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Coffee Leaf Disease Detection using Convolution Neural Network

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***Abstract*—Coffee is one of the most widely consumed beverages globally and plays a significant role in the economy of many countries, including India. However, coffee plants are susceptible to various diseases, such as Leaf rust, Leaf miner, Cercospora which can cause substantial crop losses. Hence, early detection and diagnosis are essential for effective disease management. In this study, we propose a novel approach using convolutional neural networks (CNN) with a Softmax classifier for the accurate detection of Coffee Leaf Disease. The performance of the trained model was evaluated using a separate test dataset, and achieved an impressive accuracy of 98%. The high accuracy obtained demonstrates the efficiency of proposed approach in automating the detection of Coffee Leaf Disease in coffee plants. The work contributes to the advancement of precision agriculture and offers a valuable tool for coffee farmers to mitigate the impact of coffee leaf disease on their crops.**

***Index Terms*—Convolutional neural network, Softmax Classifier, trained model, GoogleNet model, Coffee Leaf Disease, disease detection, Coffee Leaf Rust, Coffee Leaf Miner, Cercospora Leaf Spot, Artificial intelligence and Machine learning.**

I. INTRODUCTION

Karnataka, a state in southern India, has established itself as a major player in the coffee industry, being one of the largest coffee-producing regions in the country . The favorable climate and terrain in Karnataka provide ideal conditions for coffee cultivation, allowing for the growth of various coffee varieties, including Arabica and Robusta. With the significance of coffee production in Karnataka, effectively detecting and managing coffee leaf disease is of utmost importance to the local farmers. Coffee leaf disease poses a severe threat to coffee plantations, leading to significant crop losses if not addressed promptly . Therefore, there is a growing demand for more efficient and accurate methods of disease detection and management. In recent years, advancements in technology particularly in the field of artificial intelligence (AI) and machine learning (ML), we have opened up new possibilities for detecting and diagnosing coffee leaf disease . By harnessing the power of AI and image analysis techniques in application, farmers can identify the presence of leaf diseases at an early stage and enable them to take timely action to mitigate the spread of the disease and minimize crop damage .

Implementing AI-driven coffee leaf disease detection systems can significantly improve the efficiency and effectiveness of disease monitoring in Karnataka's coffee plantations . By leveraging the power of advanced technologies, farmers can gain access to automated tools that provide quick and accurate disease identification, allowing for early intervention and targeted treatment . This proactive approach to disease management can help

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minimize the economic impact on farmers and contribute to the overall sustainability of the coffee industry in the region. Coffee leaf diseases, if left unchecked, can have devastating consequences for coffee plantations. The diseases can lead to reduced yield, lower quality coffee beans, and economic losses for farmers . By developing an automated and accurate disease detection system, farmers can detect the diseases early and take appropriate measures to prevent further spread, ultimately minimizing the economic impact .

The traditional methods of visually inspecting coffee leaves for disease symptoms have inherent limitations . These methods rely on human expertise, which can be subjective and prone to error. These have the potential to spread rapidly and affect a large number of plants within a short period. Timely identification of infected plants is crucial to prevent disease propagation and implement effective control measures. With manual inspection, there is a risk of missing early signs of infection. Automated detection systems can analyze a large volume of coffee leaf, enabling early detection and prompt action . Not all coffee farmers have access to experts or specialized knowledge in plant pathology. This lack of expertise and resources hinders the ability to accurately identify and manage coffee leaf diseases. By providing an automated disease detection system, farmers can access advanced technology without the need for extensive training or specialized knowledge.

Effective disease detection and management contribute to the sustainability of coffee cultivation. By identifying and addressing diseases promptly, farmers can reduce the need for excessive pesticide use, which can have environmental implications . Automated systems can help farmers adopt targeted and precise treatment strategies, minimizing the environmental impact while maintaining crop health . Coffee leaf diseases, such as Coffee Leaf Rust (Hemileia vastatrix), Coffee Miner Disease (Colletotrichum kahawae), and Brown Eye Spot (Cercospora coffeicola), are common in coffee-growing regions worldwide, including Karnataka. These diseases can significantly impact coffee production and quality, making their accurate detection and management crucial for farmers .

II. Literature Survey

In [2], the authors explored the application of image processing techniques to automatically identify the three main diseases which affected the Ethiopian coffee leaves. To accomplish this, various segmentation techniques were employed, including Gaussian distribution, K-means clustering, and a combination of Gaussian distribution and K-means clustering. In addition to the segmentation techniques, traditional characteristics such as color, shape, and texture were utilized. However, it was found that these characteristics performed poorly when used alone. Therefore, to improve the accuracy, Gray Level Co-occurrence Matrix (GLCM) and color features were also employed to extract relevant features from Ethiopian coffee leaves [10]. To classify the extracted features, several classification techniques were evaluated, including Artificial Neural Networks (ANN), Naive Bayes, Self-Organizing Map (SOM), and Radial Basis Function (RBF). The goal was to identify the most effective classifier for the task. Upon evaluating the performance of the different techniques, it was discovered that combining Gaussian distribution and K-means clustering with a mixture of SOM and RBF classification techniques yielded the highest accuracy of 92.10% [11].

In [14] various machine learning techniques were explored and models to identify the most suitable deep learning architecture was done. As part of research, the Plantix app, was used as a source for disease identification. The synthetic nature of the image collections used in Plantix can significantly impact the accuracy of neural models when processing real-world images [14]. To overcome this limitation, it turned our attention to deep convolutional Siamese networks, which have been specifically developed to address the challenge of working with small image databases [7]. By leveraging this architecture, it was able to achieve impressive results in the detection of diseases such as esca, black rot, and albinism across nearly 16 types of crops, fruits, and vegetable leaves. The accuracy achieved in these experiments exceeded 90% [7]. Many researches have come with different models in plant disease detection. However, they noticed that a gap specifically in the area of coffee disease identification exists still now. This motivated to further analyze and develop a system that specifically targets the detection of coffee leaf diseases, providing an accurate and effective solution [14] . By focusing on this specific domain, [2] contributed to the existing knowledge and offer practical solutions that can significantly benefit coffee farmers. The research endeavors to bridge the gap in the current literature and provide a robust system for the detection and prevention of coffee leaf diseases. In this research we came across a notable study on developing an automatic system for identifying diseases and pest damage in the leaf and berry parts of coffee plants. The author in [2] employed two different color spaces, namely Lab and YCbCr, along with a texture filter segmentation algorithm. These methods aided in effectively segmenting the diseased or damaged regions of the coffee plant images. Subsequently, a feedforward artificial neural network (ANN) was employed for the classification of coffee plant diseases and pests. The performance of the ANN was compared to that of support vector machine (SVM) and K-nearest neighbor (KNN) classification algorithms [13]. Remarkably, the ANN outperformed the other algorithms and achieved an impressive overall classification accuracy of 91.9% when tested on a dataset of 8,500 images. The proposed system demonstrated its efficacy in accurately identifying various coffee plant diseases and pests. Furthermore, the articl [4] specifically focused on the recognition of two specific diseases, Cercospora (brown eye spot) and coffee leaf rust. For these diseases, two different texture attribute extraction approaches were employed: gray-level co-occurrence matrix (GLCM) and local binary patterns (LBP). The extracted texture vectors were then used as inputs for the feedforward neural network. The results were compared with the recognition rate obtained from a convolutional neural network (CNN) without the extraction of texture attributes. Surprisingly, the CNN approach showed superior results compared to the texture extraction methods, especially when an adequate training dataset was available [4].

The findings in [6] highlight the effectiveness of combining image processing techniques, machine learning algorithms, and deep learning models like CNNs in developing automated systems for the accurate identification of diseases and pests affecting coffee plants. They achieved high classification accuracy rates indicate the potential of such systems to assist coffee farmers in timely disease detection and appropriate intervention strategies, leading to improved crop health and productivity [13].

One of the studies [11] came across focused on soybean disease identification. The researchers employed a transfer learning approach by fine-tuning the last three layers of the GoogleNet model. It made adjustments to certain parameters of the convolutional neural network (CNN), such as the learning rate, number of epochs, and iterations, with the aim of improving the classification performance. To evaluate the effectiveness of their classifier, it utilized a fivefold-cross validation method. Remarkably, they achieved an impressive accuracy of 98.75% for the classification of 12,600 soybean images using GoogleNet. Additionally, they obtained an accuracy of 96.25% when applying a similar approach with AlexNet.

Another research work [6] investigated an automated system for identifying diseases in mango leaves using a deep learning-based approach. In this study, the authors employed a CNN for both feature extraction and classification tasks. By leveraging the power of deep learning, they achieved an overall accuracy of 96.67% in accurately identifying various diseases affecting mango leaves .These research findings highlight the efficiency of deep learning techniques, such as transfer learning and CNNs, in the automated identification of plant diseases. The high accuracies attained in both studies demonstrate the potential of these approaches to assist in early disease detection and subsequent management, contributing to more efficient and sustainable agricultural practices [6] including disease identification in coffee plants.

III. Design and Implementation

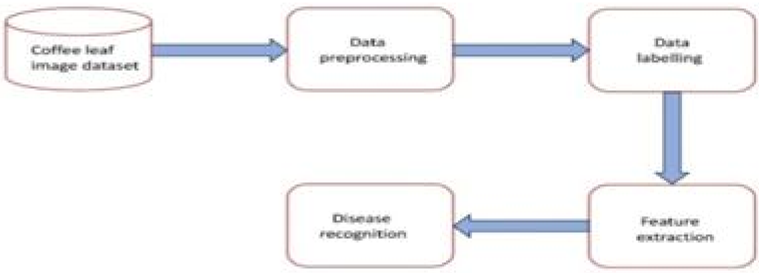
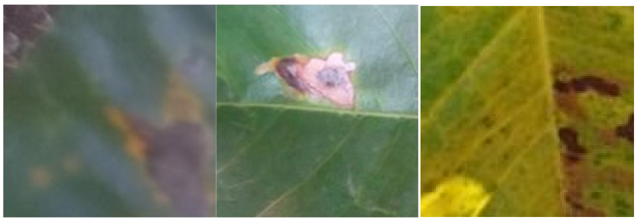


Fig. 1. Coffee Leaf Disease Detection System

Fig. 1 shows the block diagram of proposed coffee leaf disease detection system that includes 5 modules: Coffee leaf image dataset, Data pre-processing, Data labelling, Feature Extraction and Disease Recognition.

The coffee leaf dataset comprises images of coffee leaves that were sourced from ScienceDirect and Mendeley data. ScienceDirect contains images of leaves infected with leaf miner, cercospora, and rust, while Mendeley data consists of images of both healthy and unhealthy coffee leaves. The images in this dataset are of 224x224 pixel size.

The collected images are preprocessed to ensure consistency in size and format. Resizing the images to a uniform size of 224x224 pixels shown in Fig.2 and is necessary to facilitate compatibility with models designed to process images of this size. Additionally, converting the images to a standard format, such as JPEG or PNG, ensure consistent data representation.



(a)　　　(b)　　　(c)

Fig. 2. Leaf Diseases

After Data preprocessing, each image in the dataset is assigned a corresponding label based on the classification categories of interest. In this case, the labels can include Healthy, Leaf miner, Cercospora, and Rust. Proper labeling is crucial for supervised learning, where the model learns to associate the visual features of an image with its corresponding label.

Soon after data labeling, feature selection is done using Convolutional Neural Networks (CNNs). CNNs are specifically designed to analyze and extract features from images, making well-suited for identifying patterns and structures in coffee leaf images affected by diseases. Their mathematical model incorporates convolutional layers, pooling layers, and fully connected layers, allowing them to learn hierarchical representations and make accurate predictions. The ability to automatically learn relevant features from raw image data makes a powerful choice for coffee leaf disease detection, offering high accuracy and robust performance. The working of CNN model is discussed in detail in section A.

A. Working of convolution neural network

Convolution neural network (CNN) includes polling, convolution layer and fully connected dense layer. The detailed discussions are as followed:

Pooling: It is the step of down sampling the image's features through summing up the information. The operation is carried out through each channel and thus it only affects the dimensions of height (nH),width (nW) and keeps channels (nC) intact. A filter is slided with no parameters to learn. Following a certain stride, a function on the selected elements is applied on conventional equation given in (1).

$$\begin{aligned} dim(pooling(image)) &= ([(n_{H} + 2p - f)/s + 1], [(n_{W} + 2p - f)/s + 1], n_{C}) \ ; \ s > 0 \\ &= (n_{H} + 2p - f, n_{W} + 2p - f, n_{C}) \ ; \ s=0 \qquad (1) \end{aligned}$$

The convention (1) is a squared filter with size f, set to 2. This is because using a filter size of 2 with a stride of 2 reduces the spatial dimensions of the feature map by half in each dimension. This down sampling helps in reducing the number of computations in subsequent layers, making the network more computationally efficient.

Convolution Layer: In the proposed system, N×N square neuron layer is followed by convolutional layer. A m×m filter is used where, ω the convolutional layer output will be of (N−m+1)×(N−m+1). In order to compute the pre-nonlinearity input to some unit x^{ℓ}_{ij} in convolutional layer, there is a need to sum up the contributions (weighted by the filter components) from the previous layer cells and unit x^{ℓ}_{ij} is expressed using (2).

$$x^{\ell}_{ij}=\sum_{a=0}^{m-1}\sum_{b=0}^{m-1}\omega_{ab}y^{\ell-1}_{(i+a)(j+b)} \qquad (2)$$

$$conv2(x, w, 'valid) \qquad (3)$$

The convolution 2 is expressed as (3) and after applying nonlinearity, convolutional layer extracts y^{ℓ}_{ij} using (4).

$$y^{\ell}_{ij}=\sigma(x^{\ell}_{ij}) \qquad (4)$$

Fully Connected layer: Fully connected layers, also known as dense layers, are a type of layer commonly used in deep learning models, including artificial neural networks. These layers play a crucial role in learning complex patterns and making predictions based on extracted features. In a fully connected layer, each neuron or node is connected to every neuron in the previous layer. Each connection is associated with a weight, which determines the strength and importance of that connection. The output of each neuron in the layer is calculated by performing a weighted sum of the inputs from the previous layer, followed by an activation function that introduces non-linearity.

B. Adam Optimizers

The optimization algorithm is an extension of stochastic gradient descent to update network weights during training. Unlike maintaining a single learning rate through training in SGD Adam optimizer updates the learning rate for each network weight individually. The creators of the Adam optimization algorithm know the benefits of AdaGrad and RMSProp algorithms, which are also extensions of the stochastic gradient descent algorithms. Hence, the Adam optimizers inherit the features of both AdaGrad and RMS prop algorithms. In adam, instead of adapting learning rates based upon the first moment(mean) as in RMS Prop, it also uses the second moment of the gradients, i.e, uncentred variance by the second moment of the gradients(we don't subtract the mean).

$$mt=\beta 1mt-1+(1-\beta 1)[\ \delta L/\delta\omega t]vt\ =\ \beta 2vt-1+(1-\beta 2)[\delta L/\delta\omega t]^2 \quad (5)$$

Adam Deep Learning Optimizer working is represented in (3). Here, B1 and B2 represent the decay rate of the average of the gradients [12].

IV. RESULT ANALYSIS

The proposed system is tested from the dataset taken from Mendeley data dataset [15] and also from own collection of images related to both Arabica and Robusta Coffee leaves. It consisted of 2000 images and 1800 images of which are diseases related with rust and healthy, another dataset includes images on miner and cercospora diseases. These two datasets were combined as one so that we can efficiently manage the different diseases in a single unit. Disease recognition is done through phases starting at model training by dividing the dataset into separate subsets for training, validation, and testing. The typical split done here is 80% for training and 10% for testing and another 10% for validation. Hence the overall testing can be mentioned as 20%. Further, the total number of samples were divided into two folders namely training and testing. In the initial attempt, 60% of the dataset was used for training the model, and the remaining 40% was used for testing the model's performance. From the ratio of testing, accuracy of 88% was seen and however the model might encounte challenges in generalizing to unseen data. It could be a case of overfitting, where the model learned the training data too well but failed to perform well on new, unseen data. With a smaller testing set, the model might not have been exposed to enough diverse examples to develop robust generalization capabilities. Realizing the need for a more extensive testing set, the dataset was adjusted to allocate 70% for training and 30% for testing. This change resulted in an improved accuracy of 94.6%, indicating better generalization compared to the previous split. The larger testing set allowed the model to be evaluated on a more significant number of unseen examples, which likely contributed to the enhanced performance. Further, refining the split, 80% of the dataset was used for training, leaving 20% for testing. This adjustment led to a significant increase in accuracy, reaching 98% efficiency. The higher accuracy can be attributed to the model benefiting from an even more extensive and diverse testing set, helping it generalize exceptionally well to unseen data. Hence, analysis for improved accuracy can be seen with 80% - 20% split. As the testing set becomes larger (e.g., 10% to 20% to 30%), the model's performance is better evaluated on previously unseen data, which is more representative of real-world scenarios can be seen. A more extensive testing set helps in detecting potential overfitting issues that might have been overlooked with smaller testing sets. However the 80% - 20% split strikes a balance between providing enough data for training the model effectively and offering a substantial amount of diverse data for evaluating its generalization capabilities. Consequently, the model performs at its best on the 80% - 20% split due to improved generalization and better representation of the true model performance on new, unseen samples. Adjusting the training and testing set proportions played a crucial role in improving the model's accuracy. The shift from 60% - 40% to 70% - 30% allowed the model to generalize better, and the final 80% - 20% split provided the most representative evaluation, resulting in the highest accuracy of 97.37%.

Further, we analyzed that the 80/20 split is suitable for the following reasons:

1. Allocating 80% of the images for training ensures a substantial amount of data for the model to learn.
2. Sufficient training data helps in capturing patterns, features, and relationships between the input images and their corresponding labels, improving the model's ability to generalize to unseen data.
3. Over fitting occurs when a model learns to perform well on the training data but fails to generalize to new, unseen data.
4. The 80/20 split helps in mitigating over fitting by providing a separate validation set that serves as an unbiased measure of the model's performance.
5. Regular evaluation on the validation set helps in detecting signs of over fitting and applying necessary adjustments to improve generalization. The reserved portion of the dataset can be used as a testing set to evaluate

the final model's performance. Testing on unseen data provides a realistic estimation of the model's accuracy and ensures an objective assessment of its effectiveness in real-world scenarios.

By employing the 80/20 split, a balance between providing sufficient training data for the model to learn and having a separate portion of data for evaluation, validation, and testing. This approach helps in building robust and reliable models for coffee leaf disease detection while facilitating the optimization and assessment of their performance. Nearly 3000 images were taken for training and 800 images for testing process. Further self-developed datasets were provided for the testing phase. The testing of dataset personally gathered from a coffee estate nearby Chikkamagalur district of Karnataka state. This data collection process could involve physically visiting coffee plantations, interacting with the coffee plants owners, and collecting various pieces of information about the coffee leaves. Nearly 250 images were taken for this and the leaf structure vary for different seasons.

After testing and training, the result obtained from the experiment shows an increase in accuracy and decrease in loss with the number of epochs increasing. Totally 30 rounds of epochs were done and finally, the system was able to achieve 97.37% training accuracy and 7.19% training loss with 97.92% test accuracy and 5.25% test loss.

Few observations were conducted during experiments and noted below with respect to different diseases prevalence and impact of rainy and dry seasons.

Coffee Leaf Rust: During Rainy Season, Coffee leaf rust thrives in wet and humid conditions. During this season, humidity is high and there will be frequent rainfall, the spores of the coffee leaf rust fungus can germinate and spread rapidly. Warm temperatures combined with moisture create an ideal environment for disease development. However, due to reduced humidity and less frequent rainfall the spread of coffee leaf rust is sluggish. However, if the disease has already established during the rainy season, its effects might still be visible during the dry season. The fungus might survive on infected leaves or debris.

Coffee Leaf Miner: The coffee leaf miner is a pest during rainy season rather than a disease, but it can also be influenced by seasons. Rainfall can affect the activity of the coffee leaf miner. Heavy rain can wash away eggs and larvae, reducing infestations. However, increased humidity during the rainy season might create favorable conditions for the pest to reproduce. In drier conditions, the activity of the coffee leaf miner may decrease, leading to lower infestations. However, if the pest has laid eggs before the dry season, their impact might still be observed.

Cercospora Leaf Spot: Like coffee leaf rust, Cercospora leaf spot thrives in moist conditions. Rainy seasons with high humidity can promote the spread of the disease. Spores are easily spread by rain splashes and wind. However, the disease's development might slow down during the dry season due to reduced humidity. Hence, if the disease has established itself during the wetter months, its effects could still be visible on infected leaves. The behavior of these diseases can also be influenced by various other factors, including local climate, altitude, temperature, and the specific coffee varieties being grown. Apart from the root cause analysis, the effectiveness of the algorithm is classified by considering the following facts.

True Positive (TP): A true positive occurs when the model correctly predicts instances belonging to the positive class

True Negative (TN): A true negative happens when the model correctly predicts instances belonging to the negative class.

False Positive (FP): A false positive occurs when the model predicts the positive class, but the actual class is negative.

False Negative (FN): A false negative happens when the model predicts the negative class, but the actual class is positive.

By considering the above discussed factors, accuracy, precision, recall and F1 score are evaluated.

Accuracy: Accuracy is a commonly used metric that measures the overall accuracy of a classification model and is calculated using (6).

$$\text{Accuracy} = (TP + TN) / (TP + FP + TN + FN) \qquad (6)$$

Precision: Precision measures the accuracy of positive predictions made by a classification model. It calculates the ratio of true positive predictions to the total number of positive predictions, which includes both true positives and false positives. It is calculated using (7).

$$\text{Precision} = TP / (TP + FP) \qquad (7)$$

Recall (Sensitivity): Recall, also known as sensitivity, measures the ability of a classification model to correctly identify positive samples. Recall is calculated using (8).

$$\text{Recall} = TP / (TP + FN) \quad (8)$$

F1 Score: The F1 score is a metric that combines precision and recall into one value. It provides a balanced measure of the model's performance by taking into account both false positives and false negatives. F1 Score is calculated using (9).

$$\text{F1 Score} = 2 * (\text{Precision} * \text{Recall}) / (\text{Precision} + \text{Recall}) \quad (9)$$

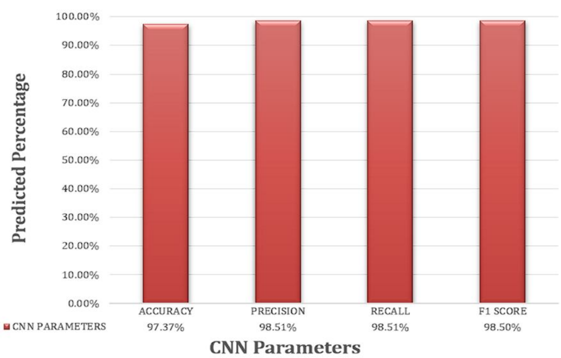


Fig. 3. CNN Parameters

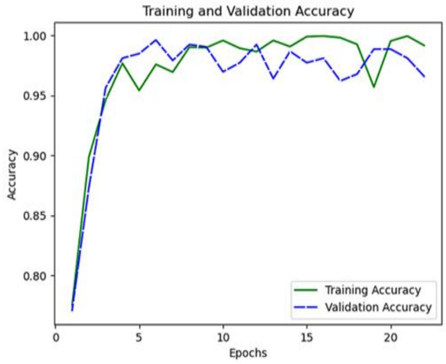


Fig. 4. Training and Validation Accuracy for epochs

From the below defined parameters, the overall performance of the parameters for CNN is depicted graphically in Fig. 3. In the same line, the Fig. 4 provides an insight to the experimental approach of training and validation for different epochs. From the analysis, it observed that after 7 epoch the system behaving appropriately or hand-in-hand.

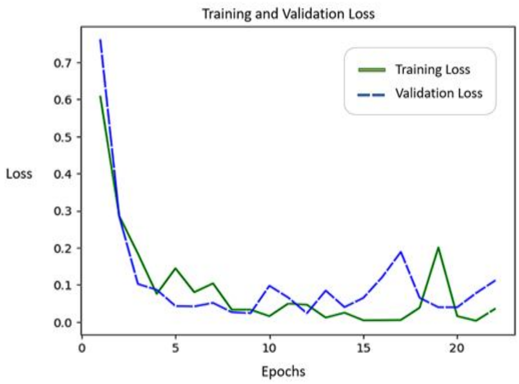


Fig. 5. Training and Validation Loss for epochs

Fig. 6. Web Interface of Disease Detection

In the similar way, the training and testing loss was also studied and can be seen in Fig. 5 for different epochs and the loss was standing after 5 epochs.

Apart from all the result analysis of system behavior, a testing was conducted with the framework. Here, a flask application was used to open web browser. Flask is necessary for lightweight web framework, enabling easy deployment of machine learning models as web services. Once the Flask application is running, it opens a web browser with local address http://localhost:5946. A web interface for all the analysis is ready and can be seen in Fig. 6. From all the testing methods, it is clear that CNN can be best classifier for coffee leaf disease detection/prediction.

V. Conclusions

The application of Artificial Intelligence (AI) in coffee leaf disease detection has shown promising results in automating the identification and diagnosis process. By leveraging CNN, the proposed system has potential to greatly improve the efficiency and accuracy to 97.37%, and enable timely interventions to prevent crop losses and improve coffee production.

Looking at the future, advancements in AI and image processing techniques the capabilities of coffee leaf disease detection systems can be enhanced with larger datasets and improved deep learning algorithms. The deep learning integration with weather patterns and geographical information [16, 17], could provide additional insights for disease prediction and management.

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