CNN'S RESNET, YOLO, AND FASTER R-CNN ARCHITECTURES ON THE DISEASE AND PEST CLASSIFICATION OF LOCAL AGRICULTURAL VEGETABLES TOWARDS SUSTAINABLE PRODUCTION

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ABSTRACT

The Philippines is known to be a country that values the agricultural sector. Agriculture is the backbone of the Philippine economy, contributing around 9% to its gross domestic product (GDP) and providing livelihood to millions of Filipinos. Local vegetables such as pechay, mustasa, sitaw, talong, and ampalaya are some of these essential agricultural crops, used in different famous dishes in the country. The emergence of technology helps individual and community improve their way of administering and managing crops, which is why it is very important to develop an innovative way to produce sustainable vegetable crops. The focus of this paper is on the creation of an application that can effectively categorize the ailments, pests, and nutrient deficiencies found in vegetable crops. This application uses different Convolutional Neural Networks architectures such as ResNet, YOLO, and Faster R-CNN to dissect information from digital photographs. By offering diverse insights into diseases, pests, and deficiencies, this application equips users with the knowledge to effectively handle and nurture crops, ensuring sustainable production. The mobile application helps many vegetable growers identify the problems and challenges of their crops. The used CNN architecture provides accurate detection, analysis, and interpretation of the content of digital photographs, and served as a way to provide information on the solutions. ResNet architecture provides a high accuracy rate among YOLO and Faster R-CNN in the detection and classification of diagnosis.

KEYWORDS

Local Agricultural Vegetables, Diagnosis, Deep Neural Networks, Classification ResNet, YOLO, Faster R-CNN

1. INTRODUCTION

Playing a vital role in the Philippine economy, agriculture contributes approximately 9% to the country's gross domestic product (GDP) and serves as a source of livelihood for millions of Filipinos. The COVID-19 pandemic has highlighted the importance of local agricultural products as the country faced disruptions in global supply chains and trade. Based on data from the Philippine Statistics Authority, there was a 0.5% growth in the value of agricultural production in the Philippines during the initial quarter of 2021, primarily driven by the significant contribution of crop production. The Department of Agriculture has also been implementing programs to support local farmers, such as the Plant, Plant, Plant program, which aims to boost food security and increase agricultural productivity. Notwithstanding the exerted endeavours, the growth of the

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domestic agricultural sector remains impeded by persistent challenges, including restricted access to financing and technology, adverse effects of natural disasters, and the ongoing impact of the pandemic. [1]

Pechay (Chinese Cabbage), Mustasa (Mustard), Sitaw (String Beans), Talong (Egg Plant), and Ampalaya (Bitter Melon) are some of the most important local vegetables in the Philippines which are used in different famous dishes in the Philippines. Technology plays an important role in the sustainable production of crops, which is why the emergence of technology and innovative ways must be implemented and embraced by the local farmers and growers as well as the community. The emergence of technology has led to the development of application software, which plays a crucial role in assisting individuals with their daily tasks. These software applications employ various methods and techniques to serve specific purposes, and one notable example is image processing, which can be utilized for diagnosing crop issues.

Detecting diseases and pests in plants and vegetables is crucial in ensuring food security and sustainability. Crop diseases and pests have the potential to inflict considerable harm, resulting in diminished yields, compromised quality, and economic setbacks. Given the escalating worldwide food demand, it is imperative to devise efficacious approaches for detecting and managing these afflictions to meet the ever-increasing need for sustenance. Leveraging advanced technologies such as molecular biology, remote sensing, and artificial intelligence has exhibited encouraging outcomes in the realm of disease and pest identification. Moreover, early detection and prompt response play a crucial role in curtailing the spread of diseases and pests, thus mitigating the necessity for expensive and environmentally detrimental control measures. [2] [3] [4]

In the agricultural sector, image processing technology has grown in importance, particularly for the identification and treatment of plant illnesses and problems. The utilization of imaging techniques such as thermal, fluorescence, and hyperspectral imaging, coupled with machine learning algorithms, has enabled the precise identification of plant diseases and pests, even in their early stages. This technology presents a more efficient and enduring alternative to conventional methods, with the potential to revolutionize the management of plant diseases. Additionally, crop development and growth may be monitored, crop production predictions can be improved, and nutrient management can be optimized using image processing technologies. As the demand for food production continues to rise and the importance of sustainable agriculture becomes increasingly evident, the utilization of image-processing technology in the agricultural industry has become indispensable. There are several technologies available used in image processing one of these is Deep Neural Networks or DNNs. [5] [6] [7]

Deep Neural Networks (DNNs) have demonstrated immense promise across numerous sectors, including agriculture. Over the past few years, their application has extended to detecting and diagnosing plant diseases and pests, as well as predicting and optimizing crop yields. By leveraging DNNs, vast datasets comprising images and spectral information can be analysed, enabling accurate pattern identification and predictions. The integration of DNNs into agriculture holds the potential to transform the industry, offering a more efficient and sustainable approach to crop management. However, there are still challenges to be addressed, such as the lack of standardized datasets and the need for specialized knowledge in machine learning. The Convolutional Neural Network (CNN) stands out as one of the widely adopted and renowned Deep Neural Networks (DNNs), renowned for its diverse architectural variations. [8] [9] [10]

CNNs, as a specific type of deep neural network, find widespread application across various computer vision tasks, encompassing segmentation, object recognition, and image classification. CNNs are designed to automatically learn hierarchical features from the input images by using a series of convolutional and pooling layers. Multiple established CNN architectures have proven their efficacy in tasks such as object detection and classification. The most well-known ones include ResNet (Residual Network), which has been demonstrated to be very effective for image classification tasks and has also been used for object detection; YOLO (You Only Look Once): this architecture divides the input image into a grid and then predicts the bounding boxes and class probabilities for each grid cell; and Faster R-CNN (Faster Region-based Convolutional Neural Network), which uses a faster region-based convolutional neural network. [11] [12] [13]

The focus of this paper revolves around creating an image-processing application that utilizes Deep Neural Networks, specifically Convolutional Neural Networks, to detect and classify diseases, pests, and deficiencies in local vegetable plants and crops. By employing image analysis and interpretation techniques, the application accurately identifies the content of digital images and translates it into valuable information. Different CNN architectures such as ResNet, YOLO, and Faster R-CNN are used to identify which is most accurate in the detection and classification.

2. REVIEW OF LITERATURE

The utilization of deep neural networks (DNN) and convolutional neural networks (CNN) has yielded promising outcomes in the identification and classification of pests and diseases in vegetable crops. To mitigate crop losses and enhance yields, there is a growing emphasis on developing accurate and reliable automated systems for the identification of diseases and pests. In one such study, Sladojevic et al. (2016) classified five prevalent crop diseases in tomato plants with an accuracy of 99.13% using a DNN technique. Similar to the previous work, Mohanty et al. (2016) classified 14 crop diseases with a 98.30% accuracy rate using a CNN technique. [14] [15]

Image processing techniques have also played a significant role in improving the accuracy of disease and pest detection systems. A study by Singh et al. (2017) used color-based image segmentation to identify the infected regions of the leaves, followed by feature extraction and selection methods for classification using a support vector machine (SVM). The system achieved an accuracy of 95.30% for the detection of early blight disease in tomato plants. Another study by Zhang et al. (2020) proposed an image processing-based approach for the detection of rice leaf blast disease using texture analysis and morphological features. The system achieved an accuracy of 98.80% for disease detection. [16] [17]

In conclusion, the use of DNN, CNN, and image processing techniques together has demonstrated enormous promise for the identification and categorization of illnesses and pests that affect vegetable crops. These automated solutions can help farmers take prompt action to minimize the spread of illnesses and pests while also greatly reducing the time and effort required for human detection. Despite progress made thus far, there is room for further advancements in terms of enhancing the robustness and accuracy of existing systems. Consequently, additional research is needed to develop more sophisticated and dependable systems in this domain.

3. METHODOLOGY

This section includes the methodology used in the development of the image processing application. Agile Scrum Methodology was applied to the application's development. Various stages, including the creation of a product backlog and a sprint backlog, were completed to identify obstacles and successes in the project's progress. To determine the overall effectiveness and features of the mobile application, additional methods and models were offered. This encompasses not only the system architecture but also the mobile application's detection process.

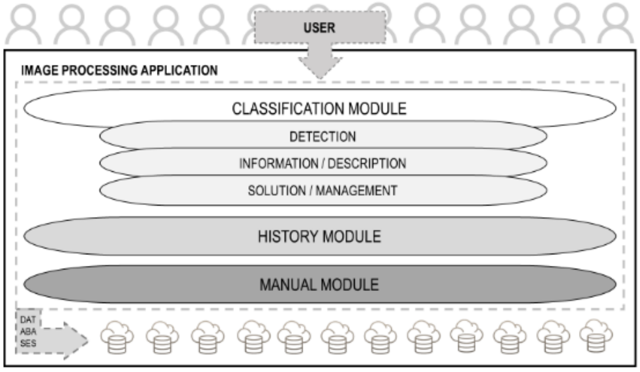

Figure 1. System Architecture

In Figure 2, the mobile application has several modules that users can access through the user interface. The Detection Module is composed of two submodules, namely disease and pest detection and condition detection. These submodules enable users to identify and classify the condition, disease, or pest affecting a specific maize plant. Additionally, users can obtain information about the type of disease, pest name, possible cause, and necessary actions to take.

Users can use previously recorded photographs and data as a reference in the History module to help identify the illness, disease, or pest. They can also remove any photos and data that have been recorded from the history. Figure 2 also shows the specific data that the app's mobile version contains, such as the app's description and details about numerous pests, diseases, and circumstances that can affect maize harvests. Users may learn more about growing, managing, and administering maize crops thanks to these features.

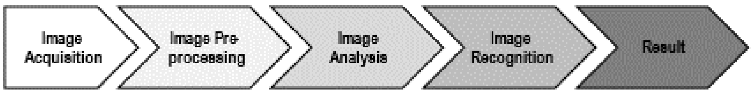

Figure 2. CNN Fully Connected Multilayer Perceptron

The implementation of the CNN can be seen in Figure 2, which was utilized for identifying and categorizing specific elements in the input data. This involved loading a set of data into the application's library. The effectiveness of the dataset is crucial for achieving accurate classification and identification outcomes.

Image Acquisition. To ensure precise detection, it is necessary to capture a digital photograph of a tilapia from a particular angle while considering various factors, such as object visibility and clarity, object focus, appropriate distance from the object, clearness of the background, satisfactory lighting, and camera quality.

Image Processing. There are two ways in which image pre-processing can handle the input data and dataset. The first approach involves using CNN to extract important information from both the original image dataset and the input image. The second method translates the dataset and input image into hexadecimal values before subjecting them to the CNN. When the digital image is saved as a .png file with lossless compression in the smartphone app, it is automatically translated into a hexadecimal format file. Similarly, the data set in the application's library is also converted into a hexadecimal format to enable comparison with the input data values.

Image Analysis. Using TensorFlow, each model in the dataset was converted into hexadecimal numbers. The CNN will analyse the input image through Multilayer Perceptron or simply called MLP discussed in the succeeding text.

For successful detection and classification, it is crucial to consider the parameters and thresholds. The threshold is essential in establishing the standard value of the potential outcomes, and both these elements are developed by loading and training the dataset into the system. By utilizing these techniques, the system can improve the accuracy and effectiveness of detection and classification. However, if the loaded dataset is unorganized or unclear, the results will be inaccurate and inappropriate. Hence, it is vital to take into account various forms of data.

Image Recognition. Once CNN has analysed the content of a digital image, it provides a list of potentially detected disorders or diseases and their corresponding confidence values as a percentage. The output is considered valid if the confidence value reaches an 80% similarity threshold.

Results. Finally, the detected object or result will be identified based on the highest confidence value that has reached an 80% similarity threshold on the list.

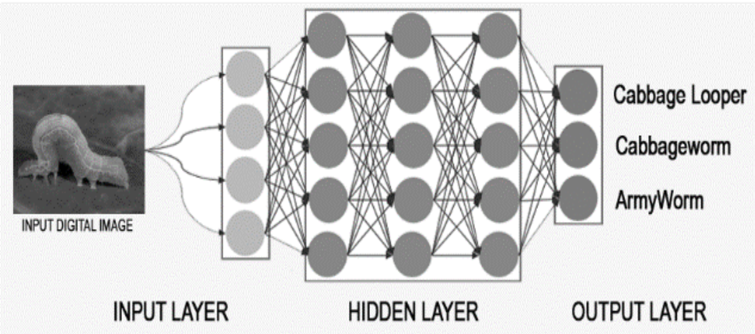

Figure 3. CNN Fully Connected Multilayer Perceptron

Figure 3 shows the process of classification of the CNN using the Multilayer Perceptron or simply called MLP. MLP is a model in Neural Networks to represents the process of solving problems and creating the best possible solution solutions. MLP is also used as a universal approximator to perform different tasks, such as measurement, calculation, prediction, classification, and analysis. This model is consisting of three layers to produce such solutions, the layers namely: The input layer accepts data from outside. All the significant data that are loaded in the MLP are composed of objects, states, and behavior.; The hidden layer or the weights are part of the MPL where all data are analyzed and perform the computation for the production of the best possible outputs.; And the output layer displays the best possible solution or solutions from the analyzed and interpreted data.

Each of the layers of MLP is very important to produce properties or outputs which can be a basis to solve a particular problem in different fields. The effectiveness of the MLP relies on factors such as the quality of data, the efficiency of the process, and the accuracy of the output. A fully connected MLP performs a more complex process than the standard MLP where all the nodes or neurons are connected in adjacent layers. When fully connected MLPs are used, analysis is more complex, efficient, and effective and it will create various significant information. From this analysed, extracted, and interpreted information, it will display more accurate solutions or outputs.

Among layers of MLP, the hidden layer performs complex and various tasks as it computes the possibilities, potentials, and opportunities in something. Such tasks performed in this layer are prediction, classification, or identification. This layer is said to be hidden because the process is in the middle of the inputted significant data and the interpreted output. The term "hidden" is used to describe this layer because, during training and data analysis, the exact values of its nodes remain unknown. The hidden layer fulfils specific tasks based on requirements and objectives, and computation and analysis formulas are established to guide its operations. The extraction, association, clustering, and classification of data were done on this layer to produce a list of the best possible outputs.

4. RESULTS AND DISCUSSIONS

This section encompasses the outcomes and discussions of the research project, encompassing the prototype of the application, the accuracy results of the CNN architectures, as well as the training and testing outcomes.

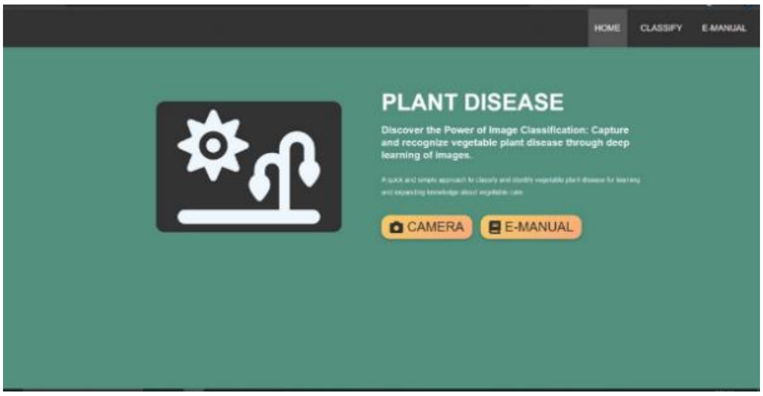

Figure 4. Home Page

Figure 4 shows the homepage of the application in which the description of the application is displayed. Two main modules were also shown such as the Classification and Detection Module and the e-Manual Module.

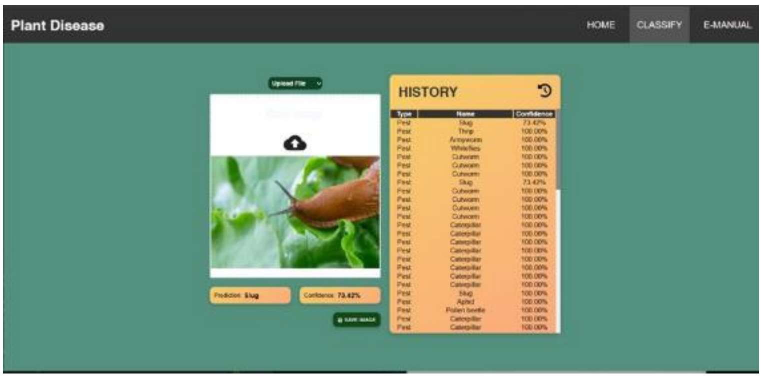

Figure 5. History Module

Figure 5 shows the history module where all of the previous successful classifications and detection and their accuracy are displayed. The user has a chance to archive the list of previously detected and classified diseases, pests, and diagnoses.

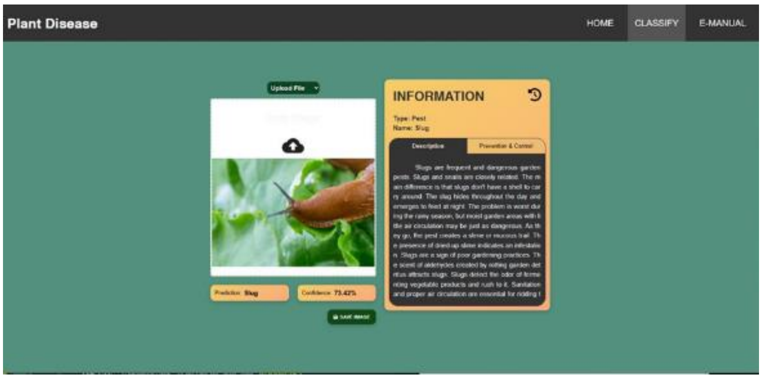

Figure 6. Disease and Pest Detection Module

Figure 6 depicts the Classification and Detection Module, which serves as the primary function of the application. To load the image for classification and detection, the object will be scanned or an available image from the gallery can be loaded. The scanned object or loaded image will be classified by the application. After the classification, the following will be displayed: accuracy of the classification and detection; description of the diagnosis (pest/disease), and other important information about the management and administration of the classified and detected pest or disease. The successful classification and detection will be automatically saved to the history module for easy browsing of the previous results.

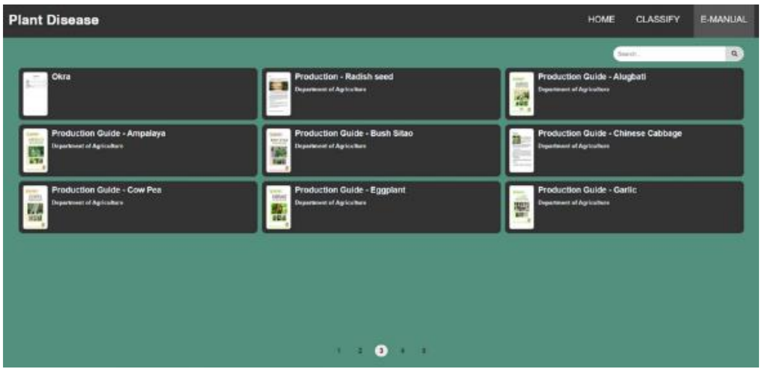

Figure 7. E-Manual Module

Figure 7 shows the module where free e-Manuals of different vegetable plants and crop management can be accessed for references and easy guides. The e-Manuals provided in this context originate from government agencies that actively support the agricultural sector, including the Department of Agriculture and the Bureau of Plants and Industries.

Figure 8. Database of the Application

Figure 8 shows how the classified and detected data are being saved into the database of the application. The user may decide if the diagnosis will be saved to or removed from the database.

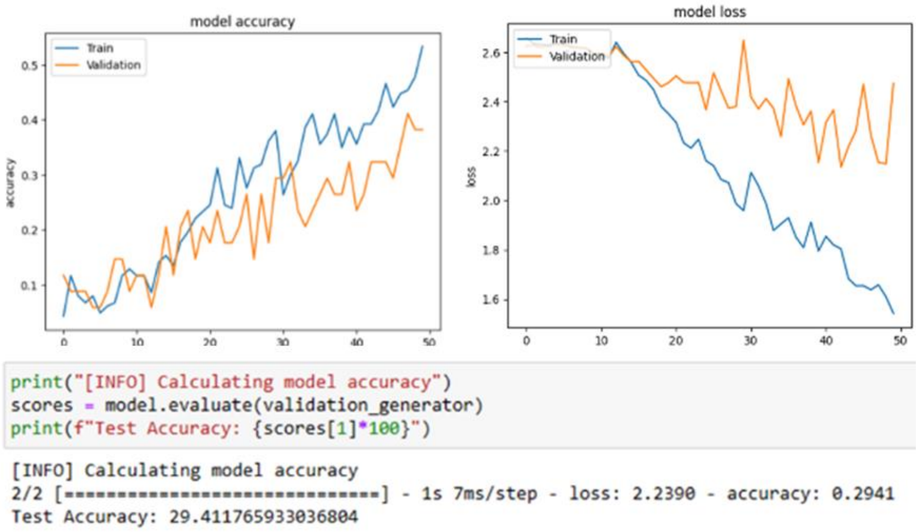

Figure 9. Training Results

Figure 9 showcases the displayed outcomes of the training data, testing data, and the model. During CNN training, adjustments to the network's weights and biases are made to minimize the loss function. The accuracy of the network is continuously monitored throughout the training process to ensure precise classification of data. Accuracy is measured by calculating the ratio of correct predictions to the total number of predictions, indicating how effectively the CNN classifies the input data. On the other hand, loss measures how well the CNN learns from the training data. It is the discrepancy between the output that was anticipated and the actual outcome, or the prediction error. The objective of training a CNN is to minimize the loss, therefore the predicted output should be as near to the real output as is practical.

Table 1. Accuracy of the CNN Architecture

CNN	Accuracy	Percentage	Remarks
ResNet	0.9421	94.21%	Passed
YOLO	0.8794	87.94%	Passed
Faster R-CNN	0.8213	82.13%	Passed

Table 1 shows the result of the testing of different CNN Architectures to identify which is best for classification and detection. As a result, all of them have higher accuracy which tells that each architecture is designed to serve a different purpose and has its strengths and weaknesses.

ResNet serves as a prevalent deep-learning architecture utilized for tasks involving image classification. It introduces the concept of "residual connections" to overcome the issue of vanishing gradients often encountered in deep neural networks. ResNet excels in accurately classifying images with numerous categories, such as those found in the ImageNet dataset. On the other hand, YOLO is a real-time object detection system extensively applied in various domains like self-driving cars and video surveillance. It stands out for its ability to swiftly and accurately detect objects, particularly smaller ones. Faster R-CNN, another well-known object detection system, finds common use in robotics and self-driving cars. It has been specifically designed to achieve faster processing speeds compared to earlier region-based methods for object detection, all while maintaining high levels of accuracy.

5. Conclusions and Recommendations

Based on the results and discussions of the research project, the following is concluded and recommended.

The application helps a lot of local growers and local farmers in the management and administration of local vegetable plants and crops as it classifies and detects the type of diseases and pests and provides some information to solve particular diagnoses. The application provides a user-friendliness environment, efficient and effective modules, and functions for the users. DNN particularly CNN has been proven again that provides accuracy in the detection and classification of objects. Two crucial criteria used to assess a CNN's performance are accuracy and loss. In order to maximize network accuracy while minimizing loss, CNNs are trained. Lastly, there is no best CNN architecture for the detection of plants and crops diseases and pests as the ResNet, YOLO, and Faster R-CNN provide accurate classification and detection. The selection of a suitable CNN architecture relies on the specific task and requirements of the application at hand. It is crucial to thoroughly evaluate the strengths and limitations of each architecture before determining the most optimal choice for a given application.

As a recommendation to the results and conclusions discussed above. The application has the potential to offer supplementary functionalities, such as a report module, which will present and analyse comprehensive results from the classification and detection processes. The application should be mobile phone responsive for easy access of the growers and farmers. An improved CNN may be applied for better accuracy of classification and detection. Other CNN Architecture should be used to identify their purpose and significance.

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