An Approach of Enhancing and Supporting to The Home Gardening in Sri Lanka (Govi Mithura)

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***Abstract*- This electronic document is a "live" template andalready People have always relied on food grown in their own gardens to meet their dietary needs throughout history. On the other hand, as the modern era progressed and people led busy lives, many people began shopping at shops and supermarkets instead. As a result of the present economic crisis in Sri Lanka, individuals are finding it more difficult to purchase the food they want on a daily basis from commercial outlets, which has led to a resurgence in interest in cultivating their own gardens at home. In spite of this, individuals confront a variety of obstacles as a result of a lack of knowledge and expertise in picking crops that are acceptable depending on the kind of soil and the climatic conditions. In response to this issue, soil prediction and time series forecasting may be utilized to make predictions on the kind of crops that are appropriate for home gardeners. In addition, identifying crop leaf diseases and then locating treatments for them is a substantial problem. Automatic crop disease detection can be of assistance in this endeavor, though. A chatbot is ready to give answers on issues such as weather conditions and the appropriate amount of waterto deliver to plants in response to questions about home gardening. Because the use of chemical pesticides can have a detrimental effect not only on human health but also on economic well-being, a cutting-edge mobile application is currently being developed in Sri Lanka to provide organicalternatives to traditional methods of pest control in residential gardening.**

***Keywords*- Home Gardening, Dietary Needs, Modern Era, Supermarkets, Economic Crisis, Sri Lanka, Cultivating, Obstacles.**

I. INTRODUCTION

Agriculture is the first stage in every nation's evolutionaryjourney, and it is the foundation of every modern society. People have hectic lives in the modern world, where they arealways in competition with one another to obtain money. Because of all of this activity, a lot of people go to grocery shops and stores that provide fast food as a convenient alternative [1]. Because they are unable to obtain fresh, natural, and nutrient-dense foods in any other way, many people have no choice but to eat at fast food restaurants [2]. Inaddition, as a consequence of the consumption of such fast food, people in Sri Lanka are suffering from a multitude of ailments that have not yet been identified, such as cardiovascular diseases, diabetes, and malignancies [3]. At the present time, the practice of home gardening has been singled out as one of the potential solutions to the problems with foodsecurity that have arisen as a direct result of the economic downturn in Sri Lanka. Home gardens in Sri Lanka aredynamic food production systems that are also sustainable, and they are arguably the oldest kind of land use activity, nextto shifting farming [4]. The practice of small-scale agriculturalsystems for sustenance is observed in urban and rural settings.A lack of understanding can hinder proper gardening practices and hinder the benefits of labor. A mobile application is being developed to address this issue, particularly aimed at individuals with a basic understanding of home gardening [5].

Manually selecting crops based on environmental conditions and soil often leads to failures [6]. Applyingmachine learning algorithms and considering factors likerainfall, crop status, and weather conditions can enable moreprecise crop forecasting [7]. Improved crop output can be achieved by adopting this approach [6]. Agricultural researchers use various forecasting techniques to identify theoptimal crops for specific land parcels [8]. Home cultivatorsface challenges in predicting crops due to limited data and resources [8]. Crop leaf diseases pose significant obstacles inhome horticulture activities [9]. Observation by trained professionals is the traditional method for detecting leaf diseases [10]. Machine learning strategies offer precise automatic detection of plant diseases, particularly in specificenvironments [11]. Deep learning methods have recently been used to automatically detect crop leaf diseases [12]. Deep learning algorithms are preferred over traditional models for disease diagnosis due to their ability to analyze large datasetsand build upon previous models. The project aims to decreasecrop losses caused by leaf diseases by employing four CNN architectures and transfer learning techniques. Chatbots, existing since the 1960s, are devices that provide suitable responses to users' daily queries and problems [13].

Agricultural data is disorganized, making it difficult to find specific information. A user-friendly chatbot utilizing deep learning and natural language processing can address thisissue [14]. The chatbot's objective is to provide accurate information on agricultural management, weather, and irrigation. It identifies user needs through keyword extractionand offers educational content to enhance knowledge. Many struggles with pest identification and crop protection.

Chemical pesticides have negative effects on health andwealth [15].
Modern humans have lost traditional insect control methods and struggle to identify pests. This response suggests using Convolutional Neural Networks (CNN) for pest identification and recommends traditional pest controlmethods based on user feedback. The focus is on providing advice and solutions to home horticulture enthusiasts [16].

II. RELATED WORKS

Previous scholars have concentrated their efforts on studies that are associated with the agriculture industry. However, they are not participating in any research that is related to home gardening. Although there have been separate studies based on mobile applications concerning crop prediction, plant disease identification, chatbots, and pest identification, these studies have not been able to predict crops. But there hasn't been any recent research that took all of these things into account at the same time [17].
Pallavi Srivastava conducted research on soil classification using image processing, machine learning, deeplearning, and computer vision. The process involves picture capture, segmentation, feature extraction, and classification. Soil classification is best defined by region due to variations.Classification criteria include texture, color, and particle size.Methods like Munsell color chart, pipette, and elutriation areused for determining soil texture and color. Deep learning approaches, particularly CNN and RNN, are gaining popularity for soil classification [18]..
Honawad et al. conducted a study using Gabor Filter to extract textural elements from soil photos. They employed color quantization and Low mask techniques for effective feature extraction. The database consisted of 100 soil photosrepresenting ten distinct soil types with unique scales, translations, and orientations. The approach demonstrated successful retrieval performance, involving photo processingand characteristic extraction for different soil samples [19].
In 2018, the research presented a proposal for an autonomous system that would automatically take photos forthe purpose of diagnosing illnesses in tomato leaf tissue. In this instance, they applied a model of transfer learning. Theyhad a success rate of 95.75%. The accuracy of the earlier studies, which was 91.67%, was reached when diagnosing illnesses in tomato leaf tissue [20].
The research presents an explanation of an effective method for diagnosing numerous illnesses in a number of different plant species. Fruits and vegetables such as apples, maize, grapes, potatoes, sugarcane, and tomatoes are examples. In this study, they compared healthy leaves againstsick leaves and utilized 35,000 photos of each. The trained model has reached an accuracy rate of 96.5 percent, and it may be used for assessing real-time photos in order to identify plant illnesses [21].
In this research, an advanced deep learning technique based on an enhanced convolutional neural network was suggested to identify apple leaf diseases in real-time. To trainthe model, a dataset of 26,377 images of apple diseases was utilized, and GoogleNet was employed. The model can accurately identify five different types of diseases found in apple plants [22].
Agribot is a comprehensive agricultural solution that includes a chatbot equipped with a Natural Language Generation Neural Network Engine, which aids farmers in making informed decisions. The chatbot was developed usinga multi-layered LSTM model that delivers high accuracy. Furthermore, the model is trained to recognize diverse soil image types, which enhances its functionality [23].
The type of soil is primarily influenced by the crops that extract nutrients from it. This study explored the use of NB, LR, and RF models to establish a correlation between soil variables and crops. Since each crop has unique soil requirements, crop prediction was accomplished by employing Ph value, temperature, rainfall, humidity, and cropname. Naïve Bayes (NB), Logistic Regression (LR), and Random Forest (RF) algorithms were utilized to forecast crop yield. The model demonstrated higher accuracy in predictingyields based on the collected data. It was determined that NBand RF were more accurate than LR [24].
A research paper documenting an investigation into the effective classification of plant diseases was published in 2019. Using image recognition, the researchers proposed a novel convolutional neural network model to detect plant diseases. This model can extract features from images of leaves and contains 16 layers with 32x32 filters. Using a dataset of 14,810 images, the model was trained to attain an accuracy of 86% [25].
The study describes a question-answering system designed to respond to agriculture-specific queries inMyanmar. The research team has devised a two-step methodfor classifying the question, which first specifies identifiers for each word of the question and then classifies the question based on a number of algorithms. Nonetheless, this paper concentrates solely on the question classification component,omitting the answer extraction component, which is an additional essential aspect of a typical Question Answering (QA) system [26]. To ensure accuracy, however, it is suggested that the research team take the additional step of using a language translator to correlate the queries with the farmer's dialect [27].
The development of an agriculture automaton using Natural Language Processing (NLP) technology was reportedin a 2022 study. The Agrobot was designed to assist farmers and is capable of predicting the future prices of agricultural products, which can aid in crop planning. However, thechatbot does not presently support multiple languages; this isan area for future development [28].
The paper describes AGRI-QAS, a strong agriculture- specific question-answering system. Although this research has addressed limitations like retrieving precise answers instead of the ranked list of documents as most applications inthis research line do, they have mentioned several other futureenhancements like adopting the system to answer list-type questions (give the list of AA disease symptoms) and using proximity algorithms to improve the accuracy of the QA system. They also recommend a larger dataset for model training [29].
henmozhi et al. conducted a study in 2019 on three insectdatasets. The first dataset consisted of 40 pest categories andwas collected via NBAIR. The second dataset contained 24 classes of insects from the Xie1 dataset, while the third one had 40 classes of insects from the Xie2 dataset. The researchers used a deep CNN model to categorize insects thathave an impact on crops. The proposed model achieved highclassification accuracy of 96.75%, 95.97%, and 97.47%,
respectively [30].

Xu Cao and associates (2020) created a model for classifying and identifying nine distinct insect species. Transfer learning was used to train several deep neural networks, including VGG16, VGG19, InceptionV3, and InceptionV4. To enhance the sample size and prevent overfitting, data augmentation was utilized. Combining the VGG19 convolutional model with transfer learning resulted inthe highest recognition accuracy of all models, reaching97.39% [31].
Esgario and associates (year not given) developed deep convolutional models for classifying the severity of biotic stress using a dataset containing 1747 images of Arabica leaves. They trained the VGG-16 and ResNet50 models to recognize various biotic diseases. The VGG-16 model obtained an accuracy rate of 95.47 percent, while the ResNet50 model effectively validated each leaf condition at arate of 95.63 percent [32].

III. METHODOLOGY

The 'Govi Mithura' mobile application has four different components, each of which is designed to promote and enhance home gardening activities in Sri Lanka .

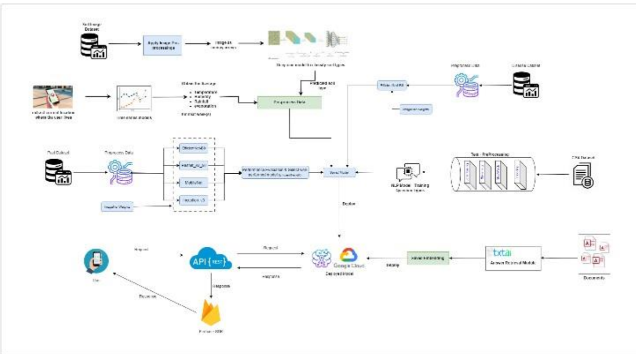

Fig 1. System Overview Diagram

A. Crop prediction and analysis using deep learning

This section discusses the techniques and parameters used in crop prediction to determine which crops are appropriate for consumers. Key components of crop prediction are soil prediction and time series forecasting. The proposed methodfor crop prediction uses machine learning to provide crop yield and crop selection based on meteorological parametersfor optimal crop output. To forecast crop yield, the method takes into account factors such as rainfall, temperature, area,and season, among others [33].
Two datasets—soil image and weather—predicted crops.The soil image collection has 700-800 photos sorted bymoisture level: dry, intermediate, and wet. The weather dataset includes temperature, rainfall, humidity, and evaporation characteristics. A Sri Lankan agriculture specialist evaluated the dataset and will gather further soil pictures. A weather dataset from December 2020 to January 2021 was used for time series forecasting. The USDA NaturalResources Management Center collected the data. Two phases—training and testing—collected crop and pH value datasets [34].
This study predicts and analyzes crop patterns using deeplearning. The suggested method uses a CNN model to predictsoil types. The user uploads a soil photograph to the mobile app and pre-processes it. Using moisture content, a deep CNNmodel predicts soil type. It predicts soil accurately. The modelthen uses XGBoost to anticipate temperature, rainfall, evaporation, and humidity based on the user's location. The program predicts the weather for the next week(s) to select thebest crops for home gardeners. By giving gardeners accurateand timely information, we think our method will help homegardening succeed. Our crop prediction methods combine deep learning and time series forecasting.
Predicting the nature of soil based on its moisture content.The soil type's moisture content can be considered as to predict the best crop, I followed several steps. Firstly, Icollected soil images and validated them with an agriculturalexpert. Then, I considered 15 crops and gathered crop details,images, and pH value data from the website of the Departmentof Agriculture Sri Lanka. Next, I built a time series model toforecast the average of each feature separately for the upcoming week. For this, I collected weather data, includingtemperature, humidity, rainfall, and evaporation, from the NRMC (Natural Resource Management Center) for the period between January 2020 and December 2021. By following these steps, I was able to obtain accurate predictions of the best crops for cultivation in a particular area.

B. Crop Leaves diseases identification using deep learning

- Image pre-processing - The process of improving thequality of an image involves minimizing noise and eliminating unwanted artifacts, making it moreaccessible for analysis.
- Image Augmentation - Expansion of an image datasetby implementing various image modifications, such asrotations, translations, scaling, and inverting, in orderto increase its size and variability.
- Transfer learning – Using pre-trained models (ResNet50, VGG19, ResNet152V2, and InceptionV3)on a dataset of 12,782 images of healthy and diseasedleaves, this study seeks to identify the 11 most prevalent diseases that infect the five most popular crops for home gardening. The dataset is divided intoa testing set and a training set, with 3,462 images for the testing set and 9,320 images for the training set, evenly distributed across the eleven classes. The proposed models' accuracy results are compared to determine which model is superior at identifying cropleaf diseases [35].

In this study, I identify the 11 illnesses that are most frequentin home gardens and how they affect the five most popular crops planted in home gardens.

TABLE I. **11 ILLNESSES THAT ARE MOST FREQUENT IN HOME GARDENS**

Crops	**Illnesses**
Tomato	Bacterial_spot, Spider_mites, Yellow_Leaf_Curl_Virus
Bean	angular_leaf_spot, bean_rust
Corn	Common_rust, Northern_Leaf_Blight
Cassava	brown_streak, mosaic_disease
Okra	yellow_vein_mosaic

By using transfer learning, we can improve the accuracy of identification compared to existing models when working with a limited dataset.

C. Answer the necessary home gardening inquiries throughmessage commands in the chatbot

Chatbots employ Machine Learning, Deep Learning, andAI to interpret Natural Language and give customised repliesto users. Chatbots were first limited to healthcare, aviation, and insurance. However, using chatbots in agriculture can improve productivity and sustainability by providing fast andaccurate information on crop management, weather, and plantwatering. We can help agricultural smallholders learn home gardening by giving extensive information and instructional content [36].

Our chatbot is equipped with a Natural Language Processing (NLP) model so that it can respond to users' questions about home gardening using English message instructions. Even if the user asks a query that containsgrammatical errors, our pre-trained model is able to locate keywords contained within the user's specific dataset. After the keywords have been identified, the model generates a group of words and then conducts an analysis of the content of the document that was extracted in order to find theresponse that is most comparable to the question based on thesimilarity scores. This method contributes to providing repliesthat are accurate as well as pertinent to the user's inquiry [37].

D. Pest Identification and Traditional Pest ControlMethods Recommendation using Deep Learning

This model utilizes deep learning techniques to identify and provide recommendations for traditional pest control methods applicable to the seven most prevalent pests found in the five commonly cultivated crops within home gardens. The model leverages pre-trained models and transfer learningapproaches to enhance its classification accuracy. The implementation of the model involves the use of both trainingand testing datasets. Based on user ratings, the system suggests appropriate traditional pest control methods for effective pest management.

This study used the IP102 dataset, which was obtained bydownloading it. The dataset consisted of 11011 photos of various insects, which were categorized into seven types, including Squash Bugs Armyworm, Corn Borer, Cucumber beetles, Flea beetles, Cutworm, and Aphids. The dataset wasdivided into 8276 photos for training and 2735 images for testing.

IV. RESULTS AND DISCUSSION

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A. Results

1) A. Crop prediction and analysis using deep learning

To predict the best crop for the user. The ML and Dl models are responsible for the accuracy. These will support identifying the best crop in home gardening. To predict the best crop, once obtain the soil type, district, temperature, rainfall, humidity, and evaporation these features cause to predict the best crop for the user. To predict the best crop, andcheck the accuracy of the best models for the best crop, I takeDecision Tree Classifier as model 1 and Random Forest Classifier as model 2. The Decision Tree Classifier accuracyis 0.9090 and Random Forest Classifier is 0.9345. By checking these accuracies I used Random Forest Classifier. To predict the soil type, used the resnet_152_v2 model, and also for the time series forecasting used Random Forest Regressor. From these models, predict the best crop for the users who are engaging with home gardening.

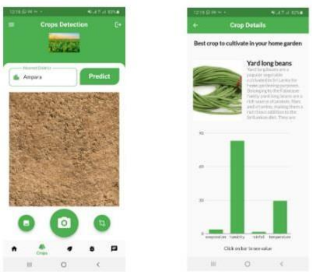

Fig 2. Interface 01

2) *Crop Leaves diseases identification using deeplearning*

We developed a deep learning model for identify crop leaf diseases. Among the transfer learning models (ResNet50, EfficientNet_B0, MobileNet, and Inception_v3, ResNet152V2), EfficientNet_B0 achieved the highest accuracy of 98.34%, followed by ResNet50 with 96.14%. MobileNet, ResNet152V2 and Inception_v3 demonstrated accuracies of 65.67%, 97.50% and 94.43%% respectively. Based on these results, EfficientNet_B0 was selected as the optimal model for diseases identification. This model shows promising outcomes for accurately detecting diseases affected crops in home gardens.

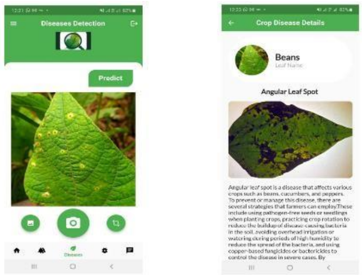

Fig 3. Interface 2

3) *C. Answer the necessary home gardening inquiries through message commands in the chatbot*

Provided home gardening chatbot is to enhance productivity and sustainability in home gardening byproviding users in the agriculture industry with quick and reliable information on various topics, such as the productionof compost, irrigation, and hydroponics culture. Furthermore,the collected data from the application will be used foranalysis purposes.

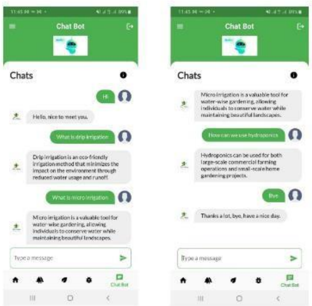

Fig 4. Interface 3

4) *Pest Identification and Traditional Pest ControlMethods Recommendation using Deep Learning.*

We developed a deep learning model for pest detection and treatment recommendation. Among the evaluated models (ResNet_v2_50, EfficientNet_B0, MobileNet, and Inception_v3), EfficientNet_B0 achieved the highest accuracy of 86.38%, followed by ResNet_v2_50 with 74.87%. MobileNet and Inception_v3 demonstrated accuracies of 72.40% and 69.29% respectively. Based on these results, EfficientNet_B0 was selected as the optimal model for pest identification after pre-training. This model shows promising outcomes for accurately detecting pests andsuggesting appropriate traditional pest control methods, improving pest management practices in home gardens.

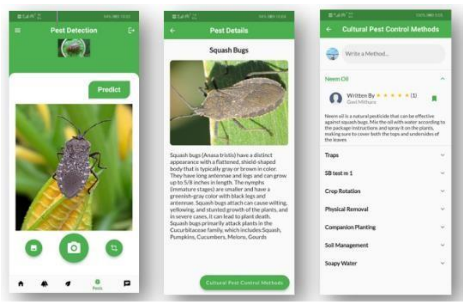

Fig 5. Interface 4

V. CONCLUSION

Various factors, including the COVID-19 pandemic, food security concerns, and a developing interest in healthful living, have contributed to the expanding popularity of homegardening in Sri Lanka. Nevertheless, many home cultivatorsencounter obstacles such as a lack of knowledge, restricted access to resources, and difficulty in identifying and treatingcrop diseases.

Using technology such as chatbots, imageprocessing, and natural language processing, we proposed inthis paper a method for enhancing and facilitating home horticulture in Sri Lanka. Our proposed chatbot can provide fast and accurate information on a variety of topics, includingcrop management, weather conditions, and plant irrigation, among others, in order to increase agricultural productivity and sustainability in our country. The image processing technique can be used to identify and classify various crop diseases, enabling amateur cultivators to take the necessary precautions to prevent the disease's spread. Even if the user'squery is grammatically improper, the model for natural language processing is able to respond to their inquiries usingEnglish message commands.

Our strategy provides an accessible and user- friendly platform for home cultivators to acquire knowledge and enhance their skills, ultimately resulting in increased agricultural productivity and sustainability in Sri Lanka. Theproposed method can be further refined and adapted to meet the unique requirements and challenges of home cultivators in various regions.

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