Designing and Developing Smart Plant Information System

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Abstract—The COVID-19 pandemic has undoubtedly impacted the way of life of all people in the world. The effect continues to worsen especially when our government-imposed lockdowns where everyone was required to stay home. Due to a long period of staying at home, boredom becomes one of the most reported negative psychological effects of quarantine. It is undeniable that people of all ages enjoy gardening and planting. Hence, this time during the pandemic can be a golden opportunity for people to get outside of their compound and grow their interest in gardening. Thus, this smart plant information system is designed to introduce the basic knowledge of plantations more easily and effectively. The system is applicable for multiple users who tend to learn more about plants and their plantation methods. Both men and women can start their garden with proper planting methods. This system has been developed using several modules such as leaf recognition using convolutional neural network (CNN), plant disease advice using knowledge-based expert system, and plant information using a chatbot. The leaf recognition using the CNN module will help the user recognize a plant by providing the plant's leaf image. The plant disease advice will diagnose certain diseases a plant might have by calculating the confidence level of provided symptoms of the disease. Finally, plant information using the chatbot module will provide information about plants by answering the user's questions. It is hoped that this system could serve as the best smart plant information system for the users.

Keywords—*leaf recognition; convolutional neural network; plant disease advice; chatbot; smart plant information system*

I. INTRODUCTION

THE COVID-19 pandemic has prompted governments all around the world to impose COVID-19 lockdowns to restrict and reduce the virus's spread. Many areas of people's lives, including psychological and physical wellbeing, as well as levels of physical activity, have been negatively impacted by key policy measures such as social distancing and self-isolation [1]. People may experience depression, melancholy, stress, and anxiety during this time. The volume of available information, which may not always provide clear facts on dangers, pandemic duration, and economic impact, among other aspects, is a major source of stress [2]. COVID-19 recovery strategies are increasingly recognizing the importance of access to nature and urban green space [1]. Visiting green spaces and being exposed to natural habitats have been found in a rising number of studies to alleviate psychological stress [3]. Due to this, there has been an increasing interest in gardening around the house. However, to start planting is not an easy thing to do as it requires knowledge and information so that the effort and time spent towards planting care are not wasted especially to the elderly. Furthermore, as people age increase, their cognitive capacities, such as memory, concentration, and learning, deteriorate [4]. Not only the elderly but there is

also research done by [5] which investigates the use of instructional gardens in childcare facilities as a means of increasing young children's fruit and vegetable consumption. Hence by having a smart plant information system that is handy and can be used everywhere will be beneficial to all types of users.

The delivery of required knowledge and information based on mobile devices has attracted a lot of attention. Smartphone-based artificial intelligence (AI) apps could help people to get information directly and helps people to identify types of the leaf as well as recognizing types of disease through the image taken by using smartphones [6]. Apart from using mobile devices, many researchers have applied the internet of things (IoT) towards smart farming concepts such as in [7], [8], and [9].

One of the common information required is leaf recognition. Many researchers have done leaf recognition using the various technique. Researchers in [10] have used shape measures such as perimeter, area, the ratio of minor and major axis length, vein structure indicating the angle of sub veins with major vein and textures. They also have stored all image databases and related information in the cloud. By using the cloud, once the image of a leaf is captured by using a smartphone, the image will be uploaded on the cloud and the complete database is trained. Plant classification results will be transmitted back to the smartphone. Another work done by [11] has proposed two methods for recognition. The first method is by using a histogram of oriented gradients and classified by support vector machine. The second method is by using deep CNN. Both methods seem good since achieving high accuracy. Work in [12] is aimed to develop a system using deep learning. Discriminative features learned from leaf images using a CNN is shown can provide better recognition. In comparison to handcrafted features, it is shown that learning features with CNN can provide superior feature representation for leaf images.

Another information that can be considered is the type of leaf disease. The suggested method by [13] for leaf disease recognition is a hierarchical feature extraction CNN algorithm

that maps input image pixel intensities and compares them to the image from the trained dataset. By minimizing the error across the training set, all adjustable parameters of the leaf parts are optimized. Work done by [14] is a project that utilizes nonimage internet of things (IoT) devices to detect rice blasts in rice crops. The agriculture sensors generate nonimage data that can be trained and analyzed automatically in real-time. By delivering real-time training and forecasts, the RiceTalk project initiative by [14] has lowered platform management costs. Researchers in [15] use state-of-the-art Bayesian deep learning algorithms and the uncertainty as a misclassification measurement, a probabilistic programming methodology for plant disease diagnosis was developed. The results reveal that Bayesian inference for fine-tuning deep learning models provides classification performance comparable to typical optimization approaches. Simultaneously, the proposed method approximates the posterior density for the plant disease detection problem and quantifies the uncertainty of out-of-sample predictions.

Conversational virtual assistants, often known as chatbots, automate interactions with end-users. We can now understand natural language and communicate with users in a more personalized way thanks to artificial intelligence-powered chatbots and machine learning algorithms [16]. According to a study conducted by [14], the chatbot application is one of the best ways to tackle agricultural difficulties. This farmer chatbot application employs the Artificial Intelligence Markup Language (AIML) approach to provide advice on how to handle rice plants. Researchers in [17] have proposed a recognition model and implemented the model for use as the bot in Telegram messenger. The Telegram messenger is accessible for all major platforms, allowing us to use it both in the field with mobile devices and in the laboratory with a stationary computer. The user can give the bot a snapshot of a plant to get an estimate of its condition (disease damage and/or developmental stage). This service allows users to identify plant diseases in the field using mobile devices.

In this paper, a smart plant information system has been proposed for the use of people

especially the elderly, and children.

People who are staying at home can use this system to get to know more information about the plants. This system can also be used to educate children on the general knowledge about the plantations and is suitable for teachers who want to introduce the basic knowledge of agriculture to their students in a faster and easier way. Other than that, it can also be used by parents who want to spend time with their children while having fun teaching the kids some new knowledge.

The remainder of this paper is organized into the following sections. Section 2 describes the methodology of the proposed work which is followed by Section 3 which discusses the experimental results. Lastly, Section 4 presents the overall findings of this work and conclusions.

II. METHODOLOGY

The development of the system will start with the architecture. Fig. 1 shows the overview of the system architecture. The architecture consists of the frontend, web server, and backend of the system. The frontend is developed using Hypertext Preprocessor (PHP) and Python while the backend is developed

using AI techniques such as Natural Language Processing (NLP), expert system, and image classification. The web server acts as a medium that links the frontend and backend. When the user sends input using the frontend, requests will be sent to the backend from the webserver and the response will be given back to the frontend thus, the results will be displayed to the user. Several open sources applications such as Jupyter and TensorBoard have been used in the development of the proposed system. Jupyter is used for the coding combination process and the machine learning process is created on TensorBoard. The developed system consists of three main modules that are leaf recognition using CNN, plant disease advice using a knowledge-based expert system, and plant information module using a chatbot. Fig. 2 shows the structure chart of the proposed developed system.

The structure chart defines the modules present in the system together with the workflow of each module. In Leaf Recognition using the CNN module, the user can do image classification, get to know information about the classified plant, view the Plant Disease Advice module and Plant Information module. In the Plant Disease Advice module, the user can
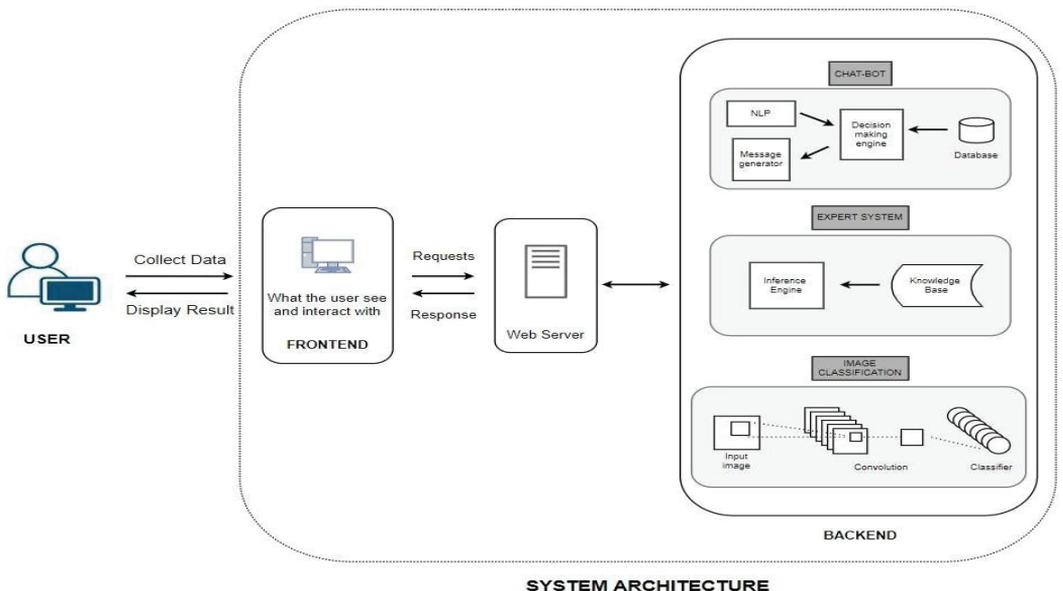

Fig. 1. Intelligent system architecture of the developed

view the gallery of some diseased plants, use the expert system to determine plant diseases, and see the display of advice on how to control pant disease. In the Plant Information module, users can see the display of general information about plants and use the chat-bot available to ask questions about plants.

The modules in the proposed system will be explained one by one.

A. Leaf Recognition

The leaf recognition is done by using CNN. The implementation of CNN to determine the type of plant using its leaf is by training our data set of plant leaf images. CNN is an algorithm that can take in an input image, assign importance (learnable weights and biases) to various aspects or objects in the image, and be able to differentiate one from the other. This algorithm helps to identify the image input based on the training and testing data. Fig. 3 shows the flowchart of the leaf recognition module.

B. Plant Advice

The next module will be plant disease advice module. In this module, the implementation of knowledge-based expert system to determine the plant diseases of a plant with a probability rate. The threshold value that has been set is 60%. If probability of a particular disease is more than 60%, then the plant is set has that disease. Otherwise, it is not having the disease. The determination is executed by some facts given by the users and chooses any possible rule that matches with facts.
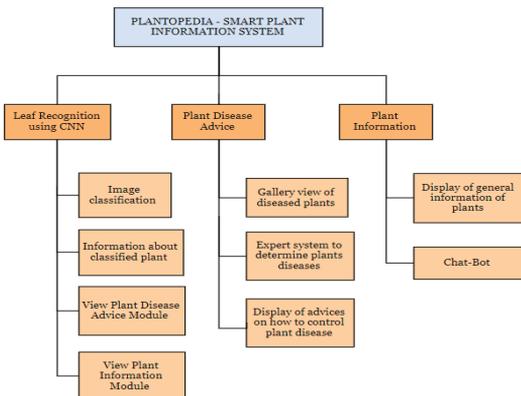
Fig. 2. Structure chart of the proposed developed system

The inference engine requires rules to address a particular question. This applies the facts from the knowledge-based that have been set. When attempting to reply to the user's questions, it chooses facts and rules to apply. Fig. 4 shows the flowchart of plant disease advice.

C. Plant Information

The proposed system also implemented the usage of NLP in our chatbot where the user can interact with the system and ask any kind of questions about the plant. For the chatbot to understand the message of the user, somewhere it must translate the unstructured human language to organized data that can be understood by computers. When a user sends a message to the chatbot, to extract data from each sentence, it must use algorithms to acquire meaning and context. This mechanism is called the Natural Language Understanding (NLU), and it is a branch of NLP. Dialogflow which is a Google-owned framework that supports NLP has been used to develop the chatbot. Fig. 5 shows the flowchart of the plant information module.
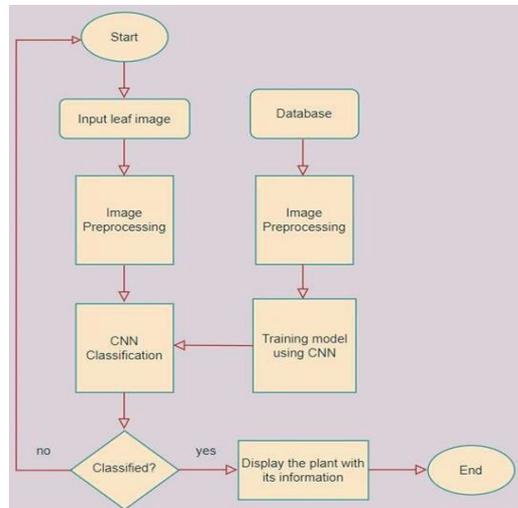
Fig. 3. Flowchart – Module "Leaf recognition using CNN"

From the explanation above, the development of this system can help the user to recognize the type of leaf, get the plant advice by checking the type of disease through

a knowledge-based expert system and get the information about plants using the chatbot.

In this proposed system, a database on leaf recognition also has been introduced. Lemon, mango, and noni leaves make up this dataset. All the leaves were gathered from the surrounding of the house. The leaves were laid out on a white sheet for a clean background, and the camera was positioned at a 90-degree angle with the flash turned on. The total number of leaves is 3030, with 1010 for each type of leaf. The example of the leaves is shown in Fig. 6. We have named this dataset Data 1.
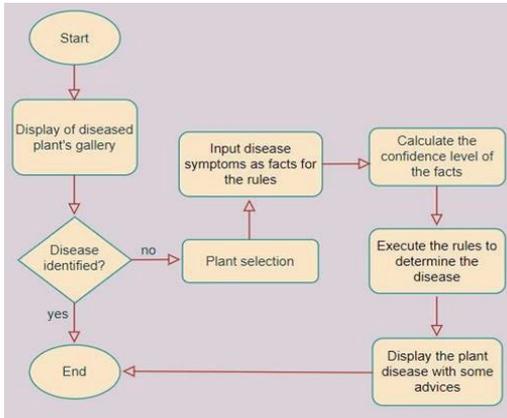

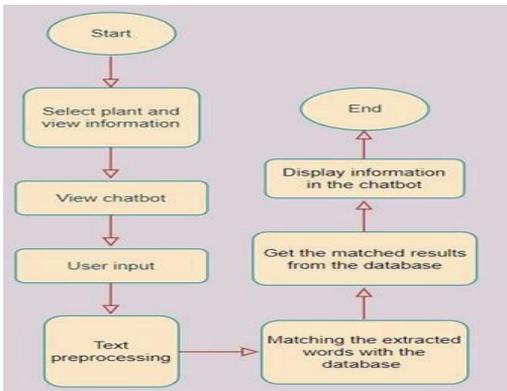Fig. 4. Flowchart - Module "Plant Disease Advice"

Fig. 5. Flowchart – Module "Plant Information"

Lemon Mango Noni
Fig. 6. Example of leaves in collected database.

Another dataset for plant recognition also has been retrieved from the Kaggle dataset [15]. This dataset consists of potato, bell pepper, and tomato leaves dataset. Fig. 7 shows an example of potato, bell pepper, and tomato leaves. We have named this dataset Data 2. There are about 1000 images of potato leaves and 46 images have been chosen for testing. For bell pepper, there are 1500 images, and 493 images are used for testing. There are 1700 images for tomato leaves and 523 images are for testing. The leaves used are all from a healthy type.

Potato Bell pepper Tomato
Fig. 7. Example of leaves taken from Kaggle [18]

The results of the recognition process will be explained in the next section.

III. EXPERIMENT AND RESULT

In this section, some interfaces of the proposed developed system will be shown and discussed. Fig. 8 shows the main page of the Leaf Recognition Module. The user can input their leaf's image in the space provided. After upload, the user should click the browse button to see the result.

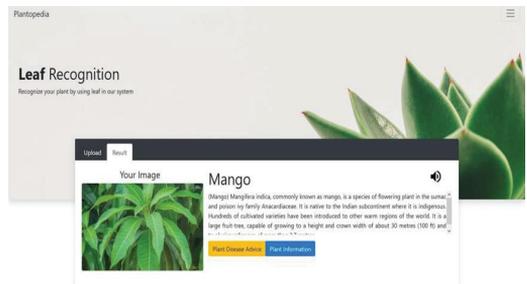Fig.8. The main page of the Leaf Recognition Module

Fig. 9. Leaf Recognition result page

Fig. 9 shows the result page that will be displayed after the user uploads the leaf's image. The result includes the plant's name and some information about the plant. There will be also two buttons displayed named 'Plant Disease Advice' and 'Plant Information' which will redirect to their respective pages after clicked. In module plant disease advice, there will be a gallery of diseased images of plants. The plants are Lemon, Mango and Noni will be displayed for the user's view. The user can click the buttons on the top with the respective plant's name to view the images. Each plant has four diseases listed. The user can see the images to identify the disease a plant might have. If the user is unsure about the disease, they can click the button 'Start Diagnosis you plant now' to go further into the plant disease diagnosis. Fig. 10 shows the plant advice for Lemon.

A question will be asked to the user indicating a symptom the user's plant might have. The user can click 'Yes' if their plant has that symptom or click 'No' if their plant does not experience the symptom. After the user answers the question, they should click the button 'Next'. Another question will be asked, and the user must do the same until the end of the question.
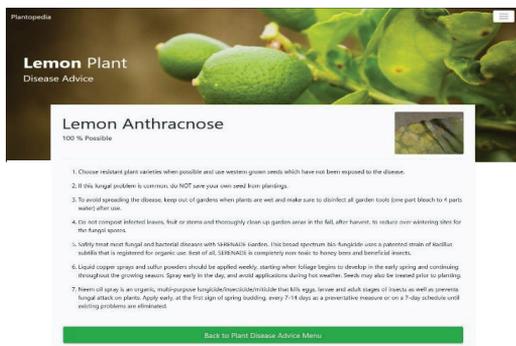

Fig. 10. Plant Disease Advice for Lemon

The possible disease of the plant might have according to the user's input will be displayed with a probability rate. There will also some advice on how to control the disease will be displayed. There will be a button that enables the user to go back to the advice menu if they wish to diagnose any other plant disease.

The same implementation has been made for the rest of the plants in this module which are mango and noni.

The next module is the plant information page. In this module, users can interact with the system using the chatbot. The users can also view general information of the respective plants after the users click the buttons with the plant's name. Fig. 11 shows an example of a chatbot that has been named as PlantBot in the proposed developed system. The user can ask the details about the plantations and the chatbot will reply to them according to the questions asked.

Fig. 11. Chatbot about the plant information

The users can view the general information of the respective plants after the users click the buttons with the plant's name. This chatbot is build using DialogFlow, a cloud engine from Google. DialogFlow uses rule-based grammar matching and machine learning matching for its intent matching.

Performance measures have been employed to assess the leaf recognition, that is [19], [20]:

$$Accuracy = (TP+TN)/(TP+FP+TN+FN) \quad (1)$$

where TP – true positive, TN – true negative, FP – false positive, and FN – a false negative.

Another measure used is the area under curve-receiver operating characteristics (AUC-ROC)[19], [20]. AUC-ROC score is a method used to measure the performance of multiclass classification problems. When using this method, a good measuring of separability (of class) will generate an excellent model that will

have the AUC near to 1 while a poor model will have the AUC near to 0. Apart from that, there is also a confusion matrix [19] that shows the results of true positive, true negative, false positive, and false negative.

Table 1 shows the results of recognition of the type of plant for both datasets that are Data 1 and Data 2.

Table 1. Results of the recognition process

Performance Measure	Data 1	Data 2
Accuracy	0.9980	0.9849
AUC-ROC Score	0.9990	0.9974
Confusion matrix	[[334 0 0] [2 327 0] [0 0 337]]	[[485 8 1] [6 40 0] [0 1 522]]

From Table 1, the results of the recognition process are very promising. We can also calculate Precision, Recall, and F-measure [19], [20] to identify which type of leaves that best classified from the confusion matrix. Precision presents the fraction of predictive positive cases that are accurate, and is calculated using the equation:

$$\text{Precision}, P = TP\,/(TP + FP) \qquad (2)$$

Recall presents to measure the fraction of positive patterns that are correctly classified.

$$\text{Recall}, R = TP\,/(TP + FN) \qquad (3)$$

F- measure presents the harmonic mean between recall and precision values.

$$\text{F} - \text{measure} = (2 * P * R)\,/(P + R) \qquad (4)$$

For each class, we can get the results for Data 1 and Data 2 respectively. Table 2 and Table 3 show the results of precision, recall, and F-measure for each class in Data 1 and Data 2 respectively.

Table 2: Precision, Recall, and F-measure for Data 1

	Lemon	Mango	Noni
Precision	1.000	0.992	1.000
Recall	0.994	1.000	1.000
F-measure	0.997	0.996	1.000

Table 3: Precision, Recall, and F-measure for Data 2

	Bell Pepper	Potato	Tomato
Precision	0.9878	0.8696	0.9981
Recall	0.9818	0.8163	0.9981
F-measure	0.9848	0.8421	0.9981

From Table 2, we can conclude that Noni is best classified by using this model while from Table 3, Tomato is best classified since their f-measure is the best compared to the rest.

For Data 1:
• For the first line [334 0 0], this is for label 0 which is the label for Lemon. The confusion matrix shows that the model prediction for Lemon is correct 334 out of 334 which is 100% correct.
• The second line [2 327 0] is for label 1 which is a label for Mango. It predicted 327 out of 329 as Mango which is the right prediction while 2 out of 329 has been predicted as Lemon. The two images that the model has predicted as lemon is probably because of the very close similarity between the lemon and mango images whether it is in the size of the leaves or it shapes.
• The third line [0 0 337] is a label 2 which is a label for Noni. It has 100% predicted the plant accurately with 337 out of 337 correct.

For Data 2:
• For the first line [485 8 1], this is for label 0 which is the label for bell pepper. It has 485 out of 494 as correct predictions while 9 of them are wrong, 8 being predicted as potato and 1 for tomato. This is probably because of its identical shape with only slight being the angle of the images taken.
• The second line [6 40 0] is for label 1 which is a label for potato. It predicted 40 out of 46 as potatoes which is the correct prediction. With 6 wrong predictions that it has made as bell pepper, this is probably because of the similarity in the shape of the leaves.
• The third line [0 1 522] is a label 2 which is a label for tomato. It predicted 522 out of 523 as tomatoes which is a correct prediction with only 1 error. This is also probably because

of the large similarities that the image has in terms of the angle of the image taken and the size and shape of the leaves.

Based on the results of leaf recognition, CNN can recognize types of the leaf with high accuracy.

IV. CONCLUSION

This paper has proposed a smart plant information system. This system consists of 3 main modules which are leaf recognition using CNN, plant disease detection using a knowledge-based expert system, and chatbot for information about plants. There are some constraints on the system that need to be addressed. There are only three types of plants that are available in the dataset. The three types of plants are mango, noni, and lemon. More types of leaves should be added in the database. In addition, because of the limited way of taking pictures for the datasets, which is in a vertical and 90 degrees position, if the users uploaded a complicated image of a plant, there is a probability that the system will not give an accurate result. The user is advised to capture a single whole leaf with a white background and flashlights to get a more accurate result.

For future development, a new language such as Malay can be implemented in this smart system so that other local users who are only able to read the advice in Malay can use it as well.

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