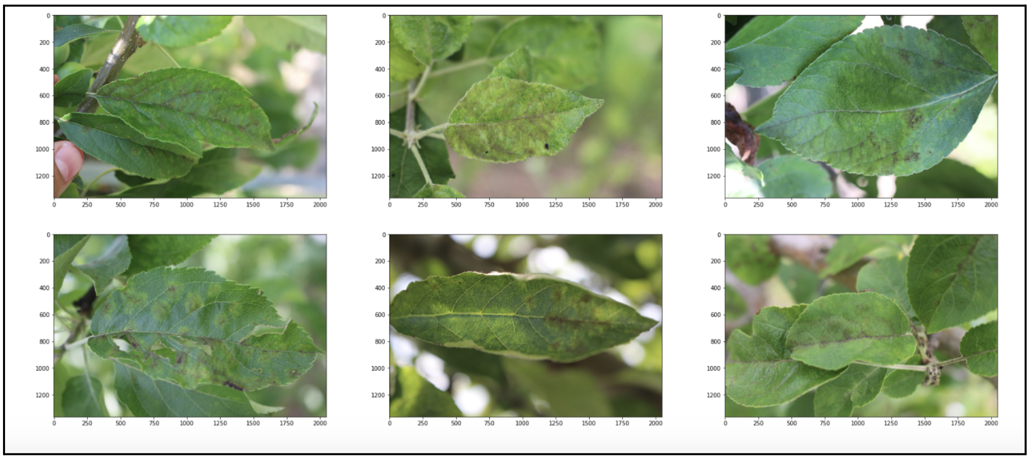

Fig. 3. Example of leaves with scabs.

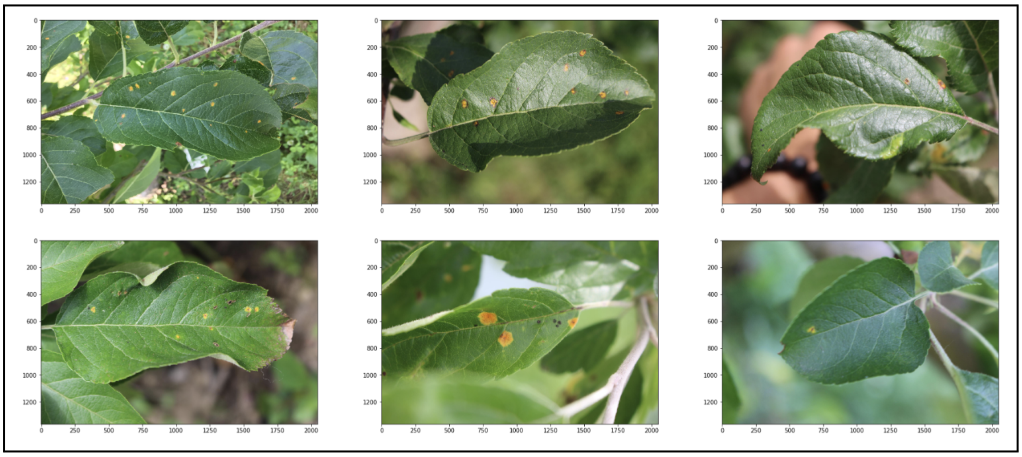

Fig. 4. Example of leaves with rust.

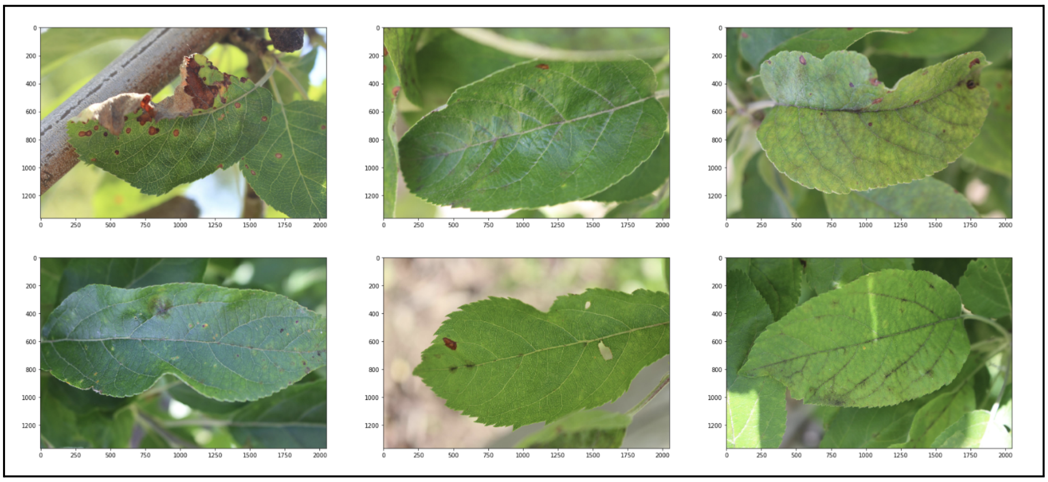

Fig. 5. Example of leaves with multiple diseases.

2.3. Exploratory Data Analysis

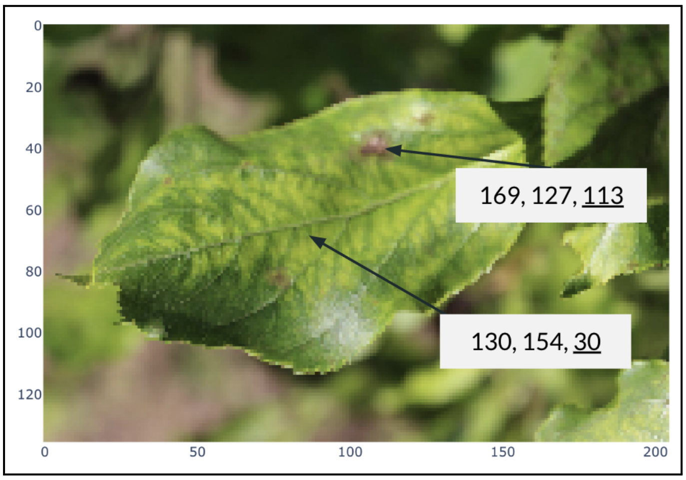

Fig. 6. Difference of color channels on leaf

Figure 6 above shows that healthy green parts of the leaf have low blue color channels, while unhealthy brown parts have high blue color channels. This finding implies that the blue color channel may be useful to identify diseases.

2.4. Data preprocessing

To begin with, we load the dataset using the Pandas library. We then assign labels to each image based on its disease classification, with "0" representing "healthy," "1" representing "multiple diseases," "2" representing "rust," and "3" representing "scab."

```
number=0
train['label']=0
for i in class_names:
    train['label']=train['label'] + train[i] * number
    number=number+1
```

After images are labeled in the csv, we created a function called "create_train_data" to iterate through the images in the directory and copy them to the appropriate subdirectories in the training and testing directories based on their label. These images are copied to the "healthy," "multiple_disease," "rust," and "scab" subdirectories within the "train" directory and to the main "test" directory for testing.

```
def create_train_data():
    images=natsort.natsorted(os.listdir(DIR))
    for img in tqdm(images):
        label=get_label_img(img)
        path=os.path.join(DIR,img)

        if search("Train",img):
            if (img.split("_")[1].split(".")[0]) and label.item()==0:
                shutil.copy(path,r'D:\images\train\healthy')

            elif(img.split("_")[1].split(".")[0]) and label.item()==1:
                shutil.copy(path,r'D:\images\train\multiple_disease')

            elif(img.split("_")[1].split(".")[0]) and label.item()==2:
                shutil.copy(path,r'D:images\train\rust')

            elif(img.split("_")[1].split(".")[0]) and label.item()==3:
                shutil.copy(path,r'D:\images\train\scab')

        elif search("Test",img):
            shutil.copy(path,r'D:\images\test')
```

After categorizing images into testing directories, we begin to set an image size of 224 for our model training. Setting image size to 224 allows us to make the program computationally effective while maintaining a good model performance. Then the “ImageDataGenerator” is used to apply data augmentation techniques including rescaling, shear range, zoom range, horizontal flip, and vertical flip to the images. The rescale parameter scales down the pixel values of the images to a range of 0 to.

```
datagen = ImageDataGenerator(rescale=1./255,
                             shear_range=0.2,
                             zoom_range=0.2,
                             horizontal_flip=True,
                             vertical_flip=True,
```

```
                                validation_split=0.2)
```

The “flow_from_directory” method of the generator is used to load the images from the directories where they are stored. The target_size parameter is used to resize the images to 224. Lastly, the method will split them into training and validation data.

```
train_datagen=datagen.flow_from_directory(path,
                                          target_size=(IMG_SIZE,IMG_SIZE),
                                          batch_size=16,
                                          class_mode='categorical',
                                          subset='training')

val_datagen=datagen.flow_from_directory(path,
                                        target_size=(IMG_SIZE,IMG_SIZE),
                                        batch_size=16,
                                        class_mode='categorical',
                                        subset='validation')
```

2.5. AI Modelling

Next we create a convolutional neural network (CNN) using Keras. From the model we have Conv2D layers that perform convolution on the input image using a kernel of size 3x3 and apply the ReLU activation function. Then we have a max pooling layer followed by each convolution layer to extract the feature and reduce their dimensionality by taking the maximum value within a 2x2 window. After the series of feature extraction, we flatten the output into one-dimensional vectors and proceed them into a fully connected layer that outputs a vector of size 4, corresponding to the 4 classes of apple diseases in the dataset. The softmax activation function is used to convert the output into a probability distribution over the classes.

```
model=Sequential()
model.add(Conv2D(64,(3,3),activation='relu',padding='same',input_shape=(224,224,3)
))
model.add(MaxPooling2D(2,2))
model.add(Conv2D(64,(3,3),activation='relu',padding='same'))
model.add(MaxPooling2D(2,2))
model.add(Conv2D(64,(3,3),activation='relu',padding='same'))
model.add(MaxPooling2D(2,2))
model.add(Conv2D(128,(3,3),activation='relu',padding='same'))
model.add(MaxPooling2D(2,2))
model.add(Flatten())
model.add(Dense(4,activation='softmax'))
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 224, 224, 64)      1792
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 112, 112, 64)      0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 112, 112, 64)      36928
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 56, 56, 64)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 56, 56, 64)        36928
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 28, 28, 64)        0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 28, 28, 128)       73856
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 14, 14, 128)       0
_________________________________________________________________
flatten (Flatten)            (None, 25088)             0
_________________________________________________________________
dense (Dense)                (None, 4)                 100356
=================================================================
Total params: 249,860
Trainable params: 249,860
Non-trainable params: 0
_________________________________________________________________
```

Fig. 7. CNN model summary

We also utilized techniques such as ModelCheckpoint to save the best model weights based on the validation loss, and EarlyStopping to prevent overfitting by stopping training if the validation loss does not improve over time.

```
checkpoint=ModelCheckpoint(r'D:\Python37\Projects\Foliar diseases in apple trees\models\apple2.h5',
                           monitor='val_loss',
                           mode='min',
                           save_best_only=True,
                           verbose=1)
earlystop=EarlyStopping(monitor='val_loss',
                        min_delta=0,
                        patience=10,
                        verbose=1,
                        restore_best_weights=True)

callbacks=[checkpoint,earlystop]
```

Lastly, we have trained our model and from the graph below, we can see that the CNN model performed very well with an accuracy of nearly 95%.

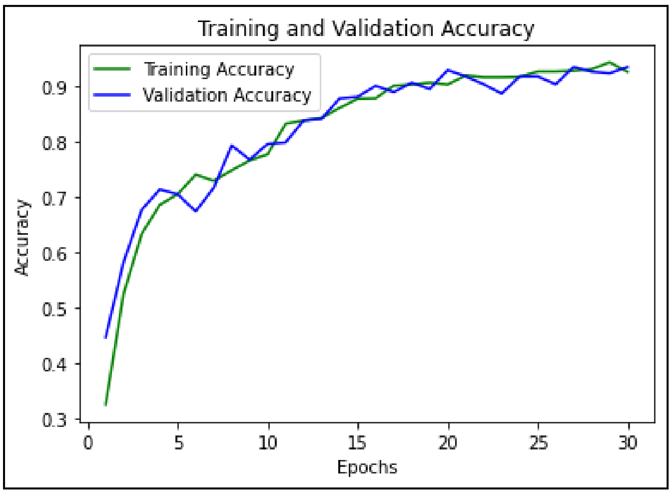

Fig. 7. Line graph of Training and Validation Accuracy

3. System Description: Prototype

3.1 System Description

In this section, the real life operation of the plant disease classification system is explained in detail. The different hardware and software tools implemented are also described. The proposed approach is shown in Figure 10.

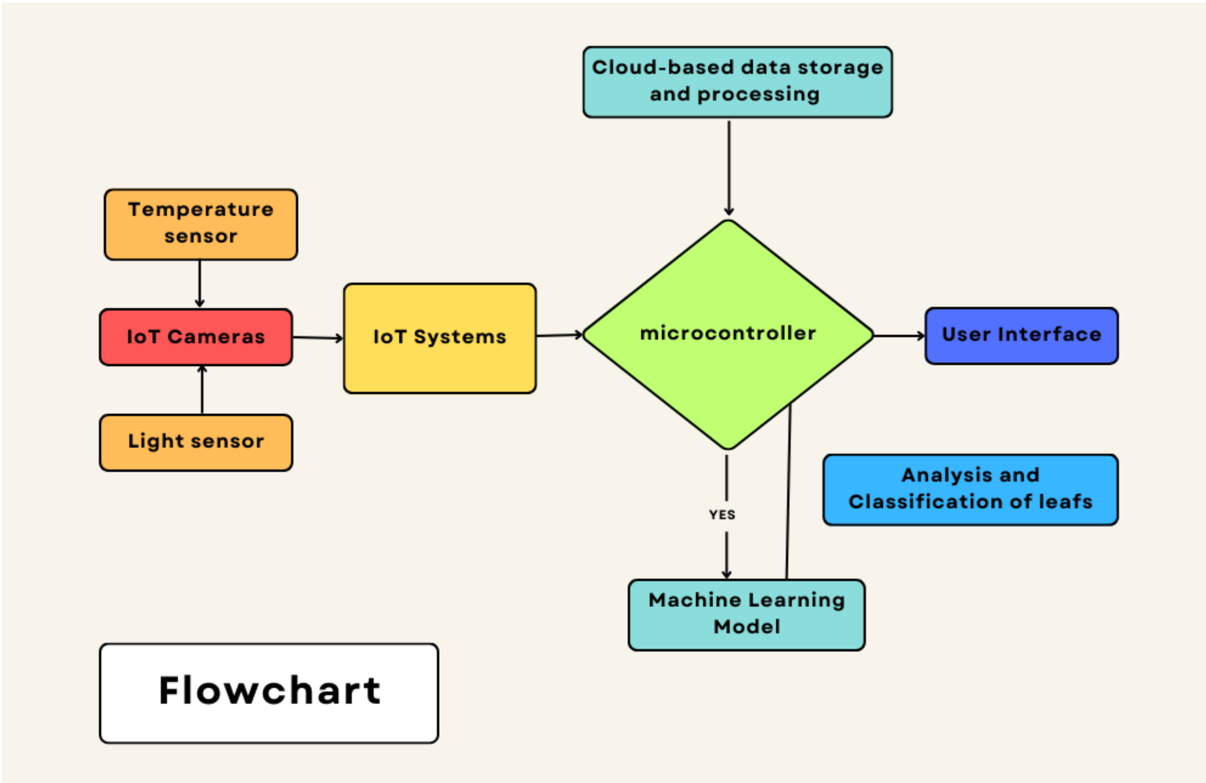

Fig. 8 Proposed Prototype

The main components integrated into this prototype are IoT cameras, which are responsible for capturing images of plants for analysis of their health and growth status. IoT cameras are added in the IoT system, which involves the implementation of other IoT sensors such as temperature, humidity, and light sensors to provide a more comprehensive data for leaf condition analysis. The data is transferred to the microcontroller that controls and manages the sensors and camera to capture data and images of the plant leaves. The next element integrates the machine learning models to analyze the sensor and image data and detect leaf diseases. WiFi communication system is applied to securely store and manage the large amounts of generated image and numeric data, as well as visualizing image data through web interface, which displays the results and allows users to interact with the system . Further details regarding the hardware components and software components are listed out in the subsequent sections. The proposed prototype is mainly designed for local application to perform early detection of common plant diseases of Hong Kong crops, such as powdery mildew, downy mildew, and rust. The classification models are designed to identify particular diseases presented in crops based on the training database set.

3.2 Hardware Description

In this section, the hardware applicable for the plant disease recognition system will be introduced in detail, including iot camera, iot sensors, microcontroller. The description is composed of the hardware's function, selection criterion, and some possible choices.

Firstly, IoT cameras are the major component added in the proposed system. It is responsible for capturing images of plants for leaf diseases and growth status analysis, which enables early detection of plant diseases. It is significant in improving the overall farm efficiency by reducing the need for manual inspections and data collection. To maintain the efficiency of analysis, IoT cameras should be selected based on several criterion, including image quality, field of view, weather resistance, night vision, connectivity. These selection standards not only enable the higher quality of image data but also enhance the feasibility and sustainability of the system in local application. Besides, considerable weather factors in Hong Kong, including high annual rainfall amount and intensity of sunlight could be taken into account in the selection of IoT cameras. For instance, Arlo Pro 3 and Wyze Cam Outdoor are suitable choices with the property of being weather resistant.

Fig. 9 IoT Cameras (Arlo Pro 3)

Besides, IoT sensors are taking the supplementary roles in the proposed system. IoT sensors, involving temperature, moisture, and light sensors are significant to accurately measure environmental factors and effectively capture and transmit data to the cloud-based data storage processing platform for plant health monitoring and analysis. To ensure its performance, IoT sensors should be selected based on several criterion, including accuracy and precision, durability, connectivity, and power source. These selection standards safeguard the IoT sensors to optimize its performance in different occasions of use, such as indoor farms and outdoor farms.

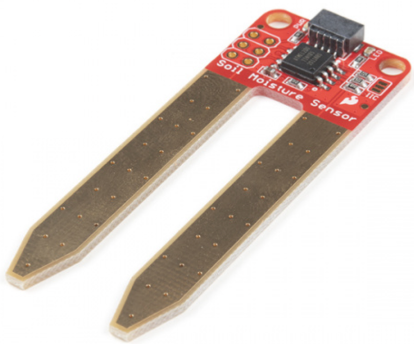

Fig. 10 DHT22 Temperature and Humidity Sensor

Fig. 11 Soil Moisture Sensor

The final hardware in the proposed system is the microcontroller, which is crucial to control and manage the IoT sensors and IoT camera to capture images and numerical data of the plant leaves. After collecting and processing the data, it sends the relevant data to the cloud-based data storage and processing platform wirelessly through the WiFi communication system. The selection of microcontroller can be based on its processing power, compatibility, and ease of use. Users could make decisions based on the scale of the system and affordability. For instance, ESP32, Arduino Uno and Raspberry Pi 4 are appropriate options for the proposed system.

Fig. 12 microcontroller ESP32

3.3 Software Description

In this section, the software applicable for the plant disease recognition system will be introduced in detail, including machine learning model, cloud-based data storage and processing, and web application development. The description is composed of the software's function, selection criterion, and some possible choices.

Firstly, machine learning models are the dominant software in the proposed system, which is used to conduct image classification. The model classifies images of leaves as healthy or diseased. More than that, data preprocessing is involved in this procedure. Accuracy, efficiency, size and complexity are essential measures of a model in the proposed system. In our demonstration, a CNN model is applied owing to its high efficiency in image classification tasks.

Next, reliable cloud-based data storage and processing is important to the proposed system, which can securely store and manage the large amounts of generated plant imaged and numeric data such as temperature and mositure. It is also favorable to easy access and sharing of data with various parties, including farmers, researchers and the authority. A desirable cloud-based data storage should be secure, scalable, and reliable. Google Cloud Platform (GCP) and Amazon Web Services (AWS) are possible choices for this software.

At last, web application development is significant to create an interactive and dynamic user interface for the frontend user, which enhances user experience. Meanwhile, it involves the backend infrastructure construction that handles data processing and storage. The application should be compatible with the chosen programming language and database management system, where availability of libraries and website templates are essential elements to speed up the development. In our demonstration, Gardio is applied to web application development. Apart from that, Node.js and Ruby on Rails are other possible choices.

3.4 Web Interface Using Gardio

To make our plant disease classification model more user-friendly and accessible, we created a web interface using Gardio, an open-source Python library for building machine learning demos. This interface allows users to input an image of a plant leaf and receive a prediction of its disease classification from our model. The prediction is displayed as a label, which includes the top four possible classes: Healthy, Multiple Disease, Rust, and Scab.

Fig. 13. Web Interface Demonstration Using Gardio

3.5 Local Application

Having a humid subtropical climate, there are numerous common diseases of Hong Kong crops, including powdery mildew, downy mildew, soft rut, and etc (Hong Kong Seed Technology and Education Center, n.d.). Therefore, the proposed system is applicable to local farms to perform early detection of plant diseases, increasing farming efficiency. To facilitate the users, important information, including time, type of diseases, farming zones are recommended to display in the user interface.

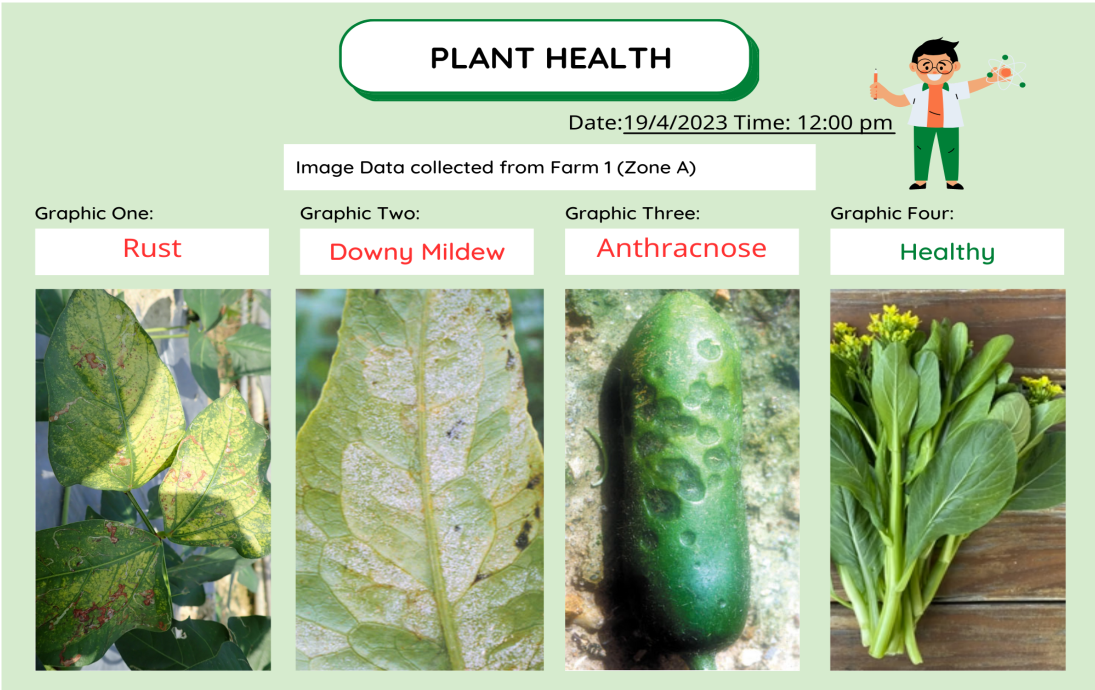

Fig. 14 Demonstration of User Interface

Moreover, the proposed system is compatible with modern agricultural technology. In recent years, the agriculture, fisheries, conservation department strongly encourages controlled environment hydroponic technology, which applies advanced hydroponic technology and facilities to the industry and investors (*Modern Agricultural Technology*, n.d.). It brings new opportunities for agricultural development and the proposed system could be a supplementary measure to the latest technology. Also, Controlled Environmental Hydroponic Research and Development Centre (CEHRDC) can offer assistance to start-up farmers in acquiring professional knowledge.

4. Evaluation

4.1 Potential Benefits and Possible Harms to Society

With the idea of fusing Internet of Things (IoT) application and machine learning algorithms into agriculture, Lele Goswami (2017) claimed that smart farming could bring changes in social structures, economy, food and supply chain business and even public policy or to be precise, any aspect related to agriculture.

Benefits

Table 1. Rate of return over cost of cultivation in Tapioca and Tomato

Particulars	1. Tapioca (ha)		2. Tomato (ha)	
	Conventional Farming (Rs)	Precision Farming (Rs)	Conventional Farming(Rs)	Precision Farming (Rs)
Seed/Setts cost	910	923	1,933	2,157
Seed treatment cost	924	671	500	500
Nursery & Planting cost	4,376	5,432	5,022	10,700
Machinery labour cost	7,417	9,400	5,944	6,193
Irrigation cost	3,552	19,606	4,367	20,000
Fertigation/fertilizer cost	3,086	7,287	8,278	19,314
Plant protection cost	2,948	3,348	12,533	7,243
Weeding cost	9,131	4,677	10,767	5,800
Stalking cost	0	0	0	9,679
Harvesting cost	2,862	4,623	9,300	18,550
Package & Transport cost	3,934	5,461	3,900	1,650
Rent cost	5,000	4,955	5,000	5,000
Interest on working capital	2,100	5,715	4,111	5,014
Total production cost	46,207	68,647	72,333	1,11,443
Gross Income	88,138	1,59,435	1,34,000	3,52,321
Net Income	41,931	1,20,789	61,667	2,40,879
BC Ratio	0.91	1.7	0.85	2.16

Fig. 15. Rate of return over cost of cultivation in Tapioca and Tomato (Krishnan et al., 2019, p8770)

According to Krishnan et al. (2021), the research aims to compare precision farming and conventional farming in India agriculture. The technology applied in Indian agriculture is space technology which includes a global positioning system (GPS) and GIS to monitor the condition of crops and derive soil fertility status. More factors of plant condition could be monitored, such as moisture of soil, disease of crop, crop phenology etc. Precision farming focuses on precise measurements which could be very similar to our application and enable us to make good use of the data to do analysis.

The table 1 retrieved from the research paper page 8770 (Krishnan et al., 2021), we could conclude that there is higher production of yield using precision farming. Even though the total production cost of precision farming is about 1.5 times of conventional farming, the gross income could bring a double more. The gross income could vary by the species of crop, weather, and demand of food. To be more general in simple benefits and cost, the BC ratio indicates that precision farming outweighs conventional farming by at least double. From the above, we could conclude using technology on agriculture could bring a higher yield of food production and decrease production cost.

On top of the above, precision farming also focuses on the environmental impact of farming. Krishnan et al. (2021) claimed that it could minimize the effects of pest and disease by reducing the fertilizers input so as to reduce the amount of chemicals. Similar research has been done by Navarro et al (2020), smart farming could help monitor the condition of plants through variable rate sprayers for pest control. The smart farming technology is very mature and successful using GPS-guided tractors and sensors which allows adjustments of different technology, such as fertilizer applicators or spray control for herbicide and pesticide application (Evett et al., 2020). The conditions of the plant are under control and input chemicals can be reduced, thus the health condition of plants can be improved, as well as the food quality and ensure food safety.

Lombardi et al. (2020) and Klerkx et al. (2019) indicated smart farming could bring positive impact to society by providing a new sense of 'responsible professionalism'. Smart farming as a new revolution towards conventional farming could be a new professionalism and university could promote the study of smart agriculture. It is a new profession that requires knowledge in data analytics, IoT application and even machine learning in the domain of agriculture and thus creating more job opportunities.

It further emphasizes that smart farming could revamp rural development. Since traditional farming is located in rural areas. Rural marginalization
argue that social innovation initiatives brought about by smart farming could provide opportunities to strengthen relationships among rural populations, improve social networking and engender a new sense of 'responsible professionalism', which may prevent rural marginalization. Rural marginalization is defined as a lack of socio-economic and natural resources. It is associated with geographical remoteness and insufficient infrastructure (Bock, 2016), if smart farming technologies are applied in rural development, it could bring opportunities for the people living there. The farmers have less time to monitor plants and it could be done by electronic gadgets, so it helps strengthen relationships among the rural population and enhance social networking (Lombardi et al., 2020).

Harms

On the other hand, there could be negative social impacts for the application. Bronson (2018) said there would be unemployment of farmers because technology could cover their duties by automation. The farming practices will be shifted from "hands-on" experience to data driven, there would be a revolution in agriculture. Government can assist and provide technical courses for farmers to transit and overcome the change in agriculture. However, it emphasizes the identity crisis towards farmers. Farmers need a revamp in their decision making and accept smart farming. The practice of farmers is no longer by labor, it is the input in data driven decision-making.
Jakkua et al. (2020) conducted a total of 26 interviews on digital agriculture and big data. With the rise of technology on agriculture, one of the key concerns would be privacy issues. One of the conversation has been directly retrieved as the following:

> *"I think the risk lies in farmers being confident that they don't need to lock up their data and make it absolutely unavailable to anyone except a very narrow limited range of providers" (Grower group 2)."*
>
> *"…the industry has done, frankly, a terrible job of explaining why they want access to farm data. Not so much an issue probably here in Australia yet, it's probably just starting to happen now, but in the US it's been going on for quite a few years, and it's even more so. ….So it's this weird thing where they don't want to tell us exactly what they're doing with it but if they don't tell us what they do with it, why would we trust them? …Probably mostly they are*

doing the right thing but that's not explained anywhere and we're certainly just trusting that's what they say they're doing, there's no way of verifying it…and that's what's holding more farmers back from adopting it, but we miss out on the benefits of it then as well. (Grower 1)"

Even the governance and different sectors have emphasized on the privacy issues with the regulation and ownership, there are trust issues on data sharing. There is guarantee in regulation and ownership, but the usage of data would hardly be identified in agribusinesses. The farmers should have trusted the third party but they do not know how the data was doing. It implies the data transparency and trust issue problems as reflected in a broad and general idea of privacy issues.

Bronson (2018) had made further research in the US market. He found that smart farming investment had been biased towards large-commodity crop farmers. Moreover, Rotz et al. (2019) has claimed that several deleterious effects could be made towards small and medium scaled farms because of limited investment, such as land consolidation and cost-price squeeze which makes small and medium sized farms marginalized and quit. The researchers criticized the marketing and distribution of resources could be a harm towards small sized farms due to imbalance in investment.

To summarize, possible potential benefits are 1.) More food supply 2.) Improve food quality as well as safety 3.) Engender a new sense of 'responsible professionalism' 4.) Rural development. Possible harms are 1) Identity crisis 2) Data privacy and security issues 3) Bring possible deleterious effects (land consolidation and cost-price squeeze)

4.2 Innovativeness and Creativity

To measure the innovativeness and creativity, it requires a holistic approach which takes into account a wide range of factors, such as patent analysis, industry recognition.

According to the US Patent, most of the patents of smart farming are about the technical system, such as "Smart Farming System", "Smart Irrigation System", "Smart Crop Monitoring System". The patent has been widely applied through IoT agribusiness. We could also see some of the research using CNN as machine learning algorithms in smart farming to detect early disease in rice. (Debnath & Saha, 2022)

One sees a lot of examples from developed countries, such as the US, Japan , Australia to smart farming. However, Chun et al.(2021) analyzed smart farming into 10 detailed technologies. Research showed that topic 7 - technology in greenhouse cultivation is relatively low. As reflected in Hong Kong Agriculture, Fisheries and Conservation Department(2023), Hong Kong focuses on the controlled environmental hydroponic technology which is technology in the greenhouse, there is a lack of monitoring plant health conditions.

Even though there is a monitor on soil humidity, automation of light intensity, temperature and irrigation, there is no monitoring plant surface and plant status. It is innovative and creative to apply our model on top of hydroponic technology which could additionally monitor the health condition more holistically.

4.3 Implementation Feasibility

To measure the feasibility of IoT application in Hong Kong, several crucial key indicators could be used, such as cost-benefit analysis, technical feasibility, and resource availability.

Firstly, based on Hong Kong situation, we could on top add IoT cameras and cloud-based data storage and processing and our machine learning model. The cost of additional hardware and software may be expensive at first, however, the benefits could be outweighed in a long perspective as reflected in Indian agriculture.

Furthermore, both hardware and software could be feasible. There are a wide range of choices for IoT cameras: Arlo Pro 3, Wyze Cam Outdoor, Reolink Argus . For cloud-based data storage and processing, some platforms such as Google Cloud Platform (GCP), Amazon Web Services (AWS)3 have provided the service in the market. Technical feasibility could be addressed by the integration of both hardware and software through different developers.

Lastly, with reference to the Agriculture, Fisheries and Conservation Department HKSAR (2023), there is a Pilot Scheme under the Sustainable Agricultural Development Fund to promote the application of agriculture with the aid of techniques and technologies. Financial funding will be granted to successful applicants to subsidize their farming equipments. This shows that local farmers are encouraged to use modern technology to enhance productivity.

To conclude, it is feasible to include IoT cameras and cloud-based data storage and processing and our machine learning model on the controlled environmental hydroponic technology.

5. Conclusion

In conclusion, plant diseases pose a grave threat to the damage of international crop yields, which are huge obstacles of achieving SDGs. With the utilization of AI technology using machine learning algorithms, IoT application in local farms can detect rust and scab diseases effectively and efficiently. Through smart farming, stable and secure food supply can be ensured. Nevertheless, there are some shortcomings on the proposed prototype regarding some ethical issues in society and thus, trade-off between attainment of SDGs and societal drawbacks should be balanced. Despite the potential negative impacts, it is believed that the proposed IoT application could be a feasible innovation in Hong Kong.

This paper may be limited to only two types of plant diseases and plants with green leaves. To further expand the identification ability of the prototype to wider variety of plants, future research may focus on modifying the existing model to enable extensive application in different farms.

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