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Original Article

Deep Learning for Coffee Disease Classification

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***Abstract** - Coffee production in Ethiopia has a long story and is also one of the major agricultural products that exported a huge amount. But coffee production faces different challenges from that widespread coffee diseases result in huge production loss in both quantity and quality. Even if different coffee diseases are still a major challenge, detection and classification of those diseases are performed only by experts, or there is not much technological advancement in this sector. This research aims to apply deep learning methods to overcome the existing problem. A deep learning model was fine-tuned and optimized to detect and classify different coffee diseases to assist farmers in applying appropriate treatment; for this research, 5600 images were captured and used for training and testing. And the best-performing model achieves 97% of accuracy. Proper tuning of hyperparameters can prevent overfitting and an appropriate choice of optimizers, resulting in an efficient classifier finally, as future research work indicated applying the model for real-life scenarios.*

***Keywords** - Deep learning, CNN, Plant disease, CBD, CWD, CLR.*

I. INTRODUCTION

As history indicates Coffee plant was first discovered in Ethiopia, and also Ethiopia is one of the largest coffee producers and exporters in the world, mainly for Arabica coffee type. And also, coffee export is a backbone for Ethiopia's economy, contributing around 20% of annual income [2]. Coffee export also contributes 60% of the annual foreign currency for Ethiopia [1].

However, due to different reasons, the annual production of coffee is lost many tons of coffee. The occurrence of different widespread diseases of coffee leads to loss both in quantity and quality. And detection and classification of coffee diseases are performed by trained individuals in the laboratory and field inspection. This requires a high level of expertise that local farmers cannot diagnose quickly and accurately. The other thing is this inspection takes much time to cover a large production area. In today's world, machine learning provides great technological opportunities for different application areas, from self-driving cars to medical image diagnoses and other areas. Also, deep learning is a subclass of machine learning based on an artificial neural network that gives the machine the ability to perform tasks like a human being. The model learns to perform classification directly from the input image, sound, and text in deep learning. And the model shows a remarkable result inaccuracy; sometimes, it achieves a result which exceeds the human level. Now a day's deep learning grows faster in the computer vision application area due to hardware advancements and a large number of data availability.
Nowadays, deep learning provides various solutions for different problems form that many researchers apply deep learning to identify different plant diseases [3]. There are different types of deep learning architecture from that deep belief network (DBN), Deep Neural Network (DNN), Convolutional neural network (CNN), and Recurrent neural network (RNN) are the major ones.
A convolutional neural network (CNN) can peak out or detect features (patterns) from images and apply that pattern for a specific task and can be used for different applications like image classification, recognition, and detection. CNN uses a small kernel or filter to extract different features from an input image ranging from low to a high-level set of details. Different researcher uses CNN for detection and classification of plant diseases. And also, for this paper CNN used to detect and classify different coffee diseases which present on Coffee Arabica. in this research VGG19 used and this study contributes an optimized VGG19 model to classify different coffee disease The primary contributions of this work are composed of an optimized VGG19 deep learning model, a dataset for different coffee diseases, and an experimental analysis of hyperparameter setups for the classification.
The remaining research section consists of the following: related works and literature, materials and methods, experimental results, conclusions, future work, and references.

II. RELATED WORK

This section will see some fundamental concepts about convolutional neural networks and plant diseases detection using different CNN architectures. Also, this section presents various recent related works to show the potential contribution of the research work.

A. Convolutional Neural Network (CNN)

A convolutional neural network (CNN) is one class or type of deep learning algorithm that shows remarkable results in the area of image-based computation like image recognition, classification, and detection, etc. [4]. Adopting a smaller kernel or filter permits the extraction of a wide range of features from a low-level set of details to a high-level range of details from an image. The first stage of learning detects Edges, curves, blobs, and other shapes [5].

Like ANN, a convolutional neural network is inspired by how mammals visualize their environment using the layered architecture of neurons in the brain. These researchers inspired and developed a similar pattern recognition model in computer vision [6]. In the human brain, visual information is processed in the cerebral cortex. In the visual cortex, we have a repetitive field with more complex stimuli for different objects [6]. In CNN, the repetitive field can be described as the region's size in the input that defines the features.

CNN is composed of a convolutional layer, activation layer, and pooling layer. Convolutional layers consist of filters and image maps. And perform a convolutional operation. Filters are a comparatively small matrix that can detect different patterns from the input image. In the convolutional layer filter slide, over the entire input image to extract the feature of the input and pass to the next layers [7].

The output from the convolution operation generates a feature map from the dot product of the kernel (filter) and the input image. Then the extracted feature map passes through an activation function like ReLU to introduce some non-linearity or reduce a negative value presented on the feature map. And the output of the activation layer feeds to the pooling layer. This layer is used to downsample the feature from the original size. There are different types of pooling functions like max pooling, average pooling, and Sum pooling. And different CNN architecture different types of activation function and pooling function also the number of total layer size differ in each model. After continuous convolution, activation, and pooling layer, the Conv layer's extracted feature passes through the flatten layer. This layer makes the extracted feature 1D then feed to a fully connected layer (FC) in FC by using the selected activation function, and the neural networks create probabilities for classifying the input [8].

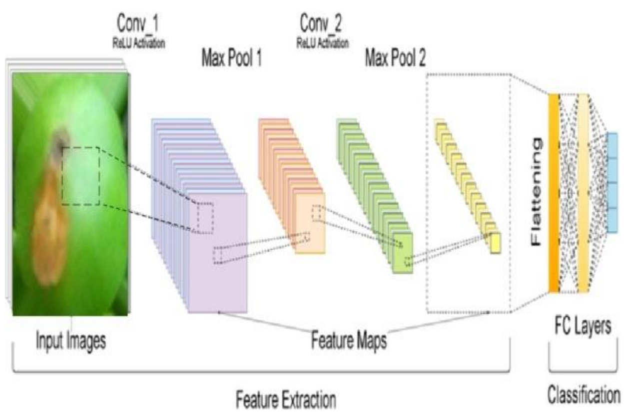


Fig. 1 Typical CNN Model Structure

B. Convolutional neural network for plant disease classification

Kamal KC et al. apply convolutional neural network models and transfer learning techniques to perform automated early plant disease detection and diagnosis using simple images of infected and healthy leaves. And diseased plants have been taken in situ and a controlled environment. They freeze a block of layer instead of individual layers this result in faster-finetuning process and, a different model trained and tested in around 23352 images from 28 classes with incorporating of 15 different plants and they select six model's architecture and finally, they got the best performance of 99.74% by fine-tuning the deep learning model which previously trained by ImageNet [9].

Vinod Kumar and Hritik Arora et al. use Resnet34 to detect and classify different plant diseases and, 15200 images of crop leaves were used during training and testing and also, they compared the proposed model with different machine learning algorithms, and the proposed model got 99.4% of accuracy [10].
Melike Sardogan and et al. apply CNN with low vector quantization to detect and classify tomato diseases presented on the leaf, and their dataset contains 500 images of tomato leaf with four classes. And in their research, they use Color information as an active component. In their proposed model, the filters are applied to three channels based on RGB components. The LVQ has been fed with the output feature vector of the convolution part for training the network. The experimental results indicate that the average accuracy in detecting and classifying different tomato diseases is 90% [11].

Sumathi Bhimavarapu and Panicker J Vinitha apply CNN for plant disease detection and classification. Different scenarios took to capture plant disease. The collected data set consists of 15617 images under restricted cases improvising a training model on CNN with transfer learning. And after training, the proposed model got an accuracy of 98.56% on the considered test vectors providing the required feasibility [12].

Ishrat Zahan Mukti and Dipayan Biswas propose transfer learning with ResNet50 to classify different types of plant disease. The data set contains 70295 for training, 17572 for validation with 38 classes of a plant leaf. And they use ResNet50 with a transfer learning approach, and also, for comparison purposes, they employ other deep learning models. The proposed model has given the best performance of 99.80% training accuracy [13].

C. VGG19 Deep Learning Architecture

For this research, VGG19 is used to detect and classify different types of coffee diseases. The term VGG comes from the first developer's visual geometry group at oxford. VGG19 is a very deep convolutional neural network used for image classification VGG19 architecture has 19 layers out of the 19 layers, 16 for convolutional layer, 3 fully connected layers, 5 max-pooling layers, and 1 Softmax layer. The overall the architecture of the VGG19 model is as input layer it accepts 224× 224×3, and as a preprocessing, it subtracts the mean RGB value from each pixel, computed over the whole training set. The first convolution layer applies a filter with the size of 3×3 and stride of 1 pixel. As a pooling function, it uses Max pooling with the size of 2×2 pixel with stride 2 as an activation ReLU is used all over the layers. The final layer uses three fully connected layers where two of which have the size of 4096, and the final layer has 1000 classes with activation function of Softmax [14].

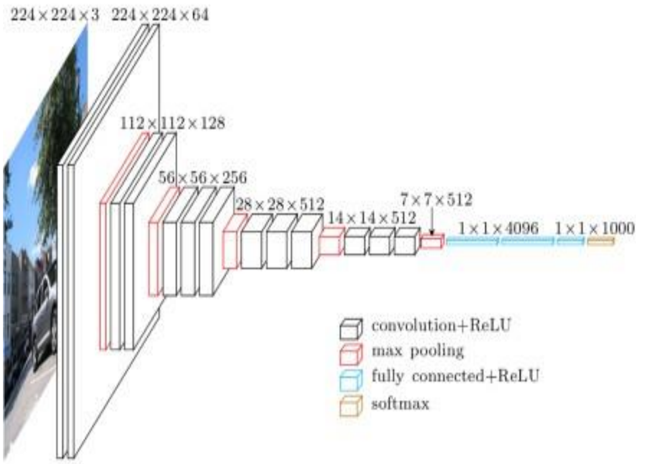


Fig. 2 Overall VGG19 Architecture [14]

III. MATERIAL AND METHOD

This section presents the detailed procedure of how to use CNN for coffee diseases detection and classification. The basic step in the working model flow is described in the figure below. The selected CNN model which is VGG19 start the learning process by accepting input image and followed by simple preprocessing performed in VGG19 which is it subtracts the mean RGB value from each pixel value. And the model uses its pre-trained weight of VGG19, and then we perform optimization of model parameters. Then, a test was performed along with model performance analysis using evaluation metrics.

A. Dataset and preprocessing

The dataset for this research is around 5600 images of seven different types of coffee diseases. And the dataset was collected from different coffee farms and research centers. The VGG19 model accepts an image with the size of 224x224 so, it resized all input images to 224x224 dimensions with a depth of 3. All the images were labeled appropriately and carefully by coffee disease experts to ensure proper labels for classification. The dataset is arranged in training, validation, and testing. The training set is used mainly for feature extraction to train the model. The validation set data takes about ten percent of the whole dataset to provide initial verification of how the model can generalize while on training. Finally, the test dataset is used to justify how the proposed model can generalize for the data it hasn't seen before or how effective the model can operate in actual scenarios.

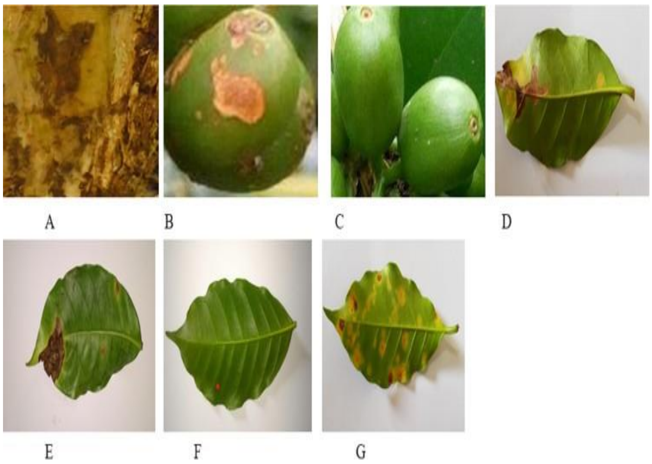


Fig. 3 Image Dataset (A) CWD, (B) CBD, (C) Normal beery, (D) leaf miner, (E) predominant stress

B. Proposed model workflow

The general workflow for the proposed model is described in the figure below.

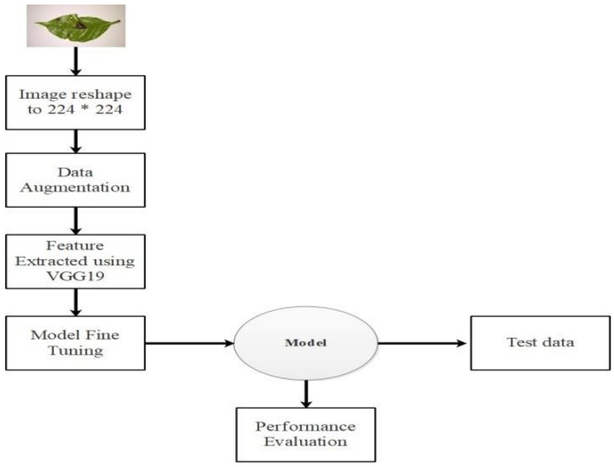


Fig. 4 General Workflow

C. Fine-Tuning

To get a model with better accuracy, the model sets to proper tuning towards the desired task. And transfer learning allows any CNN model to maintain the original weights and previously acquired parameters; this is used to deliver efficient results without intense computing power [15]. Fine-tuning is the process of making small modifications to get a more accurate model. And also, setting hyperparameter is a crucial step since it affects the result of the model.

D. Hyperparameters

In deep learning, hyperparameters have a vital role in the result or outcome of the model since hyperparameters help the model give a significant result. So, Choosing the right values can initially make an enormous difference, making hyperparameter tuning a necessary process. For this research

Table 1. Hyperparameter setup 1

Hyperparameters	Value
Number of epochs	50
Fully connected layer	512
Dropout rate	0.5
Batch size	16
Optimizer	SGD
Learning rate	0.0001

Table 2. Hyperparameter setup 2

Hyperparameters	Value
Number of epochs	50
Fully connected layer	1024
Dropout rate	0.5
Batch size	16
Optimizer	Adam
Learning rate	0.0001

Many epochs, learning rate, dropout rate, batch size, fully connected layer, and optimizer were used as hyperparameters. Based on these hyperparameters, two options were used for the experimental process.

IV. EXPERIMENTAL RESULT

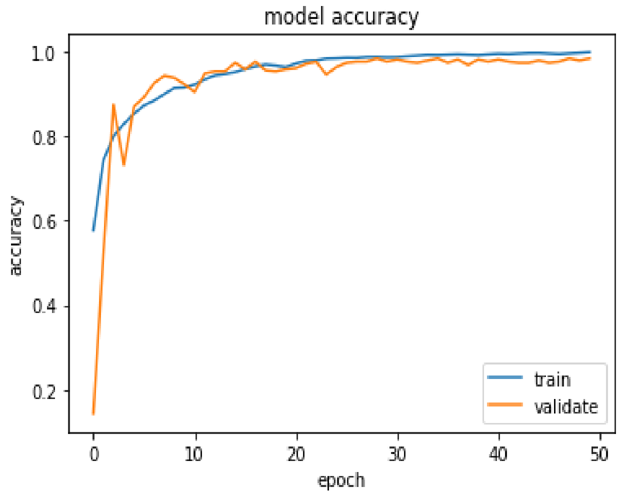
The model starts the training process using a training dataset that contains the original image and some augmented images. Also, in this stage, validation data is provided to measure the performance of the model how it generalizes for new data. Figure 1 indicates that how the model converges during the training and validation stage. And additionally, figure 2 indicates the overall loss of the model in both training and validation.

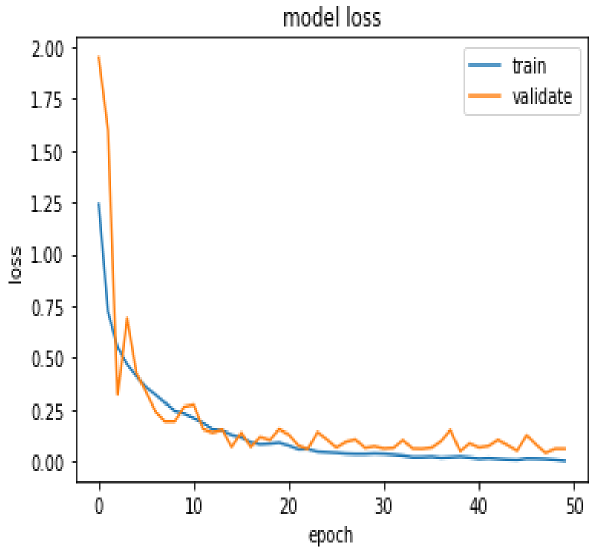
A. Learning curve

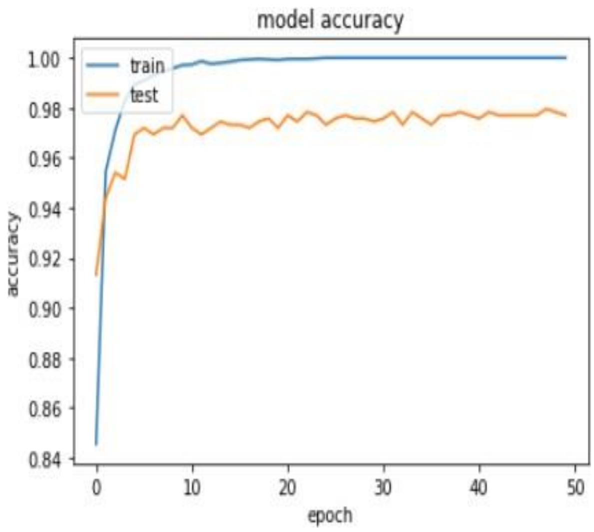
The learning curve indicates the visual representation of how the model learned and archives what percent of accuracy and loss during each epoch. In this research, 50 epochs were used, and Figure 1 illustrates the result for the first hyperparameter configuration, indicating each model's accuracy with the training and validation sets. The second hyperparameter configuration has suffered a little overfitting problem compared with the first configuration. From the above figures, we can see that the model learning curves for both hyperparameter configurations. In the first configuration, the model achieves mean training accuracy of 99% and 95% of validation accuracy and 8.52% of mean loss, and 15.6% of mean validation loss. And the model with the second configuration obtains 95.41% of training accuracy, 90.1% validation accuracy and 13.6% training loss, and 61.2% validation loss.

B. Confusion matrix

A confusion matrix is used to describe the overall per-performance of the model by using a tabular representation. To generate confusion matrices, it accepts the label of the test data and compared with predicted output from the model. In this research, 1120 images were used to test the model's performance, and each class had 160 images. Then the model was tested using the given image, and its result is presented in the below figure.







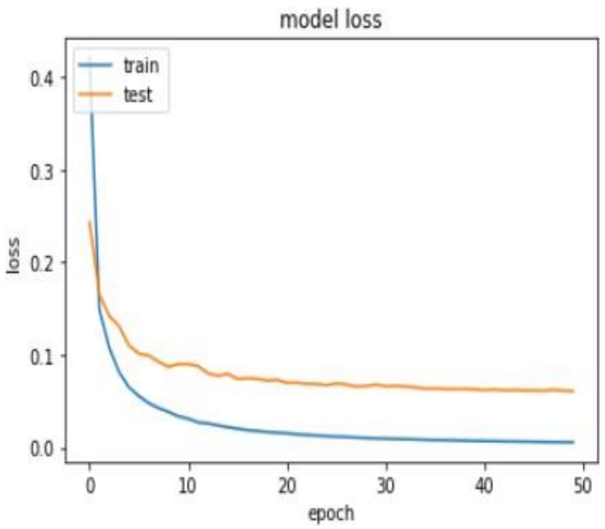


Fig. 5 Learning curve

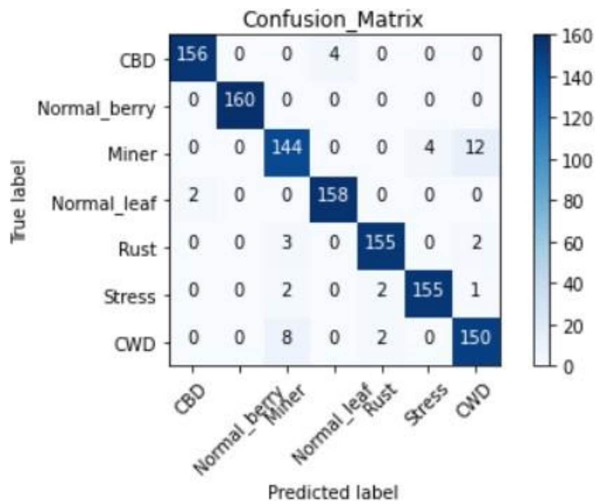


Fig. 6 Confusion matrix

C. Model Performance

Table 3 presents the overall model performance for both hyper-parameter configurations.

Table 3. Evaluation matrix

Classes	Precision	Recall	F1-score
CBD	0.987	0.975	0.981
Normal berry	1	1	1
Leaf Miner	0.917	0.900	0.900
Normal Leaf	0.975	0.988	0.981
Leaf Rust	0.975	0.969	0.972
Predominant stress	0.975	0.969	0.972
CWD	0.909	0.938	0.923
Weighted average	0.963	0.963	0.963

D. Discussion

With the given two hyperparameter configurations, the proposed model got 97% testing accuracy with the first configuration of hyperparameter, which contains 50 as the number of epochs, 512 fully connected layer, 0.5 dropout rate, 16 batch size, SGD optimizer, and 0.0001 learning rate and with the second configuration which contains 50 as the number of epochs, 1024 fully connected layer, 0.5 dropout rate, 16 batch size, Adam optimizer and 0.0001 learning rate the proposed model achieves 94.8% of testing accuracy.

V. CONCLUSION

This research applied deep learning for the detection and classification of different coffee plant diseases. Also, it indicates that the application of CNN toward plant diseases classification. The proposed VGG19 model achieved 97% accuracy with the first hyperparameter configuration. Even with the smaller number of neurons, the optimized VGG19 model became a lot more efficient with less training time consumed, delivering excellent results. Also, the help of the given set of hyper-parameters significantly increased the generalization for the classification task and prevented cases of overfitting. With this work, a new profound method of diagnosing different coffee plant diseases can now help farmers and farmlands preserve more of their resources for future consumers and the like.

For future works, the proposed model must be implemented for the actual application to help farmers in a particular time of need. Also, the model can deploy for coffee disease classification. This can serve as a real-time monitoring system since the model is MobileNet. It can be deployed in mobile de- vices and explore the potential of automating the application of treatment for coffee plant diseases.

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