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# Implementation of Convolutional Neural Network Model for Apple Leaf Disease Detection

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***Abstract*— Apple growers may suffer large financial losses as a result of apple leaf diseases. To reduce crop losses, apple leaf diseases must be identified early and treated. Nevertheless, conventional techniques for identifying apple leaf diseases, like professional manual visual inspection, can be time-consuming and difficult. Thus, the goal of this research is to detect diseases in apple tree leaves using convolutional neural networks (CNNs). By using deep learning, the disease detection process becomes automated, saving time and resources. It is proven that after roughly 20 epochs, the accuracy rise slows down and begins to fluctuate, but it keeps rising until it surpasses 90%. The results of the CNN model's performance in predicting disease types have a high level of accuracy and can be used as a model for detecting disease types in apple plant leaves.**

***Index Terms*— Apple Leaves Disease; Convolutional Neural Network; Deep Learning; Detection.**

## I. INTRODUCTION

The production of fruits and food crops around the world has been greatly affected by various diseases, especially tree-leaf diseases. One type of tree that is widely cultivated throughout the world is the apple tree, one of the most popular fruits consumed worldwide [1]. Despite its high consumption rate, apple trees is prone to a number of diseases brought on by insects and microbes like bacteria. There are various types of diseases that affect this including Altenaria Boltch, AppleScab, Blackrot, CedarAppleCrust, and Rust. Therefore, apple leaf disease can cause significant economic losses for apple farmers. An early detection method for apple leaf disease is needed to minimize crop losses. However, traditional methods for detecting apple leaf disease, such as manual visual inspection by experts, can be time-consuming and labor-intensive.

Technological advances have led to deep learning and soft computing methods being applied in this area [2] becoming increasingly helpful for automatically identifying and categorizing apple tree leaf diseases. By using deep learning, the disease detection process can be done automatically so that it can save time and resources. In addition, the true benefit of deep learning is that its methods may be used directly on unprocessed data in a variety of file types, including.csv,.jpg, and others [3], [4]. Advances in computer vision and deep learning have resulted in the adoption of convolutional neural networks (CNNs) [5], [6]. Currently, CNN models are widely used as the primary choice for tasks related to image classification. The main strength of CNN lies in its architecture and effective feature extraction and transmission to the next layer. CNN usually consists of two main modules: a feature extraction module and a classifier module [7]. The feature extraction module is responsible for extracting relevant features from the image through processes such as convolution and pooling. CNN is robust to data variance, can automatically capture the hierarchy of features from low to high levels, and can solve gradient problems and appropriately modify parameters to focus on key characteristics with designs like Improved ResNet-50. This makes it better at automatically classifying pests and diseases of apple leaves. Based on the results obtained, it is evident that the model outperforms some previously proposed models in terms of performance metrics such as accuracy. Merging has effectively minimized the prediction variance, and can improve the accuracy [8], especially in scenarios involving many diseased leaves [9]. In addition, the model proposed in this study is also implemented through a web application, thus creating convenient accessibility for apple farmers [10], [11].

## II. LITERATURE STUDY

### A. *Convolutional Neural Network*

CNN is a deep learning algorithm used to classify labeled data, such as images. CNN operates by learning patterns in the data to predict target variables. In this study, several CNN parameters were used, including:

1. Convolutional Layer: A layer that functions to extract features from an input image by

repeatedly applying a convolutional kernel to identify patterns in the image [12], [13].

2. Activation Function: This study uses the Rectified Linear Unit (ReLU). The kernel or filter size used for each convolutional layer in this study is 3×3, which aims to to increase identification accuracy and expedite the training process [14], [15].
3. Pooling: is a process that reduces the spatial size of feature maps, allowing CNNs to be trained faster. Pooling also improves CNN's translational invariance, allowing it to recognize objects even if their location in the image changes [12], [16].
4. Flattening: After the pooling stage is complete, the flattening process will be carried out, namely flattening the pooling results into a fully connected layer. Flattening is the process of changing a feature map from a 2D form to a 1D form [12], [17]. This is done because fully connected layers only accept input in 1D.
5. Full Connection: Every neuron in a fully connected layer is coupled to every other neuron in the preceding and subsequent layers, enabling it to understand the connections between the features that the convolutional layers have collected [5], [12].

### *B. Previous Research*

Several previous studies are the basis for the development of this research. Research [18] discusses the rapid development of deep learning (DL) techniques that make it possible to detect and recognize objects from images. This highlights that DL approaches have recently entered various agricultural applications after being successfully applied in various fields. According to the study's findings, farmers can increase agricultural yields by managing their crops more skillfully with the use of autonomous plant disease detection. Study [19] implements CNN as a solution used for plant disease classification. CNN consistently performs well in leaf disease classification due to its ability to automatically extract complex features, with accuracy increasing as the model is scaled up or combined with techniques such as data augmentation and transfer learning. CNNs use its layered structure—which includes pooling layers that lower the dimensionality of the input while preserving crucial information and convolutional layers that identify local variables like color patterns, textures, and shapes—to effectively diagnose plant illnesses. CNNs are able to collect progressively more sophisticated visual characteristics at each layer, ranging from basic patterns to more abstract illness representations, thanks to this hierarchical approach. Furthermore, the backpropagation technique optimizes weights to increase accuracy, and the usage of activation functions like ReLU aids the model in learning non-linearities on the data. CNNs are a potent tool for diagnosing plant diseases because of these methods, which enable them to differentiate between even similar disease signs [20]. Another study [21] found that the Deep Convolutional Neural Network (CNN) model is very effective in detecting apple leaf diseases, with an accuracy of 97.62% in classifying various diseases. The study showed that the use of data augmentation techniques and hyperparameter optimization improved the performance of the model, making it a reliable tool for automatic plant disease diagnosis. CNNs are successful in diagnosing plant diseases because it able to automatically extract and efficiently learn visual features such as color, texture, and shape that are typical for various diseases. CNNs' capabilities also include its capacity to handle vast data, adapt to changes in lighting, orientation, and image background, and be easily incorporated with transfer learning and data augmentation methods to increase diagnostic precision. Research [22] discusses the latest deep-learning methods for plant disease detection and classification. This study also addresses various challenges in this task, such as the variability of plant diseases and the lack of publicly available datasets. This study suggests that future research should focus on developing methods that can generalize well in classifying plant diseases. Research [23] compares classic deep learning and machine learning approaches in detecting plant diseases using images. The study's findings indicate that the Convolutional Neural Network algorithm has the highest performance compared to the Fully Connected Neural Network algorithm and machine learning such as SVM (Support Vector Machine) and KNN (K Nearest Neighbor). Based on previous research, we propose a solution using the CNN model to classify the type of disease in apple leaves, due to CNN's ability to accurately determine if a leaf is ill or not. According to the study published in [24], their lightweight CNN model demonstrated great classification efficacy while preserving computational efficiency, achieving an accuracy of 97.95% on a benchmark dataset for apple leaf disease. This outcome demonstrates the model's promise for resource-constrained and real-time applications, like in-field plant disease monitoring. Using CNN as a foundation for the Single Shot Detector (SSD) algorithm is suggested as a way to achieve the highest level of accuracy in detecting and categorizing apple leaf diseases. The suggested model beats other models of a similar nature, with an accuracy of 96.62% when benchmarked against models like AlexNet and ResNet-50 [25].

## III. Methodologies

### A. *Cross-Industry Standard Process for Data Mining (CRISP-DM)*

The research methodology used is CRISP-DM. The research will be continued through the following stages based on the CRISP-DM framework:

1. Business Understanding: The purpose of this project is to use a convolutional neural network (CNN) to identify illnesses in apple tree leaves.

2. Data Understanding: For this study, the dataset used [26] was images of apple tree leaves in diseased conditions consisting of 5 classes, namely AlternariaBoltch, AppleScab, BlackRot, CedarAppleRust, and Rust sourced from the Mendeley Dataset. The total size of this dataset is 861 MB with total 1,414 images. An example of apple leaf disease image data used is shown in Figure 1 below.

3. Data Preparation: Preprocessing image data to make it suitable for use in a CNN model, such as resizing images, normalizing pixel values, and dividing the data into training and testing sets.

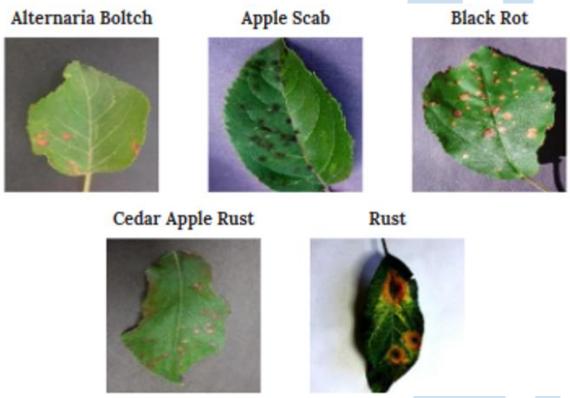


Fig 1. Apple Leaves with Diseases

4. Modeling: Creating a CNN model with CNN architecture, layer construction, and activation function selection.

5. Evaluation: To assess model performance, accuracy, and loss graphs, as well a confusion matrix will be used.

6. Deployment: Implementing a model that can classify diseases in apple leaves based on the input of apple tree leaf images on a website.

## IV. Result and Discussions

### A. *Data Preprocessing*

The data preparation stage is to perform image augmentation using the ImageDataGenerator library from Keras. Image augmentation is needed to create new training data from existing samples so that the trained data will be more. Parameters for the augmentation carried out include rescale to normalize image pixels, zoom_range for random zoom, rotation_range for random rotation, horizontal_flip and vertical_flip to flip the image randomly, shear_range for random shear transformation, fill_mode to fill newly created pixels after rotation or shift, width_shift_range and height_shift_range for random horizontal and vertical shifts, and validation_split to determine the fraction of data to be used as the validation set. Table 1 shows the parameters used for data (image) augmentation process.

TABLE I. Parameters for Data Augmentation

| | |
|---|---|
| **Rescale** | 1.0/256.0 |
| **zoom_range** | 0.4 |
| **rotation_range** | 30 |
| **horizontal_flip** | True |
| **vertical_flip** | True |
| **shear_range** | 0.3 |
| **fill_mode** | nearest |
| **width_shift_range** | 0.2 |
| **height_shift_range** | 0.2 |
| **validation_split** | 0.2 |

### B. *Convolutional Neural Network (CNN) Model*

The CNN model is made with a sequential model from Keras with one input layer and one output layer. In the first to third layers, the parameters used are a filter of 32, ReLU activation function, kernel size (3,3), and pool size (2,2). In the fourth to sixth layers, the parameters used are the same as the previous layers, but the filter used becomes 64. In the seventh to ninth layers, the filter parameters used are 128. In the tenth to twelfth layers, the filter used is 256. In the thirteenth to 17th layers, the parameters used are units of 256, 128, and 5, relu and softmax activation functions, and Dropout of (0.1). Then modeling is carried out with a total of 80 epochs. The model that is made is then loaded into h5 format for the deployment stage. Table 2 shows the details of the CNN model used.

TABLE II. CNN Models Architecture

| Layer (type) | Output Shape | Param |
|---|---|---|
| conv2d (Conv2D) | (None, 256, 256, 32) | 896 |
| conv2d_1 (Conv2D) | (None, 256, 256, 32) | 9248 |
| max_pooling2d (MaxPooling2D) | (None, 128, 128, 32) | 0 |
| conv2d_2 (Conv2D) | (None, 128, 128, 64) | 18496 |
| conv2d_3 (Conv2D) | (None, 128, 128, 64) | 36928 |
| max_pooling2d_1 (MaxPooling2D) | (None, 64, 64, 64) | 0 |
| conv2d_4 (Conv2D) | (None, 64, 64, 128) | 73856 |
| conv2d_5 (Conv2D) | (None, 64, 64, 128) | 147584 |
| max_pooling2d_2 (MaxPooling2D) | (None, 32, 32, 128) | 0 |
| conv2d_6 (Conv2D) | (None, 32, 32, 256) | 295168 |
| conv2d_7 (Conv2D) | (None, 32, 32, 256) | 590080 |
| max_pooling2d_3 (MaxPooling2D) | (None, 16, 16, 256) | 0 |
| flatten (Flatten) | (None, 655536) | 0 |
| dense (Dense) | (None, 256) | 16777472 |
| dropout (Dropout) | (None, 256) | 0 |

| | | |
|---|---|---|
| dense_1 (Dense) | (None, 128) | 32896 |
| dense_2 (Dense) | (None, 5) | 654 |

### C. Evaluation Model CNN

The results of the modeling that has been created are depicted in the accuracy and loss graphs, as well as the confusion matrix which is explained in Figure 2 below.

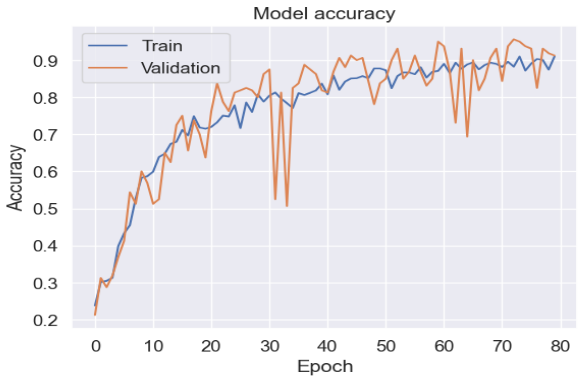


Fig 2. Model Accuracy with 80 Epochs

Based on Figure 5, training and validation accuracy increase with the number of epochs, indicating that the model learns from the data over time. After about 20 epochs, the increase in accuracy slows down and starts to fluctuate, but the accuracy continues to increase until it reaches above 90%. Validation accuracy is more volatile or has many spikes than training accuracy which is more consistent because the model generally performs better with previously seen data (training data) than with freshly acquired data (validation data).


Fig 3. Model Loss with 80 Epochs

Based on Figure 3, the model loss throughout the epoch continues to decrease significantly, indicating that the model learns from the data over time and becomes better at predicting the target.

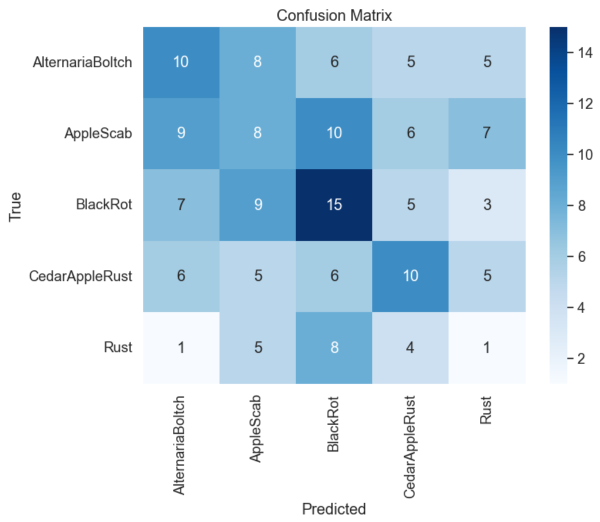


Fig 4. Confusion Matrix Result

Figure 4 shows the confusion matrix of correct predictions for each class. Based on the confusion matrix results, Table 3 below describes the Precision, Recall, and F1 Score values of each class. These results are taken from testing 164 test images.

TABLE III. SUMMARY OF THE RESULTS

| Class | Precision (%) | Recall (%) | F1 Score (%) |
|---|---|---|---|
| AlternariaBoltch | 30.30 | 29.41 | 29.85 |
| AppleScab | 22.86 | 20.00 | 21.33 |
| BlackRot | 33.33 | 38.46 | 35.71 |
| CedarAppleRust | 33.33 | 31.25 | 32.36 |
| Rust | 4.76 | 5.26 | 5.00 |

From the test results, it can be concluded that the CNN model created is the best at predicting BlackRot disease which is marked by the darkest area on the true and predicted diagonals. The model can also predict other disease classes well such as AlternariaBoltch, AppleScab, and CedarAppleRust. However, the model is not good or is still wrong in classifying the Rust class disease. This is likely because the image of the disease leaf in the Rust class is somewhat similar to the AppleScab class, predicting the type of disease slightly wrong.

### D. Deployment

After the modeling and evaluation are complete, the model is deployed to the website. This deployment process is carried out using the Flask framework. On the website that is created, users can upload photos of apple leaves affected by the disease, then the model will process it and will tell the type of apple leaf disease from the image uploaded by the user. Figure 5 shows the interface of the web-based apple leaf disease classification, starting from the initial display, image upload results, and the classification results that come out.

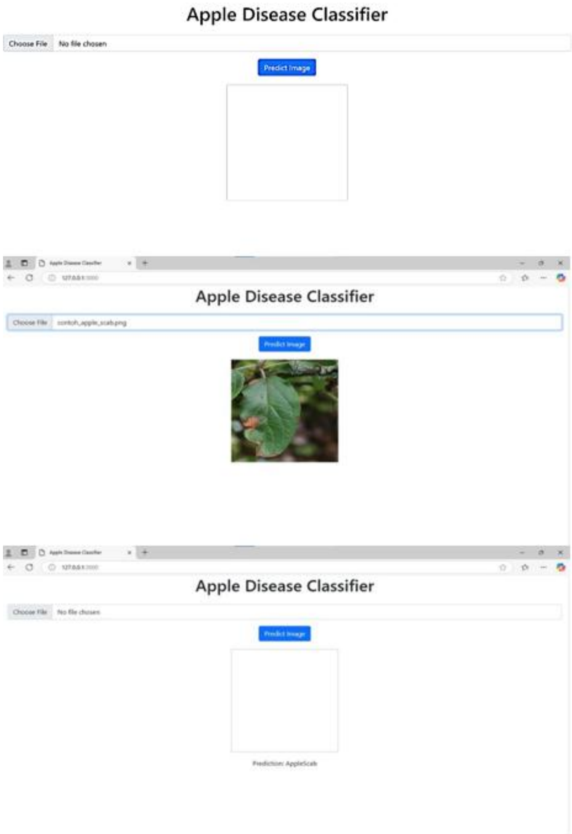


Fig 5. Deployment of Apple Leaf Disease Classification

## V. CONCLUSION

Apple leaf disease can cause significant economic losses to apple farmers. Therefore, early detection and treatment of this disease are very important to minimize crop losses. The application of Convolutional Neural Networks (CNN) in apple leaf disease detection has been proven to be efficient and accurate in several previous studies. CNN's strength is primarily found in its capacity to extract useful features from images. As the number of epochs increased, there was a noticeable increase in both the training and validation accuracy graphs, indicating that the model has learned well from the data. The evaluation results with the confusion matrix also provide an overview of the model's performance in predicting disease types. The model successfully predicted several disease classes with a high level of accuracy, however, there were weaknesses in the classification of the "Rust" type of disease which was similar to the "AppleScab" type. In addition, the developed CNN model is not only efficient in analysis but can also be integrated into web applications. This increases accessibility and convenience of use for apple farmers. Suggestions for further research are to improve the accuracy of the model in predicting certain disease classes, especially the "Rust" class which is the weakness of the model in this study. One way that can be done is by increasing the number of datasets for Rust classes, or implementing more powerful image processing techniques such as augmentation.

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