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ETHIOPIAN COFFEE LEAF DISEASES IDENTIFICATION USING DEEP LEARNING FEATURES

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***ABSTRACT*:** Coffee is the majorly traded commodity used by one–third of the world's population as a beverage and Ethiopia is the home land of coffee arabica, it covers 7-10 % of the world's coffee production. This research work, focuses on the four major types of coffee leaf diseases that reduces coffee production in Ethiopia ,these are brown eye spot (BES),coffee berry disease (CBD),coffee leaf rust (CLR) and coffee wilt disease (CWD).In this paper ,we proposed Ethiopian coffee leaf diseases identification using deep learning features. The images of the coffee leaf diseases were captured from the regions of Ethiopia where more coffee is produced, i.e. Jimma and Zegie. We compared gaussian filtering, median filtering and the hybrid of the two filtering techniques to remove noises from coffee leaf images and we have got better result from the hybrid of the two filtering techniques. And also we applied KMeans clustering for segmentation and CNN for feature extraction. Finally, we made a comparison between CNN-Softmax classifier and CNN-SVM classifier .The experimental results showed that SVM performs better than softmax classifier in terms of performance and computational time. Our proposed model with SVM classifier achieved an overall classification accuracy of 96.5%.

Keywords: Ethiopian coffee, SVM, CNN, coffee disease

1. INTRODUCTION

Coffee is the most important traded commodities next to petroleum and also consumed as a beverage by one third of the world's population (Yimeru, 2020). Now day's coffee uses as an input in some food processing industries, for instance it is used as flavoring to various pastries, ice-creams, chocolate, candies (Mengsitu et al, 2016; Aebissa, 2012).). The genus Coffea consists of over 125 species in the world (Krishnan, 2017). Among all these species only the three species of Coffea are economically important such as Arabica L. (Arabica coffee) presently accounting for about 60% of world trade; C. Canephora (Robusta coffee), accounting for most of the rest of the trade and C. Liberica (Liberian coffee) contributing less than one percent (1%) (Waller et al, 2007).

The coffee cultivation sector consists the wider range in the Ethiopian agriculture. Ethiopia is the largest producer of coffee in Sub-Saharan Africa and is the fifth largest coffee producer in the world next to Brazil, Vietnam, Colombia, and Indonesia, contributing about 7-10% of the total world coffee production (Yimeru, 2020; Teferi, 2018; Ayalew, 2014,and ICO, 2018). But if we consider only coffee Arabica, Ethiopia is the third largest coffee producer developing country next to Brazil and Colombia. The Ethiopian culture has a greatest dependency on the coffee ceremony and coffee takes a lion share in Ethiopian economy (Yimeru, 2020).

Coffee product can be degraded in Ethiopia due to different factors, especially due to coffee plant diseases like Brown Eye Spot (BES), Coffee Berry Disease (CBD), Coffee Leaf Rust (CLR), Coffee Wilt Disease (CWD), etc. Brown Eye Spot (BES is caused by the Cercospora coffeicola fungus. It creates round brown spots on the foliage which develops a gray-brown center with a red-brown margin and may be surrounded by yellow lesions (Sorte et al., 2019). Coffee berry disease (CBD) is a disease caused by the Colletotrichum kahawae fungal pathogen. This diseases develop smaller, water soaked lesions on the young, growing berries that quickly become dark brown or black and slightly sunken (Teferi, 2018). Coffee Leaf Rust (CLR) is a fungal disease caused by the fungus called Hemileia vastatrix that demolish the coffee plant at its peak growing levels (Rutherford & Phiri, 2006). The pathogen mostly affects the leaves of the coffee and causes chlorotic lesions or yellow powdery pustules on the underside of the leaves which reduces photosynthetic area of the plant. Coffee Wilt Disease (CWD) is caused by the Fusarium xylarioides fungus (Hindorf & Omondi, 2011; Rutherford & Phiri, 2006). The first symptoms of CWD are yellowing, folding and inward curling of the leaves. Then, the leaves become limped, dry up and turned into brown and ultimately drop off, lastly the trees completely become leafless.

Based on the fact that most of the plant leaves has been used as a source of food for the growing of a plant by the process of photosynthesis, disease in leaf affects the photosynthesis process thereby leading to plant death (Arivazhagan&Ligi, 2018). A timely and accurate identification of plant diseases plays an important role in preventing the loss of productivity of agricultural products (TURKOGL& HANBAY, 2019). The oldest system for identification of plant diseases was time consuming, ineffective, and expensive and labor intensive and error prone (Arivazhagan&Ligi, 2018 and Alemayehu, 2017).

Now a day's, the use of modern technologies in the agriculture industry have an important contribution to help agricultural experts. One of the emerging technologies is the use of image processing or computer vision for the identification of different plant diseases.

Image based disease analysis approach has much importance over the traditional one because of its effectiveness, efficiency and non-subjectivity. Image processing is the technique which is used for measuring affected area of disease, and to determine the difference in the color of the affected area.

The deep learning approach clearly the Convolutional Neural Network (CNN) is an outstanding tool for resolving computer vision problems for a variety number of application areas. CNN is does not required hand-crafted feature extraction (Yamashita et al., 2018) because it performs both feature extraction and classification by itself (Arivazhagan&Ligi,2018) and also it has a great ability to extract robust and high-level features due to its multiple convolution and pooling layers.

2. LITERATURE REVIEW

Image processing technique plays a vital role in the area of agricultural industry to diagnosis plant diseases at different stages of production. Now a day's, deep CNN approaches, becomes the most powerful machine learning technique in image processing. The authors (TUROGLU&HANBAY, 2019), proposed automatic plant diseases and pest detection using deep learning features. They were used transfer learning and deep feature extraction methods. The extracted features using deep learning are classified by support vector machine (SVM), extreme learning machine (ELM) and K-nearest neighbor (KNN) classification methods. Finally, the authors concluded that the CNN feature extraction with support vector machine (SVM) classification gives better results than transfer learning methods.

The paper studied by (Jadhav et al., 2020), presented an automated system for identifying the soybean diseases using a transfer learning approaches for the pre-trained deep learning AlexNet and GoogleNet classification. In this research work, the authors modified the last three layers of the GoogleNet and make modifications on some CNN parameters like learning rate, number of epochs and the number of iterations to enhance the classification performance. Finally, the authors used fivefold-cross validation methods for evaluating the performance of the classifier and they achieved an accuracy of 98.75% and 96.25% for GoogleNet and AlexNet respectively. The work done by (Arivazhagan & Ligi, 2018), proposed an automated mango leaf diseases identification using deep learning based approach. In this research work, the authors applied CNN for both feature extraction and classification. Finally they achieved an overall accuracy of 96.67% for identifying the mango leaf diseases.

The research work done by (Yimeru ,2020), the author developed automatic identification of diseases and pest damage from the leaf and berry parts of the coffee plant using image processing and machine learning. The author used two color space (such as L*a*b and YCbCr color spaces) and texture filter segmentation algorithm .He was applied feedforward artificial neural network (ANN) to classify coffee plant diseases and pests. ANN result was compared to the results obtained from support vector machine and K-nearest neighbor classification algorithms. Finally, ANN performed better performance and achieved an overall classification accuracy of 91.9%. In (Sorte et al, 2019), the authors proposed an automatic coffee plant diseases recognition system for Cercospora (brown eye sport) and coffee leaf rust diseases. They were used two texture attribute extraction approaches GLCM and LBP and also the texture vector computed for a set of images and used as an input for the feed forward neural network. The results compared to the recognition rate of CNN without extraction of texture attributes. At the end, the CNN approach showed better results than texture extraction methods with sufficient training dataset samples.

The authors Manso et al., (2019) have been developed a mobile phone system (App) to detect and classify the coffee leaf rust and coffee leaf miner and automatically identify or calculate the degree of severity. They applied k-means clustering, Otsu Algorithm, and iterative threshold algorithm over the two color spaces (such as HSV and YCbCr color spaces) for segmenting the diseases and pests from the healthy parts of the coffee leaves. They trained the model using artificial neural network (ANN), Back propagation neural network (BPNN) and Extreme learning machine (ELM). Finally, the results of ELM is slightly better than ANN and BPNN. Vassallo-Barco et al., (2019) presented automatic identification of nutritional deficiencies for Calcium (Ca), Iron (Fe), Boron (B), and potassium (K) using shape and texture descriptors in images of coffee plant leaves. The authors used Otsu's method of segmentation and Blurred Shape Method (BSM) with Gray-level Co-occurrence matrix (GCM) feature extraction. Then extracted features classified using KNN, Naïve Bayes and Neural network classification algorithms. Finally, they obtained good accuracy associated with Boron (B) and Iron (Fe) deficiencies but they got poor results for Calcium (Ca) and Potassium (K) deficiencies.

The authors (Mengsitu et al., 2016), proposed automatic identification of the three major Ethiopian coffee leaf diseases using image processing. They used five different segmentation techniques such as Otsu, K-means, Gaussian distribution, FCM and the combination of Gaussian distribution and K-means clustering. The authors applied Gray-level co-occurrence matrix (GLCM) and color features for extracting features from Ethiopian coffee leaves but they used traditional features like color, shape and texture, these features gives poor performance when used alone (TUROGLU&HANBAY, 2019). And they trained the model using artificial neural network (ANN), Naïve Bayes and SOM and RBF. Finally, the combination of Gaussian distribution and K-means clustering with the hybrid of SOM and RBF classification methods gives better accuracy of 92.10%.

3. STATEMENT OF PROBLEM

Agriculture is the most important economic activity in Ethiopia and one of the most important agricultural exports are coffee crop products. But Coffee production is constrained by many factors, including losses due to damage caused by diseases like brown eye spot (BES), coffee berry diseases (CBD), coffee leaf rest (CLR), coffee wilt diseases (CWD),and others. The methods of coffee diseases identification in Ethiopia is through a traditional inspection and previous experiences which are subjective and non-efficient (Aycheh, 2008). The advanced solution is automating the diseases identification and classification process using different algorithms or approaches. There are previous studies on plant diseases recognition and identification technique using imaging and machine learning including coffee plants.

The paper studied by (Mengsitu et al., 2016), the authors proposed automatic identification of the three major Ethiopian coffee plant diseases but they used a traditional feature extraction methods such as color, shape and texture features. These traditional methods had very low performance when used alone (TURKOGL& HANBAY, 2019). Deep learning features have better performance over traditional feature extraction methods. This study will try to address the following questions:

- Which preprocessing technique is suitable for Ethiopian coffee plant diseases identification?
- Which classification Algorithm is suitable for Ethiopian coffee plant diseases classification?

4. EXPERIMENTATION

4.1. Materials and Tools

For collecting images of Ethiopian coffee leaf images, we used Redmi note 6 pro smart phones. When we capture the Ethiopian coffee leaf images, we fix the smartphone on a stand to reduce hand movement and helps to capture uniform images of Ethiopian coffee leaves. The Research work done by (Mengsitu et al., 2016), we captured the Ethiopian coffee leaf image at a distance of 130mm from the coffee plant up to the smartphone camera for better coffee plant image quality. The required Ethiopian coffee images are collected from the most coffee producer regions of Ethiopia i.e. from Jimma and Zegie. The labeling process is done by experts found in vegetable and fruit health clinic in Amhara region, because of some of the diseases looks similar depending on the infection status.

4.2. Implementation tools

4.2.1. Programming Language

We used python programming language for our research work. Python is an open source and the most powerful programming language for image processing or computer visions.

4.2.2. Development Tools

Experimentation was carried out on the keras prototype with Tensorflow backend on window's 10 pro operating system with Intel(R) Core(TM) i3, 4GB RAM and 2.40 GHz processor.

4.3. Design Of Coffee Image Identification Model

The proposed model architecture for Ethiopian coffee leaf diseases identification consists of a series of steps; namely image acquisition, preprocessing, segmentation, feature extraction and identification (classification). The architecture for the proposed model is graphically represented in figure 1 below. The first step in any image processing system is image acquisition. As shown in figure 1, there are two phases; the training phase and the testing phase. The training phase starts before the testing phase to train the proposed model whereas the testing phase follows the preceding training phase to evaluate the trained model performances by giving new dataset image. The proposed model starts by taking the whole Ethiopian coffee leaf image dataset for preprocessing. In preprocessing step, image resizing, noise removal by using gaussian filtering, median filtering and the combination of gaussian filtering and median filtering is applied to select the best filtering technique. After preprocessing, the next step is image augmentation. Image augmentation helps to prevent overfitting by increasing the number coffee leaf images, and then splitting the augmented coffee leaf image dataset into 80% train dataset and 20% test dataset. These train dataset and test dataset are segmented parallelly using KMeans clustering segmentation methods. The next major task is feature extraction, extracting useful information from the segmented coffee dataset for both train and test data using CNN. CNN mainly composed of three layers, these are Convolution layer, pooling layer and fully connected layers .The convolution and pooling layer used for feature extraction and the fully connected layer is used for classification .Finally, the extracted features from the train dataset feed into the Softmax and SVM classifier to train the model and then the extracted features from the test dataset feed into the previously trained Softmax and SVM classifier.

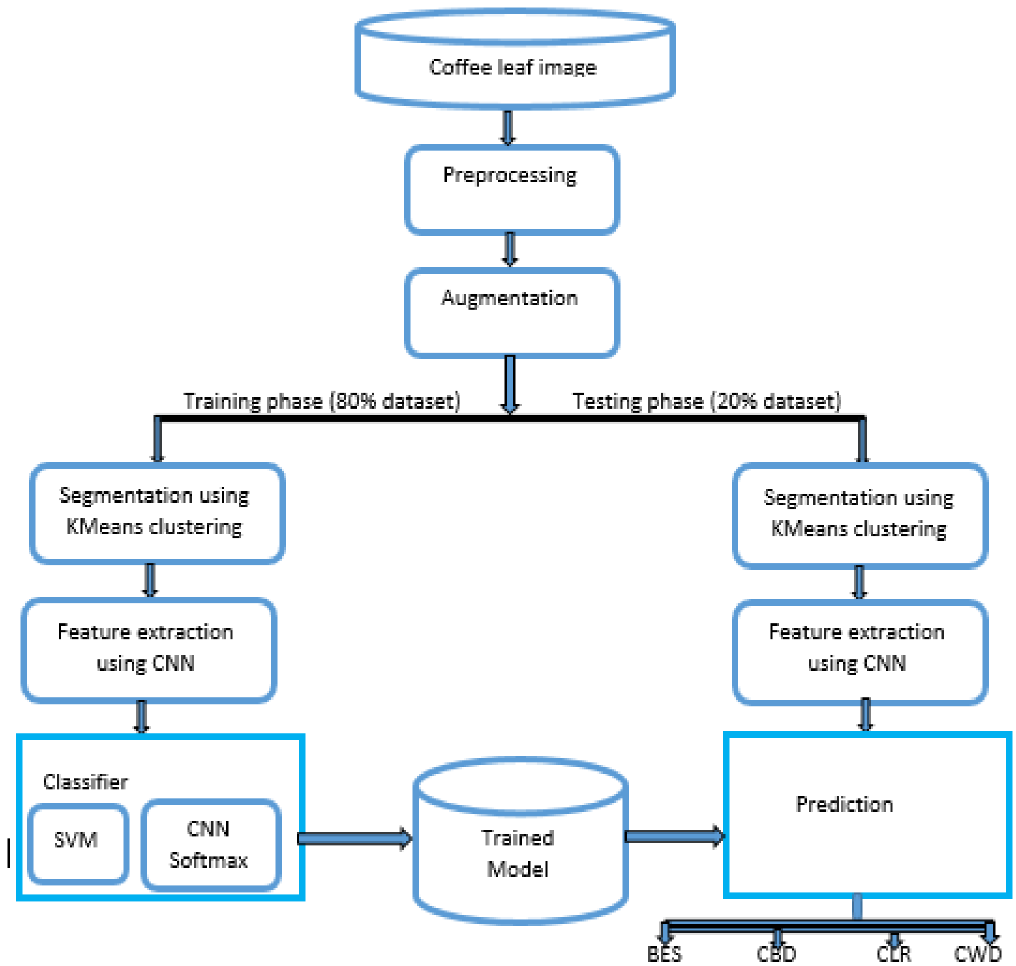

Figure 1 .The proposed model architecture

4.3.1. Convolutional Neural Network(CNN)

CNN is a feedforward multilayered hierarchical neural network which has shown good performance on different competitions related to Computer Vision and Image Processing (Khan et al.,2020). The most crucial attributes of the CNN are hierarchical learning, automatic feature extraction, multi-tasking, and weight sharing (Khan et al., 2020). A typical CNN architecture composed of repetitions of a stack of numerous convolution layers and a pooling layer, followed by one or more fully connected layers existing in between input and output layers (Yamashita et al., 2018, Sultana et al., 2018).

The Convolution and pooling layer of a CNN are helps to extract useful features from an input image, and the fully connected layers are receive the extracted features from all previous neurons as input to map them in to the output layer. In addition to the core CNN layers, batch normalization and dropout are also incorporated to enhance CNN performance. In this paper, we have used three convolution layer, three pooling layer and two fully connected layers. The last fully connected layer is the same as the class labels. To solve the problem of overfitting in our CNN model, we used Dropout layer below each Maxpooling layers and also we used on the first fully connected layer.

The convolution layer is the basic layer of CNN that performs convolution operation. It extracts meaningful features from an input image. We have used 96, 64, and 32 number of filters sizes and a 5x5 and 3x3 kernel size to extract features from coffee leaf image. The pooling layer is another layer of CNN that performs down sampling operations. This layer takes the convolutional output as an input and subsamples it to reduce the in-plane dimensionality of the feature maps (input images), number of parameters and the computational complexity of the model. We used 2x2 pool size for the first two pooling layers and a 3x3 pool size for the last pooling layer.

Activation function is a non-linearity mapping operation that helps to accelerate the learning process of our CNN model. We have used the Rectified Linear Unit (ReLU) non-linearity activation function. ReLU is the most common and more efficient non-linearity activation function than sigmod or hyperbolic activation functions (Sorte et al., 2019). Dropout is the mechanism of preventing or reducing overfitting on the training dataset by randomly skipping some units or connections. We used a dropout layer after each Maxpooling layer and also after the flatten layers with a dropping probability of 0.25 for the first two dropout layer and we used 0.3 dropping probability for the rest layers. Batch Normalization is a normalization technique used to speed up the learning process of the CNN by controlling the change in the distribution of the hidden layer values by setting a learning rate to small values for minimizing the convergence time (Khan et al., 2020).

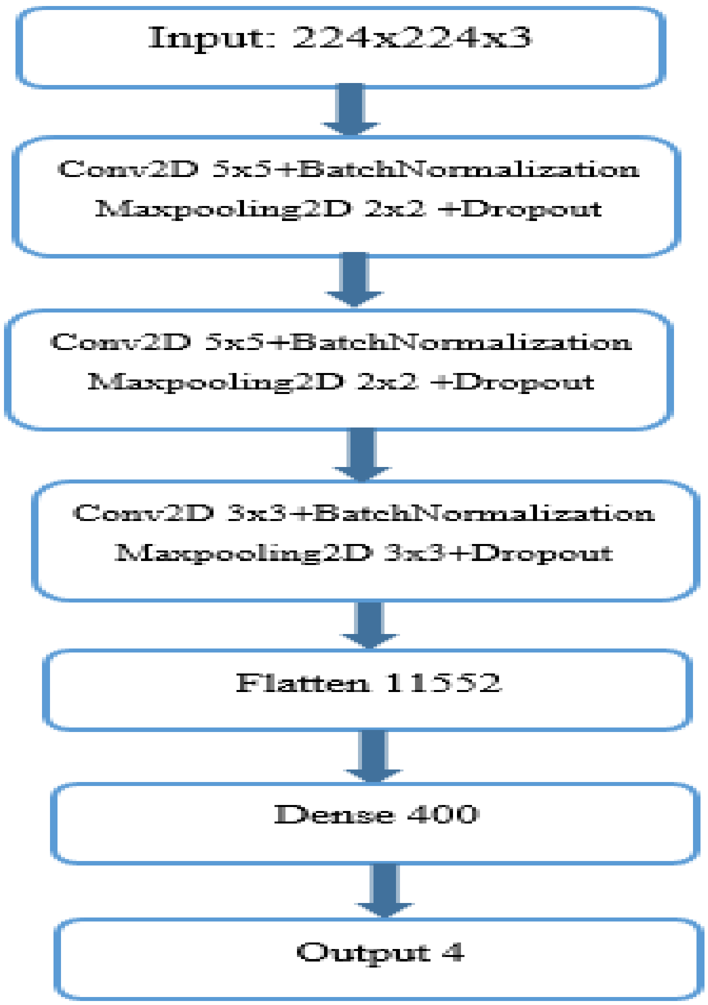

Figure 2. The proposed CNN model architecture

5. RESULTS

5.1. The proposed CNN model Experimental results using Softmax Classifier

In this experiment, we divide the total coffee image dataset into three various sets, train set, test set and validation set. Primarily, we partitioned the whole coffee image dataset into 80/20 for training phase and test phase respectively. After these, again we divide the 80% training phase dataset into 80/20 for training and validation. Finally, we have got 1280 coffee images (320 images for each class) for training, 320 coffee images (80 images for each class) for validation and 400 coffee images (100 coffee images for each class) for testing. We trained the model for 20 epochs, batch size of 32, and an initial learning rate of 0.001 (1e-3).We perform three experiments with the end to end CNN for comparing the three filtering techniques.

5.1.1. Comparison between noise filtering techniques

In this sub section, we made three experiments for choosing the best preprocessing techniques. We compared Gaussian Filtering (GF), Median Filtering (MF) and the hybrid of the two (GF-MF) filtering techniques using the proposed end to end CNN model .We have got experimental results of 92.5%, 90.5% and 95.75% accuracy for the GF, MF and GF-MF filtering techniques respectively. The GF-MF filtering technique is better than the two individual techniques because it gains the advantages of GF filtering for removing the gaussian noises and the advantages of MF filtering for removing the Salt and pepper noises. Therefore, we have used GF-MF filtering for the rest of our experiment.

Table 1. Comparison between noise filtering techniques

Experiment number	Type of filtering techniques used	Accuracy in (percentage)
Experiment 1	GF	92.5%
Experiment 2	MF	90.5%
Experiment 3	GF-MF	95.75%

5.1.2. Performance of the proposed CNN model

In this sub section, we made an experiment for measuring the training, validation and testing accuracy of the proposed CNN model. This experiment is done using the combination of GF-MF filtering techniques. We trained the proposed CNN with 1280 training coffee images and 320 validation coffee images, and we test the trained model with 400 coffee images. The model validation is done at the end of each epochs while the model trains every time per epoch. Finally, at the end of the last epochs (epochs 20), our CNN model achieved a training accuracy of 98.25%, validation accuracy of 96.88% and testing accuracy of 95.75%.

	precision	recall	f1-score	support
BES	0.98	0.92	0.95	100
CBD	0.93	0.93	0.93	100
CLR	0.92	0.98	0.95	100
CWD	1.00	1.00	1.00	100
accuracy			0.96	400
macro avg	0.96	0.96	0.96	400
weighted avg	0.96	0.96	0.96	400

Figure *3*. The precision, recall and f1_score of the end to end CNN

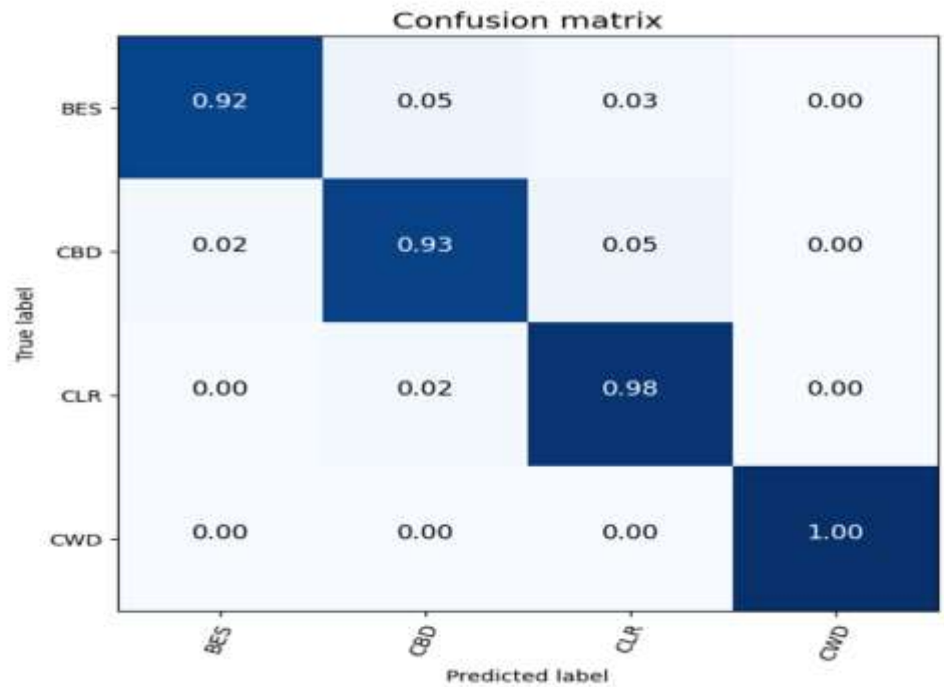

Figure 4. Confusion matrix of the testing performance of our CNN model using softmax classifier

5.2. Experimental results using SVM Classifier

The total time taken to train the proposed CNN model using Softmax classifier is around 6 hours approximately 950 seconds per epoch. So, using CNN for the classification takes huge computational time. As a result, we need to use the SVM Classifier after the flatten layers of the proposed CNN model architecture. We used radial basis function (rbf) kernel function to use SVM classifier in our multiclass classification.

In this experiment, we have used the proposed CNN for feature extraction and SVM for classification and we have achieved 96.5 % accuracy. This accuracy is greater than the proposed CNN model with Softmax classifier by 0.75 %. The CNN-SVM model takes less processing time compared with the CNN-Softmax model. The precision, recall, f1-score and confusion matrix for this experiment is presented in Figure 5 and 6 respectively.

	precision	recall	f1-score	support
BES	0.99	1.00	1.00	100
CBD	0.89	0.99	0.94	100
CLR	0.99	0.87	0.93	100
CWD	1.00	1.00	1.00	100
accuracy			0.96	400
macro avg	0.97	0.96	0.96	400
weighted avg	0.97	0.96	0.96	400

Figure 5. The precision, recall, and f1-score of the proposed CNN with SVM classifier

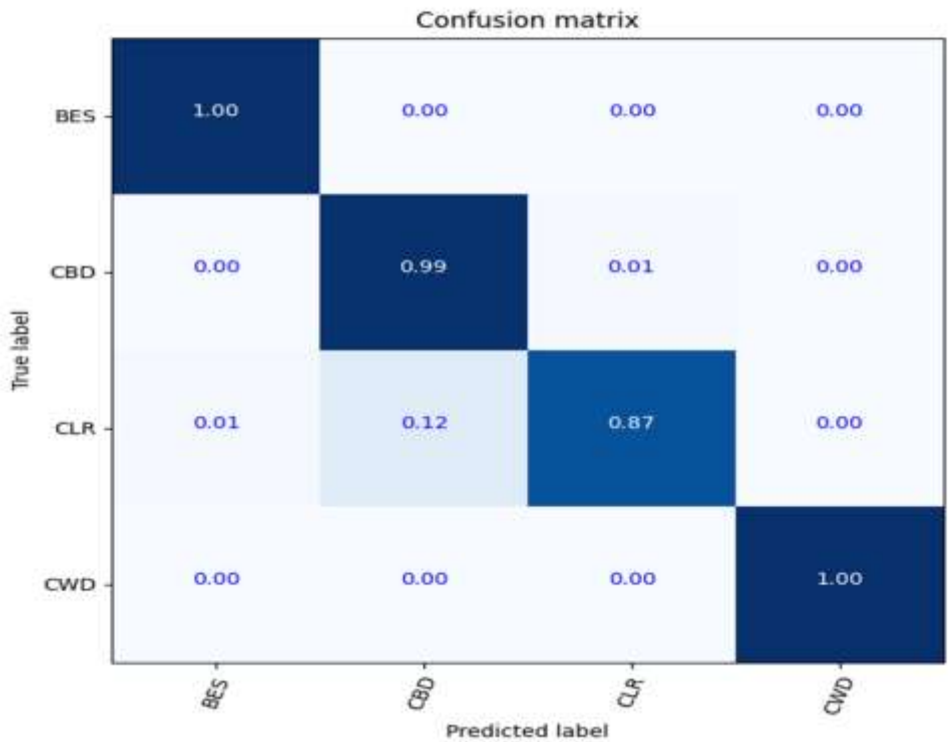

Figure 6. The confusion matrix of the proposed CNN model with SVM classifier

Table 2. Comparison between Softmax and Support Vector Machine (SVM) classifier

Feature extraction	Classifier	Accuracy	Computational time
CNN	Softmax	95.75%	6 hrs.
CNN	SVM	96.5%	Max. ½ hrs.

6. CONCLUSION AND FUTURE WORK

Coffee is the majorly traded commodity used by one –third of the world's population as a beverage. Coffee is the backbone of the Ethiopian economy that covers 7-10% of the world's coffee production, and it is the first exported commodity in Ethiopia. To maximize the revenues from the sales of coffee crops, the major hazards or treats that hinder its production (i.e. coffee diseases) should be controlled.

Coffee disease is the major treats that affects the quality and quantity of coffee production in Ethiopia. Some of the most common coffee diseases that cause damage to coffee production are brown eyespot (BES), coffee berry diseases (CBD), coffee leaf rust (CLR) and coffee wilt diseases (CWD). In order to control the damages caused by these diseases, an accurate and timely diagnosis and identification of the diseases type is very important. The main objective of this thesis work is to develop an automated Ethiopian coffee leaf diseases identification via image processing and deep learning features. For this study, we proposed a model architecture that encompasses preprocessing, segmentation, feature extraction, and identification phases.

The preprocessing phase reduces the size of the input coffee image into 244x244 and removed noises from the coffee image using GF, MF and the combination of GF-MF filtering techniques. Then GF-MF filtering performs better than GF and MF filtering techniques. In the segmentation phase, we used KMeans clustering segmentation algorithm to outline the damaged regions of coffee leaves.

The third phases of the proposed model architecture is feature extraction. We used CNN feature extraction to extract high-level features from the segmented coffee images and stored these features as a feature set in the database. After feature extraction, the classification phase is built using softmax and SVM classifier. The experimental results showed that the proposed CNN feature extraction model with SVM classifier performs better than softmax classifiers and achieved an overall classification accuracy of 96.5%. This study focuses only on the leaf parts of the coffee plant diseases. We recommend for future studies can extend this research work by incorporating additional classes (roots, stems) and new feature extraction and classification machine learning algorithms.

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