Enhancing Tea Plant Health Through Machine Learning: EfficientNet-B0 for Tea Sickness Detection

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ABSTRACT
Tea is a globally important crop that is prone to numerous diseases that can significantly affect its quality and production. This study proposes a novel work of improving the health of tea plants through Machine Learning (ML) for tea sickness detection from the EfficientNet-B0 convolutional neural network (CNN). By training the model on a comprehensive dataset of tea leaf images, significant improvements in disease detection accuracy were achieved. The architecture of the EfficientNet-B0 was well optimized explicitly for the use of this study and its test accuracy is 94.64%. This performance highlights the ability of the model as a classifier of the healthy and diseased tea leaves. EfficientNet-B0 is a promising solution to better manage and detect diseases in the initial stages, which confirmed the effectiveness when applied in this context. This stays in contrast to the traditional disease diagnosing approach in agriculture. This approach is an improvement by combining Deep Learning (DL) with real-life applications in farming.

General Terms
Machine Learning (ML), Neural Networks, Image Classification, Deep Learning (DL), Computer Vision, Agriculture Technology

Keywords
Tea Sickness Detection, EfficientNet-B0, Crop Disease Detection, Convolutional Neural Networks (CNNs), Transfer Learning, Plant Health Monitoring

1. INTRODUCTION
Tea (Camellia sinensis) is one of the most widely consumed beverages, which holds significant cultural and economic relevance around the world and in key producing countries including China, India, Sri Lanka, and Kenya [1]. The stead to demand high quality tea requires close observation in the general health and yield of tea plantations to produce high quality tea as well as in enormous quantities. However, tea plants undergo many constraints from biotic stresses like pests and diseases and abiotic stresses by environmental factors. All these can have severe effects on plant health, thereby causing huge loss to farmers economically [2][3].

Symptoms identification and management of diseases in tea farming have mostly been under observation and experience of agronomists. Although these approaches form part of the current practices, they are cumbersome in terms of time and work input and may not be sensitive enough for early disease diagnosis [4]. Such limitations may lead to delayed interventions and optimal crop quality and yield as a result.

ML and computer vision technologies offer a promising solution to these challenges due to several reasons. These technologies can further improve the efficiency of tea plant health monitoring because they are automated, accurate, and dynamic. Integration of the ML models with techniques that analyze images means that diseases may be detected in their incipient stage hence can be managed thus minimizing such effects on the economy [5][6]. This advancement marks a major step forward towards better practices in agriculture.

Artificial intelligence (AI) is a broad umbrella that encompasses ML, which is a method employed to make predictions from patterns upon analyzing data. In the recent past, the application of ML has helped in the agricultural sector to revolutionize precision farming and crop management [7]. This one uses enormous quantities of data to improve many aspects of agricultural production to reduce time and increase yields. Some common use cases of ML in agriculture include detection of crop diseases, prediction of yields, soil analysis, and pest management [8]. The use of complex algorithms allows an ML model to discover unexpected patterns in data and make recommendations for more effective decision-making in the process of managing resources.

When combined with computer vision, ML has had a significant impact on plant disease identification. Some of the previously used techniques of identifying plant diseases require direct or physical observation and previous knowledge, which is boring and at times produces wrong results. ML algorithms in conjunction with computer vision can be used to auto classify plant images, including leaves and stems, to diagnose diseases with a high degree of accuracy [9]. This enables rapid identification of the ailments compared to the traditional methods while also increasing the accuracy of diagnosis, which is central to efficient treatment.

Another potential that can be derived from employing ML for plant disease diagnostics is the capacity of the algorithm to perform image analysis of plant images. The collected images may be complex, but these can be analyzed using sophisticated ML algorithms that can identify early signs of diseases that are often not easily identified by the human eye [10]. This capability results in shorter times between the onset of the pathologies and the degree of interference. As a result, it enhances the general management packages and reduces crop damage, making it a more useful tool for today's farming [11][12].

Further, the development and application of ML in the agricultural sector has helped realize improvements in disease control by enhancing effectiveness and efficiency of intervention measures. Thus, by automating the disease detection process and offering accurate prediction of diseases, ML aids in quicker diagnosis and preventive intervention [13]. It not only contributes to the protection of crops but also to sustainable agriculture as it limits the use of chemicals and enhances resource management [14]. Currently, the use of ML technologies is still a growing area, and thus, their application in the field of agriculture is also likely to expand in the future and stimulate further development and enhancement of agricultural activities.

The improvement of the CNNs has been employed by Tan and Le in 2019 with useful effects such as high accuracy rates with fewer parameters and computational needs referred to as Efficient Net [15]. The concept of Efficient Net is the compound scaling that scales network depth width, and resolution in such a way that the network is efficient and fast as can be [16]. This approach allows Efficient Net to obtain high accuracy at the same time and use fewer computations, which is very beneficial for those applications that need high accuracy, on the one hand, and low computational resources, on the other.

EfficientNet-B0 is a base model of Efficient Net, which aims to achieve the best performance on many benchmarks of image classification including standard ImageNet [17]. This design focuses on this compromise between accuracy and compute and is used where there is a low differential like in plant disease classification. This makes EfficientNet-B0 able to recognize any signs of concern in plant health at higher efficient rates using a light model for real time application [18].

As for the application of EfficientNetB0 in the context of tea sickness detection, the following benefits can be identified. First, it helps process large datasets of tea leaf images fast, thus not consuming a lot of computational power. Second, the high accuracy of the CNN predicts a better ability to detect and differentiate between different diseases in tea plants, thereby lessening the need for manual inspection and chemical applications.

Recent studies have demonstrated that DL models are efficient in plant disease classification. For instance, ResNet and DenseNet based models have been successfully trained for other crops as they yielded high accuracy for disease detection [19][20]. But the efficiency and performance of EfficientNetB0 suggests its suitability to tea sickness detection especially when speedy analysis is critical.

Thus, the purpose of this study is to establish an ML model with the aid of a more enhanced model, EfficientNet-B0, for the accurate identification of diseases affecting tea plants. Training involves generating a technique capable of discriminating specific tea plant diseases such as Anthracnose, Algal leaf, Bird eye spot, Brown blight, Gray light, Red leaf spot, White spot from the healthy ones. The objectives are to achieve greater accuracy and speed in the diagnostic process compared to conventional approaches, fine-tune the model based on a large set of tea plant images associated with these diseases, and enable the use of an efficient application for monitoring tea plant status in real-time. This approach would benefit tea farmers as they would have a valuable tool to detect the diseases early enough to avoid huge losses that are likely to be a result of diseases affecting tea plants.

The remainder of this paper is organized as follows: Section 2 provides a brief related work highlighting previous work and notable developments in tea sickness recognition and machine learning. Section 3 illustrates the mathematical formulas and theories used in the process of model development. In section 4, information on data preprocessing, model architecture, and the training of the EfficientNetB0 model is provided. In section 5, they presented the result and performance analysis of the proposed model in detail. Finally, Section 6 provides the conclusion of the paper with a summary of the contributions and suggestions for future research directions.

2. LITERATURE REVIEW

The presence of diseases can either help or hinder the efficiency of tea production as well as affect the quality of tea. Conventional disease identification involves visual examination, which is time-consuming and can lead to inaccurate results. But the latest technologies in AI have produced other techniques to automate and improve the identification of diseases in the tea plant.

Heng, Yu, and Zhang [21] develop an AI-based solution using deep neural networks with hybrid pooling for automatic tea leaf disease identification. Their method performs preprocessing by pruning images and using the efficient. CNN with hyperparameter tune able pooling layers for feature extraction and Random Forest (WRF) model which is fine-tuned with Cuckoo Search Optimization (CSO) for classification. This approach yielded the overall average accuracy of 92.47%, which tended to outcompete the discrete methods significantly.

In another study, Srivastav, Gulcria and Sharma [22] used CNNs for classification of tea leaf disease. After fine-tuning over different epochs, they obtained the training accuracy of 99% and the testing accuracy of 89%. The findings of this study underscore the efficiency of CNNs in quickly and accurately diagnosing numerous types of leaf diseases.

Recent developments in tea disease detection also show that manual observation is replaced with AI systems to increase efficacy and accuracy. Li, Zhang, and Li [23] proposed the integration of a novel model called VCRUNet that includes a Channel Reconstruction Unit (CRU) and VanillaNet architecture. This method proves to be a more accurate and efficient solution in tea disease management with 92.48% accuracy and a detection speed of 4.5 seconds per 100 images thus marking an improvement from the previous studies.

Similarly, in related domain, Kulkarni, and Shastri [24] focused on the identification of rice leaf diseases using the CNN model. Its approach which was tested under different background/illumination conditions yielded 95% accuracy. This shows the benefit of ML in improving disease diagnosis and hence could be applied in improving agriculture.

Apple leaf diseases have a significant impact on the generation and production of apple fruit in a sustainable manner. Zhang et al. [25] presented an improved Bole Convolution Module (BCM) and Bidirectional Transposed Feature Pyramid Network (BCTNet) for identifying multiple sizes of apple leaf spots in unadjusted scenes with an accuracy of 85.23% and a detection rate of 33 FPS. Gong and Zhang [26] enhanced Faster R-CNN with Res2Net and feature pyramid networks, yielding 63.1% average precision. Each augment health risk identification, presenting solutions to tackle difficulties with standard approaches.

In Ethiopia, one of the leading exporters of coffee, Yoseph [27] concentrated on the identification of coffee leaf disease. Employing 4000 images from the Jimma and Bonga agricultural Research Centers, the researchers developed a CNN-based model with an accuracy rate of 95.3%. They argue that this is the rationale for this research to demonstrate how digital image processing and DL can be used to diagnose some of the coffee leaf diseases and how CNNs can be used to solve some of the challenges in agriculture.

Lekha et al. [28] proposed a disease identification model for tomato leaves using CNN, SVM, and KNN algorithms. Their work contrasts such algorithms for recognizing tomato leaf diseases, exploring difficulties in disease identification in India's sizable tomato production industry.

Kansal, Jaiswal, and Sachdeva [29] proposed an empirical study to compare the performance of the CNN model with the conventional ML algorithms for detecting the tomato leaf disease. CNN was accurate at 96% and could be applied in identifying all the 10 diseases using a dataset of 30,000 images, outcompeting classic classifiers such as AdaBoost, KNN, and Random Forest.

Plant diseases have been identified as potential threats to food security since they harm the quality and quantity of crops. Previous studies have developed crop-specific DL models using CNN for better performance and time efficiency. Verma, Kumar, and Singh [30] presented a unified lightweight CNN model to detect diseases in corn, rice, and wheat, with an accuracy of 84.4% and parameters of 387,340 only. This model surpassed benchmark CNNs, and its accuracy was high for identifying diseases in each crop. Ramadan et al. [31] reviewed how additional techniques could be used to help overcome the lack of the wheat leaf disease datasets. The authors leveraged CycleGAN and ADASYN to enhance classifier performance, attaining 100% accuracy with MobileNetV2 on the augmented sets. Their research also establishes the significance of data augmentation in advancing the performance of disease classification for successful automation in agriculture.

Khalid and Karan [32] discussed the effectiveness of DL models, CNN, and MobileNet particularly for plant disease identification with accuracies of 89% and 96%, respectively. Their work, which entails the use of DL through GradCAM for Explainable Artificial Intelligence (XAI), demonstrates that DL can contribute to improving plant disease identification techniques and subsequently agriculture protection.

The reviewed studies further emphasize the revolutionary role of DL in improving plant disease diagnosis for different crops. Several studies have shown the advantages of CNN and other DL techniques compared to traditional ones in terms of accuracy, speed, and the ability to scale the solutions to different contexts. These models have enormous potential in the matter of identifying plant diseases as evident through teas and coffees, tomatoes, rice, and wheat. These approaches are enriched by new techniques such as data augmentation and Explainable AI, providing real-world solutions to address the urgent concerns of crop disease management. Overall, the conclusions point to the importance of AI-based approaches for enhancing knowledge in agriculture, enhancing the quality of yields, and securing food sufficiency in the world. Future investigations should further advance these models, increase computational performance, and think other crops to expand on these breakthroughs.

3. MATHEMATICAL EQUATIONS

The mathematical formulas in our tea sickness detection system with EfficientNet-B0 cover key aspects of model training, evaluation, and optimization. These are the Cross-Entropy Loss for classification, the SoftMax function for the probability distribution and hidden layers for feature extraction through convolution, and optimization algorithms as Adam. From the mathematical standpoint, these equations create the basis of the model that can detect sickness in tea plants accurately.

The Cross-Entropy Loss function is used to calculate the dissimilarity between the actual label and the probability distribution anticipated by the model. In Equation (1):

$$L(y,\hat{y}) = -\sum_{i=1}^{C} y_i \log(\hat{y}_i) \tag{1}$$

Here, $L(y, y_i)$ represents the loss value, y_i is the true label, and $\hat{y}_i$ is the predicted probability for class i. The variable C denotes the total number of classes in the classification task [33].

The Convolution Operation is fundamental in extracting features from an input image by applying a filter or kernel over the image. In Equation (2):

$$(I,K)(x,y) = \sum_{i=0}^{m-1}\sum_{j=0}^{n-1} I(x+i, y+j) * K(i,j) \tag{2}$$

This equation defines the convolution that is performed on an input image I with a kernel K, where m and n are the dimensions of the kernel. Here, $I(x+i, y+j)$ is the pixel value from the input image, and $K(i,j)$ represents the corresponding value from the kernel. Finally, you obtain a feature map that emphasizes potentially useful features of an input image. The convolution operation plays a significant role in identifying features such as the edge, texture, and other intricate functions within image data [34].

The SoftMax activation function converts the output logits of a neural network into a probability distribution, as shown in Equation (3):

$$\hat{y}_i = \frac{e^{z_i}}{\sum_{j=1}^{C} e^{z_j}} \tag{3}$$

In this equation, $\hat{y}_i$ is the predicted probability for class i and $\hat{z}_i$ is the logit for class i. The sum in the denominator runs over all classes C [35].

The Gradient Descent algorithm adjusts the parameters of the model by adjusting the loss function. The update rule is given by Equation (4):

$$\theta \leftarrow \theta - \eta \nabla_\theta J(\theta) \tag{4}$$

Here, θ are the model parameters, η is the learning rate, and $\nabla_\theta J(\theta)$ is the gradient of the cost function $J(\theta)$ with respect to the parameters [35].

Adam Optimization is used to achieve more efficient convergence during training by adaptively adjusting the learning rate based on first and second moment estimates of the gradients. The equations (9) governing Adam optimization are:

$$m_t = \beta_1 m_{t-1} + (1-\beta_1)\nabla_\theta J(\theta) \tag{5}$$

$$v_t = \beta_2 v_{t-1} + (1-\beta_2)(\nabla_\theta J(\theta))^2 \tag{6}$$

$$\widehat{m_t} = \frac{m_t}{1-\beta_1^t} \tag{7}$$

$$\widehat{v_t} = \frac{v_t}{1-\beta_2^t} \tag{8}$$

$$\theta \leftarrow \theta - \eta \frac{\widehat{m_t}}{\sqrt{\widehat{v_t}} - \epsilon} \tag{9}$$

Here equations (5)(6)(7)(8)(9), m_t and v_t are the first and second moment estimate of the gradients at time step t regulates the mean and variance of the gradients, respectively. The hyperparameters β_1 and β_2 control the decay rates for these estimates β_1 impacting m_t and β_2 affecting v_t. The bias-corrected estimates $\widehat{m_t}$and $\widehat{v_t}$, represent the raw estimate with added initial bias towards zero in m_t and v_t. The learning rate η calculated from moment estimates and $\in$ is a small constant to avoid division by zero [36].

The Learning Rate Schedule dynamically adjusts the learning rate training process to enhance convergence. The equation (10) for the learning rate schedule is:

$$\eta_t = \eta_0 * decay\_factor^t \tag{10}$$

Here, η_t represents the learning rate at epoch t, η_0 is the initial learning rate, and the decay_factor is a constant that controls the rate of decay. However, this decay decreases the learning rate over time, allowing the model to fine-tune its parameters as training progresses [37].

Batch normalization is used to normalize the inputs of each layer, improving the training process. It is represented by Equation (11):

$$\hat{x} = \frac{x-\mu}{\sqrt{\sigma^2+\epsilon}} \tag{11}$$

Here, $\hat{x}$ is the normalized input, x is the input to be normalized, μ is the mean of the batch, σ^2 is the variance of the batch, and $\in$ is a small constant to avoid division by zero [38].

Dropout is a regularization technique that reduces overfitting by randomly setting a fraction of input units to zero during training. In Equation (12):

$$Dropout\ (x) = \begin{cases} \frac{x}{p} & with\, probability\ (p) \\ 0 & with\, probability\ (1-p) \end{cases} \tag{12}$$

Here, x represents the input, p is the dropout rate, and the remaining units are scaled by $\frac{1}{P}$ to maintain the expected value of the activations [39].

The ReLU (Rectified Linear Unit) activation function introduces non-linearity into the model, defined by Equation (13):

$$f(x) = \max\,(0, x) \tag{13}$$

Here, x is the input value to be passed to the activation function [40].

The accuracy metric evaluates the overall performance of the model by calculating the ratio of correct predictions. In Equation (14):

$$Accuracy = \frac{Number\ of\ Correct\ Predictions}{Total\ Number\ of\ Predictions} \tag{14}$$

Here, the numerator represents the number of correctly predicted labels, and the denominator is the total number of predictions made by the model [33].

Precision measures the relevance of positive predictions made by the model, as shown in Equation (15):

$$Precision = \frac{TP}{TP+FP} \tag{15}$$

In this equation, TP denotes true positives, FP denotes false positives [41].

Recall evaluates the completeness of the model's positive predictions and is calculated using Equation (16):

$$Precision = \frac{TP}{TP+FN} \tag{16}$$

Here, FN denotes false negative [41].

The F1-score provides a balance between precision and recall, especially useful in cases of imbalanced datasets. It is given by Equation (17):

$$F1 = 2 \times \frac{Precision * Recall}{Precision + Recall} \tag{17}$$

The confusion matrix is a table used to evaluate the performance of a classification model by showing the true vs. predicted classifications, as depicted in Equation (18):

$$Confusion\ Matrix = \begin{bmatrix} TP & FP \\ FN & TN \end{bmatrix} \tag{18}$$

Here, TN denotes true negatives [42].

4. METHODOLOGY

This study proposes a method for identifying diseases in a tea plant by using the EfficientNet-B0 model which is a CNN. This means that the methodology to be employed in this study has several crucial steps – data preparation, data augmentation, model creation, model training, and model evaluation – with each step established to help in improving the accuracy of the model in diagnosing the various tea leaf conditions. The entire detection process is described in Figure. 1 where all the steps are presented in terms of data preprocessing and augmentation, network training and evaluation, as well as the potential deployment of the model.

4.1 Data Preparation

The data set applied in this study is Tea Sickness Data, obtained from Kaggle. It is made up of images sorted into eight categories: Anthracnose, Algal Leaf, Bird Eye Spot, Brown Blight, Gray Light, Healthy, Red Leaf Spot, and White Spot. This dataset comprises images of both healthy leaves and leaves affected by major tea diseases, thus making it worthwhile for training.

- **Image Filtering**: Every image was preprocessed by its format and converted only to JPEG or PNG for compatibility with the model.
- **Resampling**: The images were rescaled to adjust to a standard size that fits the requirement of EfficientNet-B0 model input dimension, which is 224 by 224 pixels.
- **Data Splitting**: To prevent outflow between the two sets much effort was placed into splitting this dataset into a training and validation set. The training set is made up of 80%, while the validation set is made up of 20%.

4.2 Data Augmentation

To further improve the models also in terms of generalization and reducing data dependency, data augmentation strategies were applied. These techniques artificially increase the size of the set by producing variations of the learning images, so the model learns on a different set of inputs. The augmentation methods used comprise of:

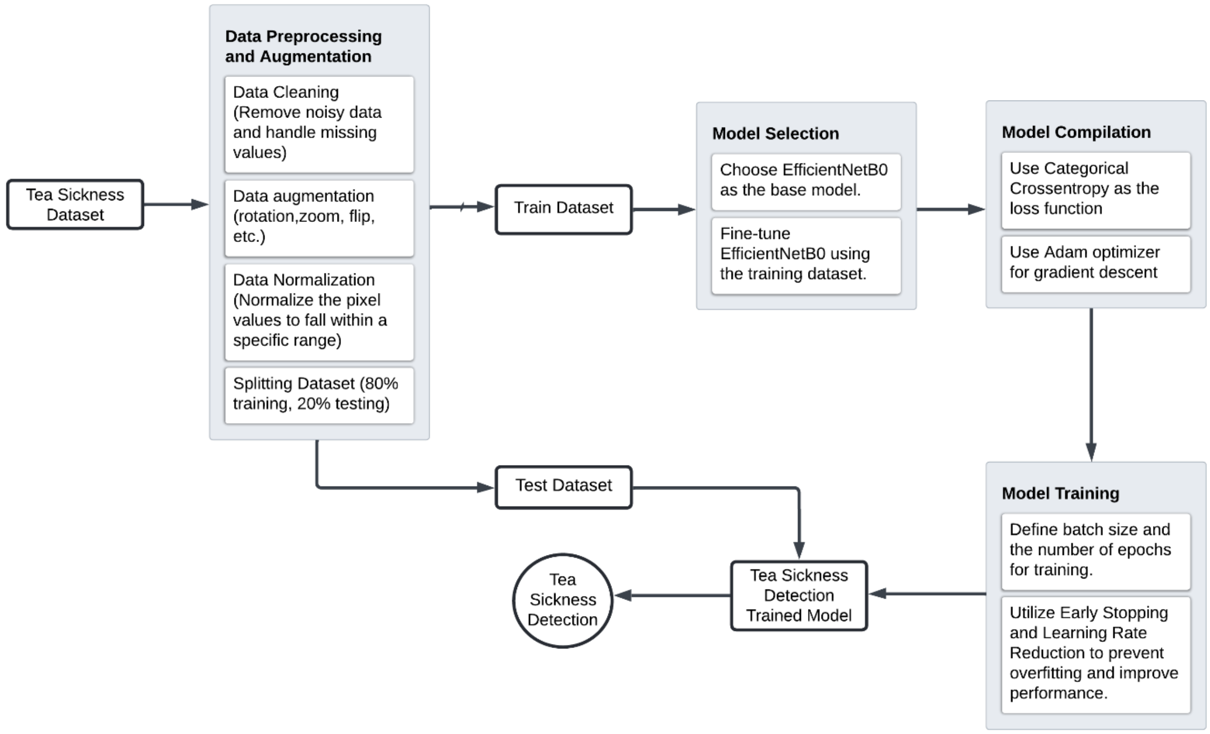

Figure 1: Block Diagram of Tea Sickness Detection Using EfficientNet-B0

- **Random Rotations:** Rotational invariance was applied by permitting the rotation of images randomly in each range.
- **Width and Height Shifts:** Images were shifted horizontally and vertically to mimic small changes in orientation.
- **Shearing:** Shear transformations were used to distort the images along a particular axis of an image.
- **Zooming:** Different effects of scale distortion were achieved through zooming in and zooming out of the images.
- **Horizontal Flipping:** Images were flipped horizontally to prepare mirror images for training.

These augmentations make sure the model is more capable of dealing with new data as it broadens the training dataset.

4.3 Model Creation

Hence, the EfficientNet-B0 model was chosen for this study because of its good trade-off between accuracy and efficiency. In transfer learning approach, the high-level feature extraction layers of EfficientNet-B0 were discarded along with addition of some new layers developed for this task. This included:

- **Global Average Pooling Layer**: This layer subsamples the spatial dimensions of the feature maps and produces just one value per feature map which assists in avoiding overfitting.
- **Dense Output Layer with SoftMax Activation**: This layer is used to output probability for each of the eight disease classes and this enables multi classification.

4.4 Model Training

During the compilation phase, the model was configured with the following parameters:

- **Loss Function**: Categorical Cross-Entropy was chosen to measure the performance of the model during training.
- **Optimizer**: The Adam optimizer was utilized for efficient weight updates.
- **Performance Metric**: Accuracy was selected as the primary performance metric.

To fine-tune the model, certain layers of the base EfficientNet-B0 were "unfrozen," allowing them to learn features specific to the tea sickness dataset. The training utilized Early Stopping to halt training when the validation loss ceased to decrease, preventing overfitting. Additionally, Learning Rate Scheduling was implemented using the ReduceLROnPlateau technique, dynamically adjusting the learning rate based on validation performance.

Model checkpoints were created during training to preserve copies of the model with the best validation performance. The model was trained for a total of 20 epochs, with real-time metrics visualized using TensorBoard to monitor training progress.

4.5 Model Evaluation

Upon completion of training, the model's performance was evaluated on the validation set to gauge its effectiveness. The following metrics were computed:

- **Accuracy**: The proportion of correctly predicted instances over the total instances.
- **Precision**: The ratio of true positive predictions to the total predicted positives, indicating the accuracy of the positive predictions.
- **Recall**: The ratio of true positives to the total actual positives, evaluates the potential of the model in identifying Positive cases.

- **F1-Score**: A balance between accuracy and recall is provided by the harmonic means of the two metrics.

To compare correct and incorrect predictions the confusion matrix was created to get better understanding of the model and its mistakes during classification according to different classes.

4.6 Model Testing

To check the reliability and generalization ability of the model, testing was performed on the test set already preprocessed. The trained EfficientNet-B0 model was used to make predictions on this dataset that is used in this research. The same performance measures such as accuracy, precision, recall, F1-score and confusion matrix were applied to assess a model's capacity and effectiveness in identifying and categorizing tea sicknesses correctly. The final testing of the model endorsed its run on fresh data and thereby finalized the model as an effective means to identify diseases in tea plants.

5. RESULT & DISCUSSION

The various performance parameters indicate beyond any reasonable doubt the capabilities of the model in identifying tea sicknesses thus making the model reliable and efficient in real life. Our approach, which is DL training of the EfficientNet-B0 model, is accurate not only in the training set but even more accurate in unseen validation set. In this segment, the specific findings and interpretation of results are presented, including highlighting key performance indicators and their utility for practical contexts.

These results were obtained in the training phase with a training loss of 0.0244 and an accuracy of 0.9993, which means that the model is now capable of identifying patterns in the data with an extremely high accuracy. In the validation phase, the loss which is slightly higher than that from the training phase is 0.1471 was still able to calibrate it to an impressive accuracy of 0.9524. This discrepancy between training and validation metrics is typical for a well-regularized model that does not overfit. Figure. 2 shows the training and validation loss and accuracy in each epoch to show how the model progresses through epochs, and how it gradually overcomes the loss to achieve better accuracy and is stable at the end of epoch.

The confusion matrix and the classification report offer a detailed analysis of how the model performs with respect to each class. Analyzing the classification report in Table 1 shows that the model has been able to provide a precision, recall, and F1-score for each category of tea sickness. The mean accuracy of the results was found to be 0.95, the model performs very well in differentiating 'healthy' from 'red leaf spot' where precision and recall are both at 1 for these classes. However, there is variability in performance across other classes such as 'bird eye spot' and 'brown blight,' where the model's ability to classify is less consistent.

Table 1: Classification Report for the model, including precision, recall, and F1-score for each class

Class	Precision	Recall	F1-score	Support
Anthracnose	0.90	0.95	0.93	40
Algal Leaf	0.99	0.99	0.95	160
Bird Eye Spot	0.83	0.75	0.79	20
Brown Blight	0.83	0.87	0.85	23
Gray Light	0.90	0.90	0.90	20
Healthy	1.00	1.00	1.00	15
Red Leaf Spot	1.00	1.00	1.00	29
White Spot	0.89	0.83	0.86	29
Accuracy			0.95	336
Macro Avg	0.92	0.91	0.91	336
Weighted	0.95	0.95	0.95	336

Figure. 3 shows the confusion matrix that illustrates the overall classification ability of the given model for each class of tea sickness. It highlights the number of true positive, false negative, true negatives and false positives identified by the model, which gives an overall picture of its efficiency and misclassification. This matrix is essential for pinpointing specific classes that would benefit from the improvement of the model. In the end, using the confusion matrix, it is easier to identify the classes that are often inaccurate and enhance the model's accuracy for such classes.

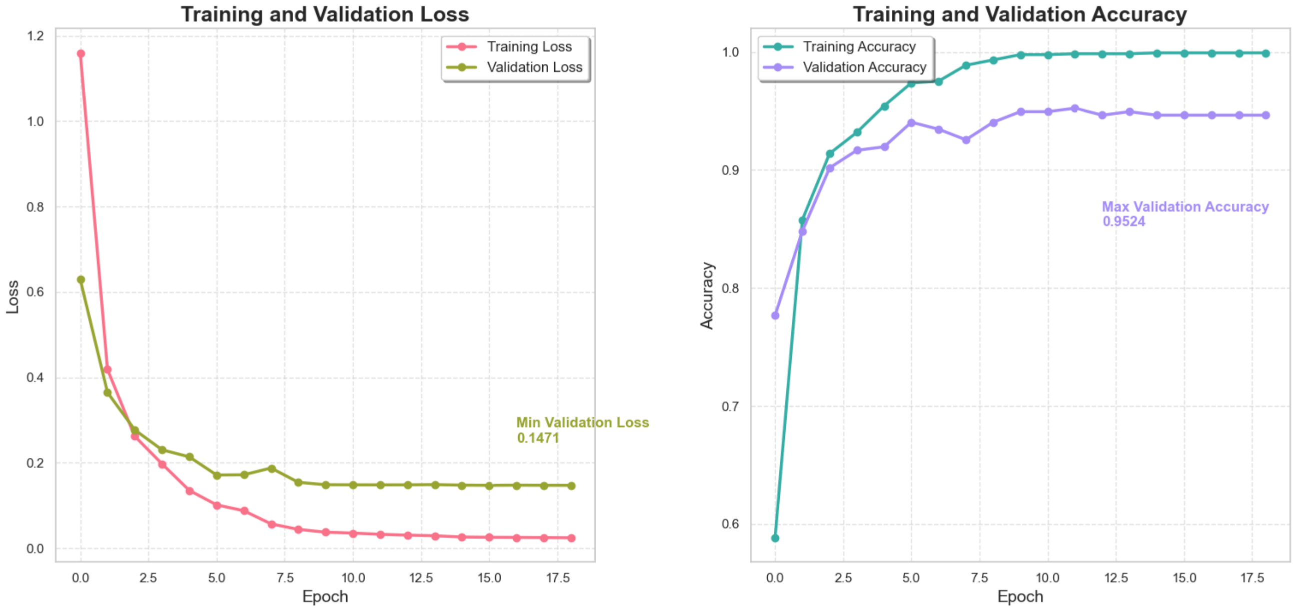

Figure 2: Training and Validation Loss and Accuracy curves

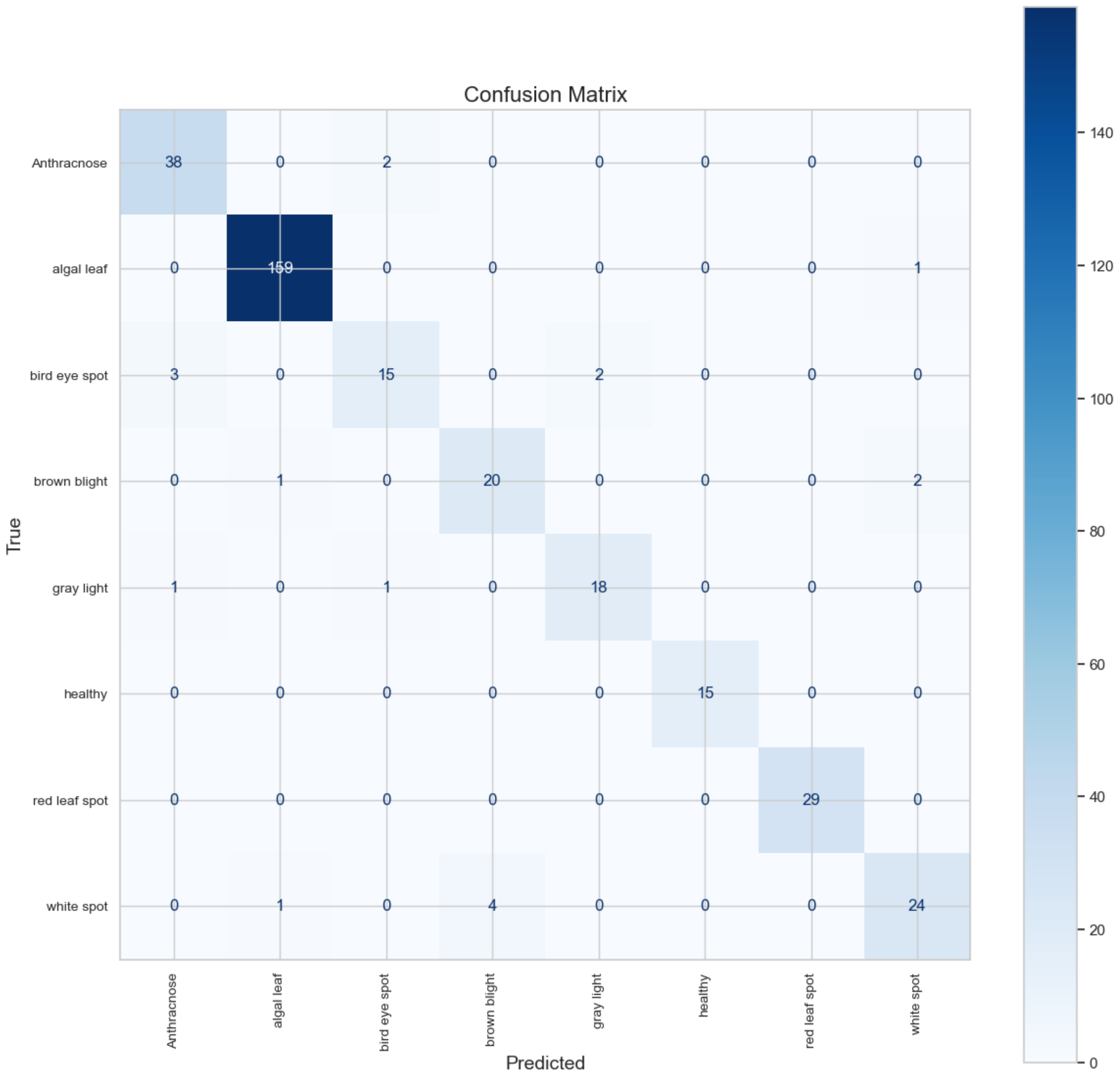

Figure 3: Confusion Matrix illustrating the model's performance across different classes.

The learning rate schedule, which was initialized at 1.0000×10-4, however after that it started to decline at the rate 8.0000×10-7 over 20 epochs was crucial for optimizing the model's training efficiency. Starting with a higher learning rate allowed the model to search through the parameter space more aggressively in the first few epochs. During the training process, learning rate reduction can be utilized for the detailed adjustments and to achieve the better solution. The adjustments

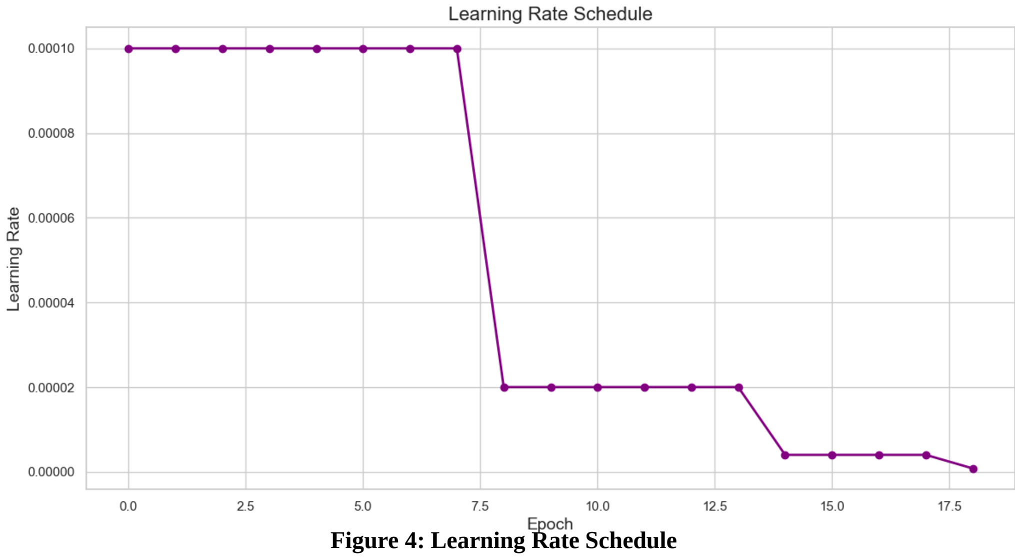

Figure 4: Learning Rate Schedule

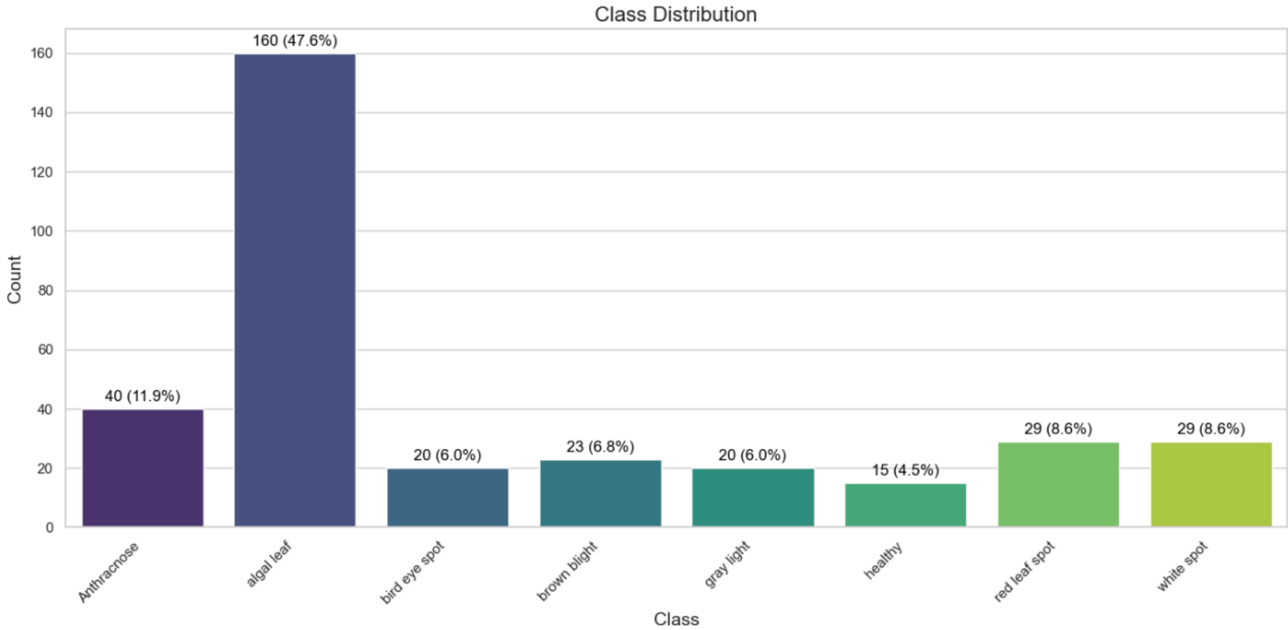

Figure 5: Actual Class Distribution

are depicted in Figure. 4 where the different modulations of the learning rate helped to achieve a more efficient and stable learning process.

Both Class Distribution and Prediction Distribution can provide a clear idea of whether the model is accurate on all classes of the dataset or not. The class distribution plot also shows the actual percentage of different classes of tea sickness in the data set and the balanced classes. This distribution determines the level of times that each of these categories happens and provides the platform upon which the efficiency of the model will be measured across these various classes. This distribution knowledge is helpful if we are investigating whether the model has been trained using a random sample from the data

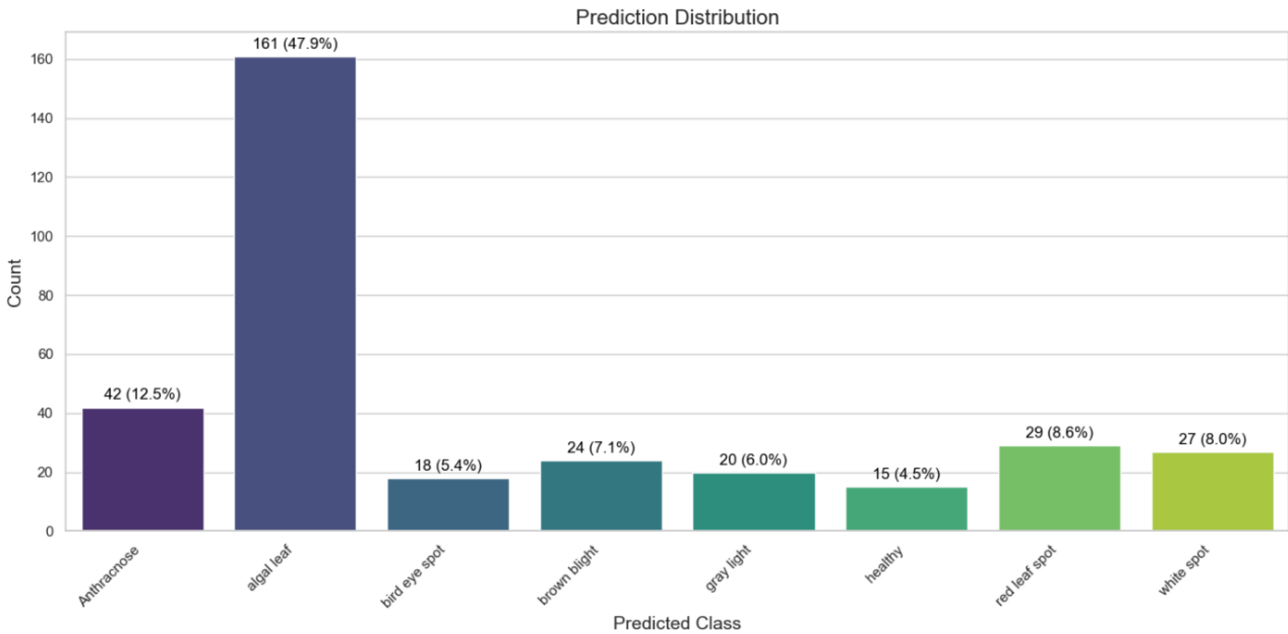

Figure 6: Prediction Class Distribution

By contrast, the prediction distribution plot illustrates the relationship between the model's prediction and the true class probabilities. It is a relative comparison which is very useful in determining the effectiveness of the model in the diagnosis of different tea sicknesses and in the discovery of potential blind spots or the bias of the model. For example, it is detected that certain classes are predicted in a particular way devoid of the right proportions, then it means that the model may be poor in handling such classes. Figure. 5 represents the class distribution while Figure. 6 shows the predicted class. This will be helpful to measure the effectiveness and unbiased nature of the model to predict and classify each tea sickness based on the plot shared here and identify the limitations.

The smoothed loss curves provide further improvement of training and validation loss patterns using certain smoothing techniques and moving averages. These curves assist in establishing the steadiness and reliability of the process of learning in the model. Smoothed curves enable a clearer vision as to how the model progresses over time, and whether the learning process is converging optimally or not, by removing excessive noise or oscillating in the loss values. This refined view also helps in following up the development of models and ensures that the learning process is on the correct track.

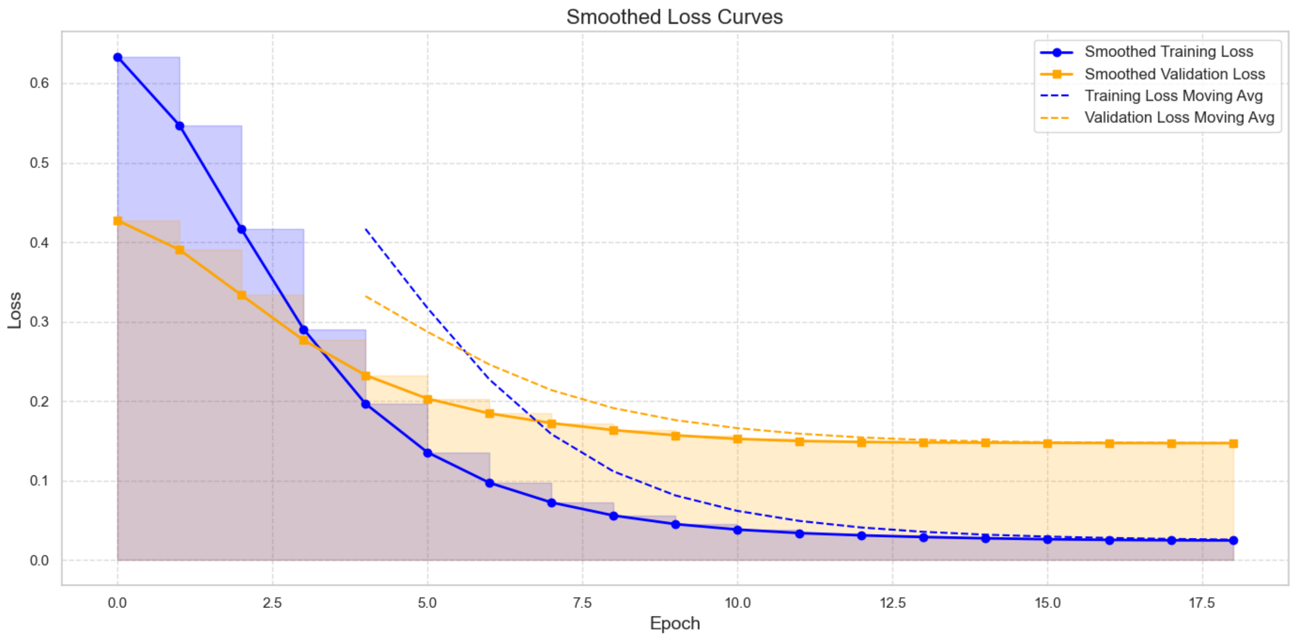

Figure 7: Smoothed Loss Curves for training and validation

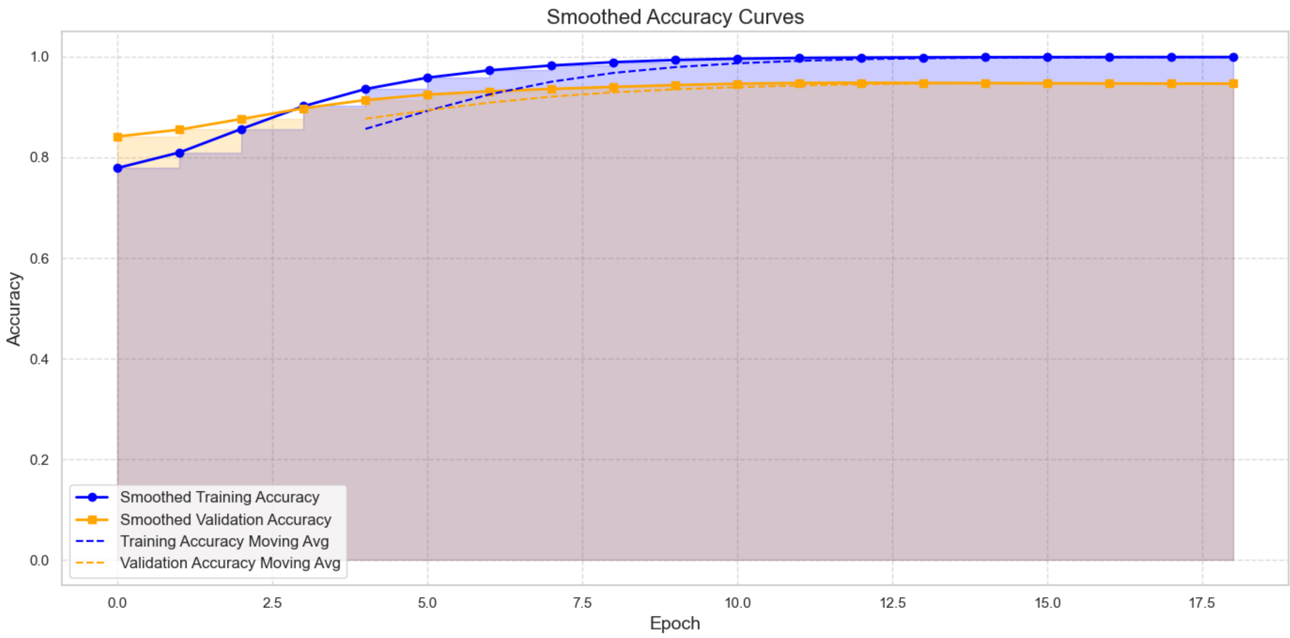

Figure 8: Smoothed Accuracy Curves for training and validation

Figure. 7 illustrates key aspects of these loss curves: the smoothed training loss, smoothed validation loss, training loss moving average, and validation loss moving average. The final plots of training and validation loss smoothed give the overall trend of the losses as a function of epochs which describes the model training sessions. The moving averages aid the understanding of the general trend of the losses and if the model is constantly getting better or if there are signs of overfitting, which occurs when the training loss decreases but the validation loss begins to increase. These are especially important in evaluating the efficiency of the training process and identifying its shortcomings.

The smoothed accuracy curves provide a clear and refined view of the model's performance by applying smoothing techniques and moving averages to the training and validation accuracy

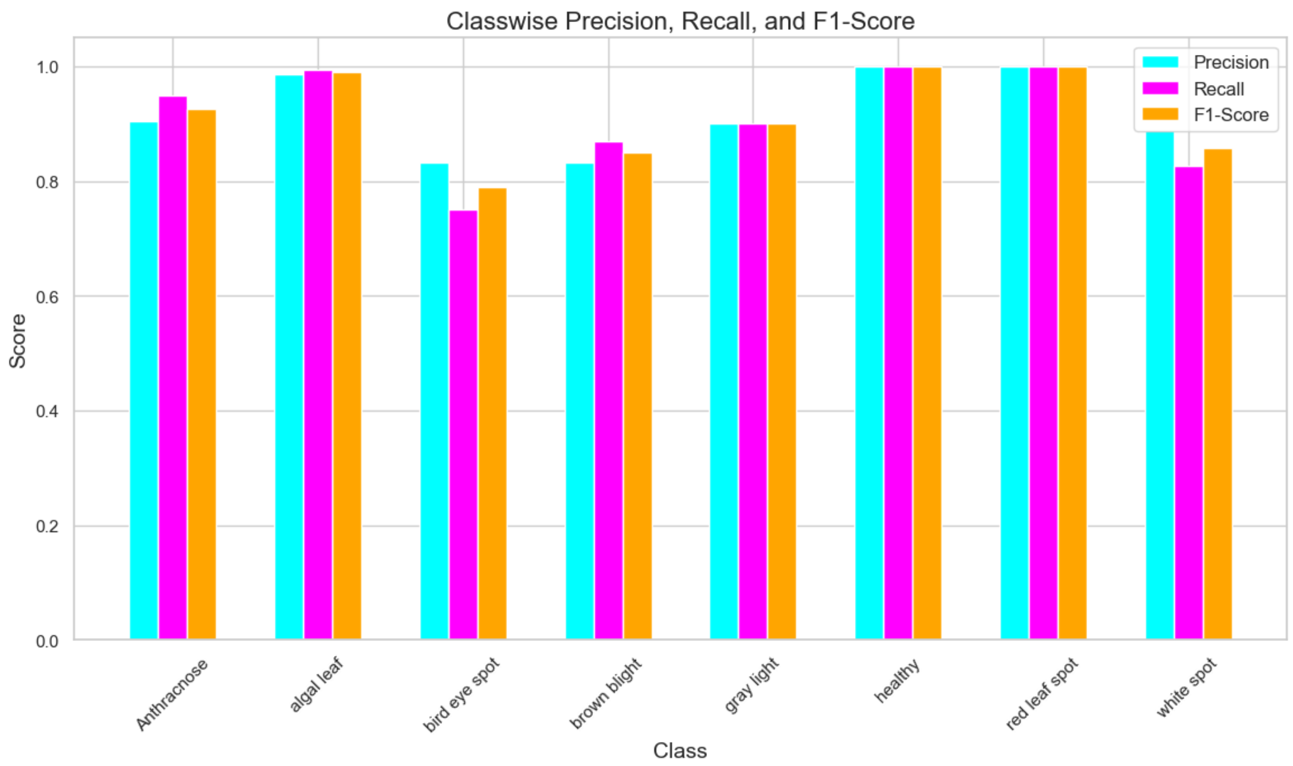

Figure 9: Class wise Precision, Recall, and F1 Score

data. These curves also assist in smoothing out noise and oscillations that would otherwise obscure an accurate measure of how well the model is learning to classify the data at a given epoch. This way, the idea of smoothed training and validation accuracy as well as the averages of the moving means will help to make the inspection of the model's capability to enhance gradually the quality of the predictions more manageable. This is useful in preventing the model from training at an unhealthy pace and or rapidly resulting in overfitting which is bad for performance on unseen data. These are the smoothed accuracy curves depicted in Figure. 8 where one can observe the overall improvement and stability of the model.

The proposed approach can be used to achieve satisfactory results for all specific categories of tea sickness through the assessment of class wise precision, recall, and F1 score. This segregation is important when attempting to determine whether the model is performing well for different classes of tea sickness and where it is struggling. Precision class and recall class are shown in Figure. 9, in addition to F1-score to determine areas of improvement for each class of the model.

From the perspective of the detailed analyzing offered in this section, the validity can be proved that the model applied in this study can primarily identify the tea sicknesses. Accuracy, training and validation metrics, and confusion matrices as well as class-specific performance all demonstrating the model effectiveness. The advantages of smoothed curves and distribution plots are also useful and help to support an argument that stated the model will perform well on unseen data. These results provide strong evidence that DL can be used for configurable agricultural diagnostics and demonstrate the potential of the model for practical use. Therefore, from the outcomes of this study, one can infer that there is lots of improvement and innovation possible in the future.

6. CONCLUSION

To enhance the development of a better tea sickness detection system, EfficientNet-B0 was used in this study. Due to this, the accuracy at training phase reached 99.93% whereas, at the validation phase it was 95.24% when using this advanced convolutional neural network. As additional regularization techniques to avoid overfitting of the model, learning rate reduction, early stopping and model checkpointing were employed alongside TensorBoard for monitoring of training progress. The final evaluation of the test is presented, and it provides 94.64% accuracy and 0.1471 of the test loss, indicates the stability of the model, as well as the possibility of its utilization in practical applications. The implication from this study has certified the model in disease diagnosis which increases the output and quality of the production due to early detection. Future work could improve the model's performance by using more data and active real-time monitoring and therefore promising future developments in agricultural disease detection.

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