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Classification of tea leaf disease using convolutional neural network approach

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ABSTRACT

Leaf diseases on tea plants affect the quality of tea. This issue must be overcome since preparing tea drinks requires high-quality tea leaves. Various automatic models for identifying disease in tea leaves have been developed; however, their performance is typically low since the extracted features are not selective enough. This work presents a classification model for tea leaf disease that distinguishes six leaf classes: algal spot, brown, blight, grey blight, helopeltis, red spot, and healthy. Deep learning using a convolutional neural network (CNN) builds an effective model for detecting tea leaf illness. The Kaggle public dataset contains 5,980 tea leaf images on a white background. Pre-processing was performed to reduce computing time, which involved shrinking and normalizing the image prior to augmentation. Augmentation techniques included rotation, shear, flip horizontal, and flip vertical. The CNN model was used to classify tea leaf disease using the MobileNetV2 backbone, Adam optimizer, and rectified linear unit (ReLU) activation function with 224×224 input data. The proposed model attained the highest performance, as evidenced by the accuracy value 0.9455.

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1. INTRODUCTION

Computer technology has advanced fast in recent decades, revolutionizing various industries, including agriculture. The advancement of computer technology in agriculture has offered benefits to farmers, including increased productivity, efficiency, and competitiveness. Computer technology has been used in a variety of applications, including land management [1], fruit ripeness [2]–[4], and plant diseases [5]–[7]. Tea leaves may harbor plant diseases. It requires extra care because tea is one of the world's most popular beverages, consumed by millions daily. Tea production is frequently impeded by illnesses that harm the tea leaves. These diseases can cause significant crop yield loss and negatively influence tea production. In recent years, researchers have been exploring various computer vision models to detect and classify tea leaf diseases at an early stage. Tea plants, regarded as a prominent component of the agricultural industry, are cultivated in Indonesia, positioning the nation as the fifth-largest global producer and exporter of tea [8].

Tea leaf disease is a dominant issue encountered in tea cultivation, resulting in substantial reductions in yield and compromising the quality of the tea produced. Tea plants are susceptible to various diseases induced by fungal, bacterial, and viral pathogens, including leaf blight, leaf spot, anthracnose, and grey blight [9]. Tea leaf disease indications are usually visible on the leaves, making it hard for humans to track each plant throughout a large area. A computer vision model has been created to identify and categorize tea leaf disease in its initial phases. Since the disease's symptoms are most visible on the leaves, an image is adequate to provide the necessary information. Consequently, a computer vision model was required to investigate the illness signs that appeared and could be seen visually [10].

The convolutional neural network (CNN) model was developed to categorize plant leaf disease using various frameworks [11]–[15]. MobileNet and visual geometry group 19 (VGG19) were used to compare and investigate the effects of the proposed approach in the initial procedure, among other things. The test was conducted using three CNN models-proposed CNN model, VGG19, and MobileNet-on two different plant species: grape and potato. The accuracy rate of potatoes for the proposed CNN, VGG19, and MobileNet models were 93.78%, 95.56%, and 77.33%, while grape leaves were 93.90%, 96.30%, and 80.00%, respectively diseases [7]. Several contributions were made towards developing an automated deep feature-based classification system for subtypes of rice leaf disease. Healthy leaves, mild and severe blight, mild and severe hunger, mild and severe blasts, and moderate and challenging brown spots were among the various groups that covered a range of statuses. The model's performance was examined with different ways to transfer learning, such as Inception V3, Inception residual network V2 (ResNetV2), Xception, DenseNet121, VGG16, and ResNet50. The ability of the suggested custom VGG16 model to generalize to previously unseen images was used to evaluate its efficacy. It produced an astonishing accuracy of 99.94%, exceeding the standards set by current state-of-the-art models [11].

Additionally, a strategy for predicting potato leaf disease that uses an end-to-end hybrid deep learning framework is proposed. Pre-processing, segmentation, feature extraction and fusion, and classification are all included in the framework. In order to create more potent features, an ensemble approach was used to combine deep features from two well-known models (InceptionV3 and VGG19). For its ultimate prediction, the hybrid approach used the notion of vision transformers. The public potato leaf dataset, which includes early blight, late blight, and healthy leaves, was applied to train and assess the model. The suggested method obtains an F1-score of 96.33% and an overall accuracy of 98.66%. Using datasets from Apple (4 classes) and Tomato (10 classes), a thorough validation analysis is carried out, yielding remarkable accuracy of 96.42% and 94.25%, respectively [12]. The color attributes of the foliage image were utilized to localize the region of interest by the mixture model for region growth. Afterward, the feature extraction using a deep convolutional neural network model was proposed, and the leaf images were classified. The deep learning model employed color images to acquire knowledge of attributes representing distinct patterns, which could be differentiated using a CNN model. The examination of the proposed model's execution measure was conducted by employing the PlantVillage dataset. The results of simulating replicas indicate that the proposed model outperformed existing, well-known methods in the domain by a significant margin, with a mean classifying accuracy of 95.35% and an area under the characteristics curve of 94.7%, respectively [13].

The primary objective of this study is to create a reliable model for disease classification in tea leaves, focusing on differentiating between healthy and several diseased plants. A plant illness is indicated when spots appear on the leaves. There are several problems with the mottling on the surfaces of the leaves in this area. The proposed model was implemented using the CNN trained using various frameworks.

2. METHOD

The main objective of this work is to develop a robust model to identify diseases in tea leaves with high accuracy. The model determined the difference between healthy tea leaf plants and those with spots. Spots on the leaves were a telltale sign of a plant disease. This part has a problem with the mottling on the vegetation surfaces. The proposed model was implemented by applying the CNN across several frameworks. Figure 1 shows each main process of the disease classification model for tea leaves.

2.1. Tea leaf dataset

This work employed the Kaggle dataset, which comprises a total of 5,980 images of tea leaves, with each image belonging to one of the following six categories: healthy (1,000 images), algal spots (1,000 images), gray blight (1,000 images), helopeltis (1,000 images), red spots (1,000 images), and brown light (980 images). A plant expert classified these images with extensive knowledge of the subject issue. The dimensions of these images varied and were captured using the joint photographic experts' group (JPEG) format. The images were captured utilizing a synthetic background in which tea leaves were arranged on a sheet of white paper, serving as the subject matter. Subsequently, the dataset was divided into three used in the training, validation, and testing processes. The illustration of each class of the tea leaf image is shown in Figure 2.

2.2. Pre-processing

This process was carried out on all of the images in the dataset using two techniques: resizing and normalizing. In order to minimize the computation time, the original image was resized to 224×224 pixels. Meanwhile, the normalization was rescaled for each pixel's color value by dividing by 255 to produce values ranging from 0 to 1 [16].

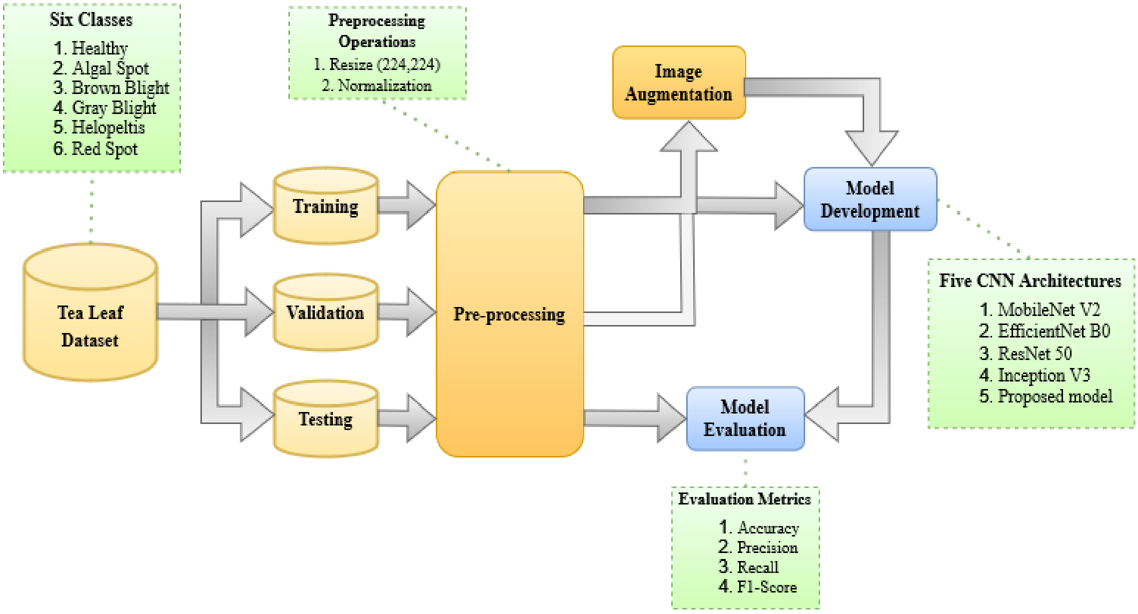


Figure 1. The main processes in the proposed model for classifying the tea leaf disease

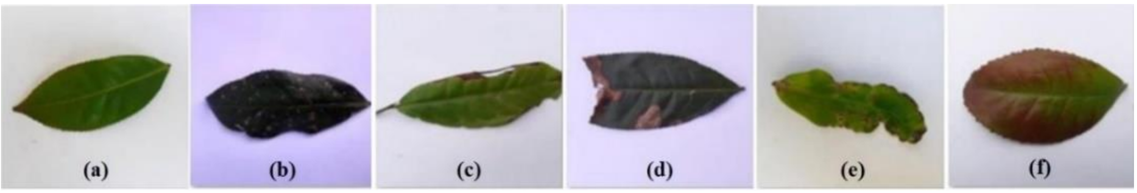


Figure 2. The example tea leaf image of each class: (a) healthy, (b) algal spot, (c) brown blight, (d) gray blight, (e) helopeltis, and (f) red spot

2.3. Augmentation

Augmentation is necessary to rectify data imbalances and inject variety into the data. This work used several augmentation techniques, including rotation, shear, horizontal flip, and vertical flip, resulting in four additional images. These augmentations were exclusively performed for the training set. Figure 3 depicts an example of augmentation results from an original image.

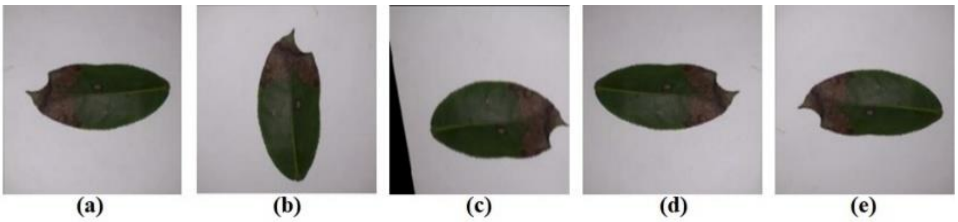


Figure 3. The example image of augmentation results: (a) original image, (b) rotation 90°, (c) horizontal flip, and (d) vertical flip

2.4. Model development

CNNs were executed to assemble the illness classification model for tea leaves. Feature extraction layer and classification layer are the two main categories of CNN layers. The features are taken from the image by the feature extraction layers, and the image is classified using these features by the classification layer. Since the model tends to be on a mobile device for farmers to use in the fields, the CNN model needs to be a tiny architecture. Hence, in order to train a lightweight CNN model that could support the robust model with minimal computational time, the model used MobileNetV2 [17], [18], EfficientNet [19], [20], ResNet50 [21], [22], and InceptionV3 [23]. Lightweight versions have the advantage of being small enough to be deployed in embedded devices. The model structure that was established in this work is as follows: i) the size of the input layer was 224×224×3, and ii) a top-down design with a flattened layer, eight dense layers with relu6 activation, 256 thick layers with ReLU activation, batch normalization, 0.1 dropout, and six dense layers with softmax activation. In addition, the following hyperparameters were utilized by the Tensorflow 2.9.0 framework: i) a binary cross-entropy loss, ii) an epoch value of fifteen, and iii) the Adam optimizer used with a learning rate of 0.0001.

2.5. Model evaluation

The suggested model of disease classification in tea leaves was tested for predictive stability using accuracy, precision, and recall as assessment parameters in this work [24]–[26]. A measure of accuracy is the percentage of data points that have accurate predictions relative to all data points. On the other hand, recall is the accurately predicted class out of all actual classes, and precision is shown as a separate class that is correctly anticipated in all class predictions. These parameters were calculated using (1), (2), and (3) [16], [25].

$$Accuracy = \frac{Number\ of\ correct\ prediction}{Total\ number\ of\ prediction} \tag{1}$$

$$Precision = \frac{Particular\ class\ predicted\ correctly}{All\ class\ predictions} \tag{2}$$

$$Recall = \frac{Correctly\ predicted\ class}{All\ real\ classes} \tag{3}$$

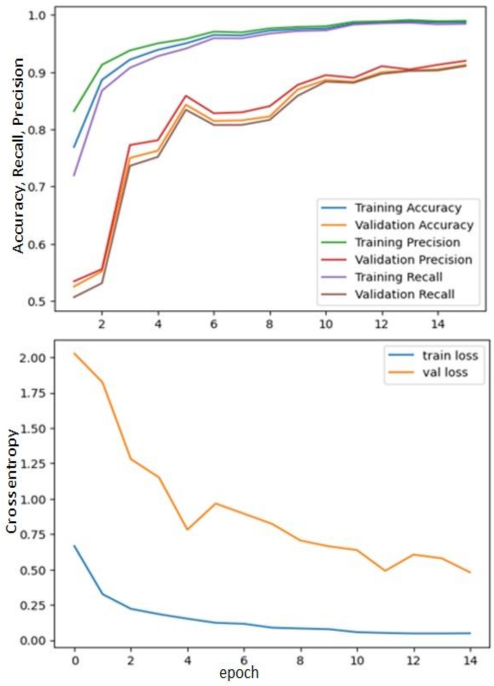
3. RESULTS AND DISCUSSION

The accuracy value has been used to evaluate the pre-trained models on the testing set. The experiment was conducted with the following network types: InceptionV3, MobileNetV2, EfficientNetB0, and ResNet50. Table 1 summarizes the outcomes of the experiment. There is a straightforward success among the networks. The parameters that MobilenetV2 generated were 2,003,174 for the overall amount of parameters and 2,000,294 for the training parameters. Compared to EfficientNetB0, InceptionV3, and ResNet50V2, MobilenetV2 required the fewest parameters. The duration that it takes to train depends on how many parameters are used. The number of parameters affects the training time. Therefore, the training time from the lowest to the highest generated by MobilenetV2, EfficientNetB0, InceptionV3, and ResNet50V2 is 19 m 1 s, 88 m 8 s, 140 m 8 s, and 248 m 6 s.

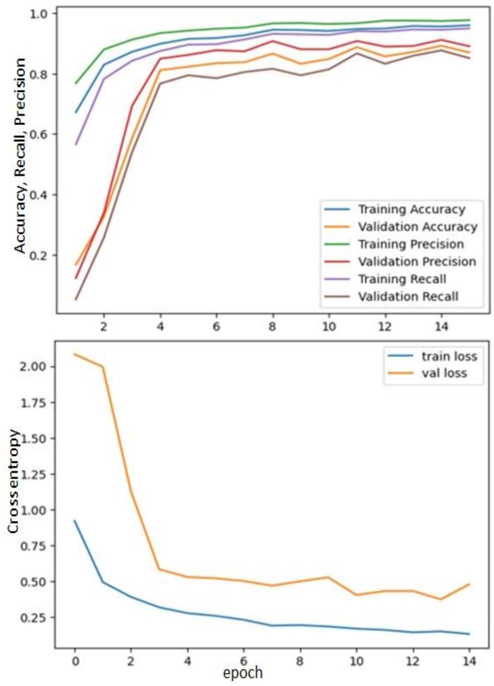
Table 1. The performance comparison of the CNN model with three types of networks

Experiment parameters	Network types			
	MobilenetV2	EfficientNetB0	ResNet50	InceptionV3
Training params.	2,000,294	5,493,960	6,107,430	5,745,702
Non-training params.	2,880	61,161	19,096,128	16,647,264
Total params.	2,003,174	5,555,121	25,203,558	22,392,966
Training time	19 m 1 s	88 m 8 s	248 m 6 s	140 m 8 s
Training loss	0.1738	0.1335	0.0912	0.2187
Training accuracy	0.9762	0.9598	0.9598	0.9252
Training precision	0.9807	0.9768	0.9768	0.9431
Training recall	0.9696	0.9495	0.9495	0.9100
Validation loss	0.4975	0.6422	0. 4795	0.8405
Validation accuracy	0.8696	0.8696	0.8578	0.8284
Validation precision	0.8647	0.8903	0.8896	0.8392
Validation recall	0.8461	0.8510	0.8529	0.8137
Testing loss	0.1692	0.2077	0.2689	0.2804
Testing accuracy	0.9455	0.9386	0.9080	0.9034
Testing precision	0.9549	0.9544	0.9153	0.9128
Testing recall	0.9375	0.9273	0.8966	0.8920

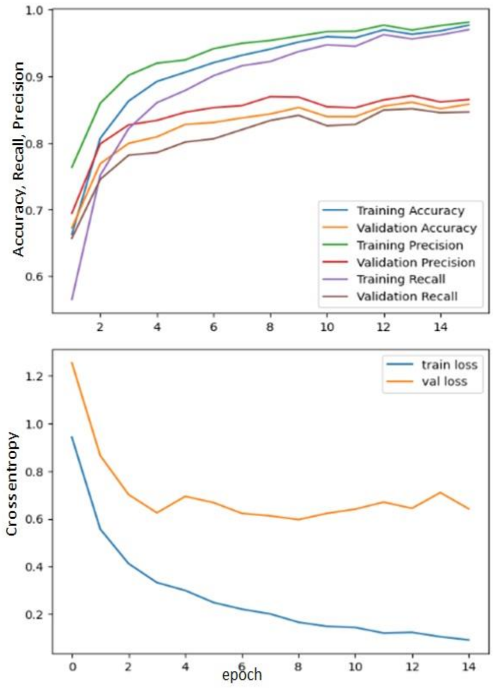
The ResNet50 model had the best results in terms of training and validation loss values, coming in at 0.0912 and 0.4795, respectively. With training and validation recall values of 0.9696, 0.9807, and accuracy of 0.9762, respectively, MobilenetV2 earned the best results in terms of misclassification. Recall=0.8461, accuracy=0.8696, and precision=0.8647, respectively, were those parameters' validation values. The outcomes for MobileNetV2, EfficientNetB0, ResNet50, and InceptionV3 models employing epoch 15 are depicted in Figures 4(a)-4(d).



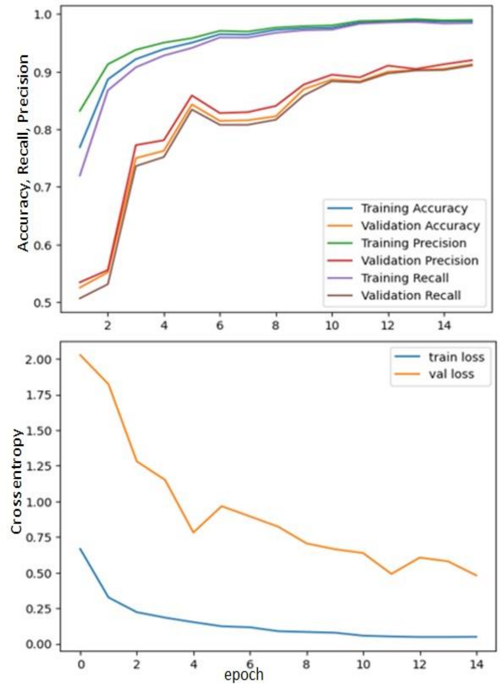
(a)



(b)



(c)



(d)

Figure 4. The CNN model's performance in disease classification of tea leaves utilizing several frameworks: (a) MobileNetV2, (b) EfficientNetB0, (c) ResNet50, and (d) InceptionV3

MobileNetV2 was the model with the lowest testing loss value, followed by EfficientNetB0, ResNet50, and InceptionV3, which produced values of 0.1692, 0.2077, 0.2689, and 0.2804. The training model that has been carried out demonstrates each of these results. On the other hand, all of the models were able to attain a testing accuracy of up to 0.9. It was determined that MobileNetV2 had the greatest accuracy value, which was 0.9455. This was followed by EfficientNetB0, ResNet50, and InceptionV3, each with values of 0.9386, 0.9080, and 0.9034, respectively. Once it involves the implementation of the MobileNetV2 model, it demonstrates the least amount of misclassification occurred. The MobileNetV2 model was found to have the greatest performance in terms of the maximum attainment of accuracy value, the lowest number of parameters, and the computing time, according to the assessment carried out against the testing set. The confusion matrix presents a detailed description of the categorization results of a disease that affects tea leaves, as shown in Figure 5. It demonstrates that the Healthy class is prone to misclassification. Five images from the healthy classes were erroneously placed in the red spot (three images) and the helopeltis (two images) classes.

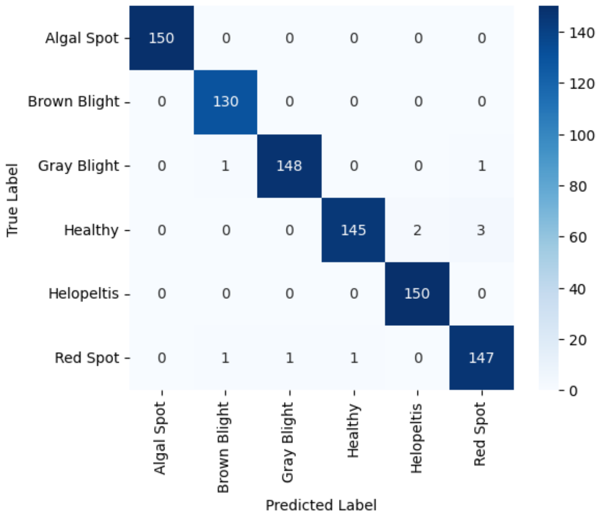


Figure 5. The example tea leaf image of each class: algal spot, brown blight, gray blight, healthy, helopeltis, and red spot

4. CONCLUSION

The illness usually emerges on the tea leaves. The overall output and quality are both negatively impacted. Therefore, early illness detection is crucial for prevention. This project aims to develop a system for categorizing plant diseases that affect tea plants. The model's formation was predicated on deep learning employing CNN with input data measuring 224×224. With an epoch value of 15 and a learning rate 0.0001, four different kinds of networks were used for the training: MobilenetV2, EfficientNetB0, ResNet50, and InceptionV3. Throughout the training, validation, and testing phases, MobilenetV2 attained the highest accuracy values of 0.9762, 0.8696, and 0.9455, respectively. Regarding computational training time and parameter count, MobilenetV2 is also the best. Based on these findings, the model is anticipated to be used for datasets that contain more data for future research. So, it is better for illness classification and prediction and can boost accuracy values.

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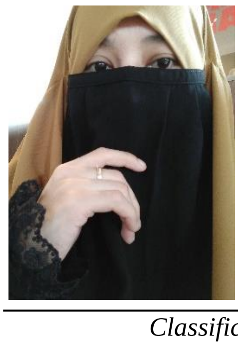
BIOGRAPHIES OF AUTHORS



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