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Article

Image processing–based stage-wise visualization and severity assessment of coconut leaf diseases

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Abstract: The timely identification of coconut leaf diseases is essential to reduce the loss of yields and be able to intervene in precision agriculture. The present paper suggests an Earlier Disease Diagnosis in Coconut Leaves (DD-CL) model to add together transfer learning-based convolutional neural networks and symptom progression analysis to attain precise disease identification and severity prediction at the initial stages. The model uses a pre-trained VGG16 architecture with a SGD and Adam optimizer and is trained on a Kaggle coconut leaf dataset with five classes, inclusive of: healthy, flaccidity, yellowing, drying of leaflets and CCI-leaflets. To support robustness and minimize overfitting, the images are 300 × 300 pixel, normalized and augmented. In addition to classification of the disease, DD-CL does severity estimation by examining changes in the symptoms of flaccidity to uneven yellowing and tip browning. Experimental analysis shows that the highest classification accuracy is 97.3, and precision, recall, and F1-score are 97.3, 96.5 and 96.9, respectively, which is higher than ResNetV2 and MobileNet by 3–5%. The analysis of confusion matrices proves that there is minimum misclassification between the visually similar stages of the disease, especially during early disease transitions. The suggested DD-CL framework offers a scalable, interpretable, and reliable solution to automated surveillance of coconut disease and the severity at an early stage. *N* performs better than the single models, thereby raising accuracy and an f-measure.

Keywords: earlier disease diagnosis in coconut leaves, convolution neural networks, Adam optimizer and classification accuracy

1. Introduction

Agricultural sector therefore may be considered the kernel in any emerging economy. He or she should be given the best tools and practices to ensure that the farmers produce the best yields in agriculture. In fact, the use of coconut palm plantation has not been lost since other uses are numerous including the fruit of the coconut palm trees as well as the trunk of the trees. India ranks third in the world in terms of the production of coconuts and the products. Much of the production in the country is done in the southern part of India. This is a very important plant that is applicable in numerous plantations because it is used with the fruit and the truss. Third most popular and the main producers are in India particularly the southern region of the country [1]. The strict need of coconut production transcends far beyond the economic value of coconut production as any disease that strikes coconut productivity affects the concerned industries and puts the lives of communities that rely on the fruit at stake.

Identification and classification of plant diseases are part of such a task to assist in the promotion of organic farming and precision farming. This is because the human process or seeing of the physical symptoms on the leaves and subsequently arriving at the conclusion is not only unscientific but it is also highly inefficient and inaccurate. Conversely, criticality is of great essence, in the realization that biotechnological methods are tedious, difficult to control, demand some form of knowledge and skills thus not applicable when there is need to undertake urgent monitoring. As everyone knows, these techniques cannot satisfy the need of the contemporary agricultural intelligence and information. Although detection of disease has been conducted through biotechnological and other traditional methods of observation, image-based methods are the best because they are simple to work with as one capture image of the plants. In case of large backgrounds to the subject areas or any inverted or low light or even shadows in the photograph, the former individuals would fail in the aspects of presenting a clear segmentation or origin information extraction. Image-based deep learning has provided major benefits to the identification of diseases in agricultural plants since the introduction of deep learning, and various improvements have been made in the field ever since [2]. These strategies have also removed or minimized the constraints of the traditional methods and the efficacy is greater when compared to the use of the conventional methods. Deep learning has a number of advantages to the application in plant disease diagnosis in such cases.

Most of all, it eliminates lengthy and cumbersome steps of feature extraction and some form of preprocessing with which image recognition methods would have involved themselves. It was found that without the input of man, deep learning algorithms can learn several and meaningful features on their own [3]. Deep learning may also be used to make the design of plant disease diagnosis system more robust and adaptive in nature. The unexpected changes in the frequency of the disease in the year and across geographic regions within the dynamic agricultural industry can be dealt with reasonably or rather simply integrated into the above models in order to increase their reliability and accuracy since it is flexible enough to be updated using new data. To sum up, the use of the deep learning in plant disease detection opens new directions of the research and development of precision agriculture [4]. It promises to bring a radical shift in the idea of disease diagnosis and management; would transform the sphere of sustainable development and agri-business introducing greater productivity to the produce output. Advanced image processors, and the popularity of Convolutional Neural Networks (CNNs) that are based on deep learning have also been helpful in the development of artificial intelligence, owing to the presence of a solid hardware platform and numerous technical innovations [5]. Because of this sequential abstraction of the features of concrete pixel space to relatively abstract conceptual space, deep learning models exhibit one of the most interesting and distinctive capabilities of learning meaningful properties without human intervention. They have an intrinsic advantage enabling them to collect international data of photographs with the aim of identifying diseases on plants [6]. Zhang et al. [7] introduces the so-called transfer learning as the means of managing the problem of having to train deep learning models with large quantities of data. In transfer learning of deep learning to refine the training process and enhance the learning performance on target areas of recognition, it involves application of parameters of the already trained models in newly trained models. In addition, it also prolongs the idea of training the efficient model, reducing training cycle as well as augmenting the testing results at a price of reducing the training loss rate [8]. In this case, the work of the proposed model is presented in the following

- To diagnose and classify the coconut leaf diseases at its earlier stage and measure the model effectiveness.
- The transfer learning CNN in Stochastic Gradient Descent (SGD) and Adaptive Moment Estimation (Adam) optimizers were used to measure how severely a disease is being evaluated.
- Testing the suggested model on the samples within Coconut Leaf Dataset on Pest Identification of Kaggle.
- Comparisons evaluations are used in the basis of the evaluation measures like, sensitivity, specificity, accuracy and error rate.

The rest of this paper is presented in the following way Section 2 is an overview of what the existing models are on detecting disease in plants using machine and deep learning methods. Section 3 provides the entire narration with regards to the working procedure of the proposed model. The findings and discussions and description of the dataset are reported in Section 4. Lastly, the paper is summed up with the future work directions and is found in Section 5.

2. Related works

A number of studies have been undertaken to determine the usage and efficacy of DL techniques in detection and intervention of illnesses. As an example, CNN-based models have been proven to identify the nutritional deficiency in black gramme and to use the biologic classification of the healthy and sick foliage [9,10]. Moreover, the existing studies by Miriyagalla et al. [11], Wijekoon et al. [12], Hahn et al. [13] and Huang [14] have also helped in the development of facilities where near infrared spectroscopy along with deep neural networks are used to detect some diseases that affect plants and behavior of the disease. There are several other studies, which have proven the effectiveness of the application of the DL technologies to the image analysis along with it, but none of these studies focused on the coconut industry and, therefore, can be called a quite limited sphere of implementation of the sophisticated technologies.

Technically, the diseases that exist in the oil palm fields have been characterized. Nonetheless, minimal research has been conducted to the coconut palm farms despite the fact that the two plants are part of the palm family. Piyush Singh et al. [15] created and trained a deep 2D CNN that takes into account all these factors to predict illnesses and infestations by pests. Second, the transfer learning was utilized to overfit the recent Far-Gadro Keras-pretrained CNN architecture which comprised of VGG16, VGG19 and InceptionV3 to identify the images as healthy or sick. In addition, the Inception-ResNetV2 achieved 81.48 percent and MobileNet achieved 82.10 percent of classification accuracy. In order to categorize rice leaf disease, Krishnamoorthy et al. [16] used transfer learning on deep convolutional neural network of Inception-ResNetv2. To achieve the recognition task, they adjusted its parameters that led to 95.67 percent recognition accuracy. Yue et al. [17] enhanced the VGG network along with shared parameters in feedback and high-order residual sub networks. The identification of high order residual sub-network was a more specific diagnosis of the disease given that it determined the potential nature of the disease in crop.

In coconut, one disease called the leaf rot is referred to as a disease that affects the leaves of the coconut trees. It is in the study [18] that the way these leaves can be classified is specially formulated. To determine the specific leaf rot disease in the leaves of Cocos nucifera trees, they used a neutrally network-based system. Another method that used an NVIDIA Tegra System on Chip (SoC) and a camera loaded drone to develop a technique to a precision agriculture to identify different species of pests on coconut plants is the work of the authors of [19]. In order to locate the sick and pest infected trees the drone must fly over the coconut farm and take photos and through the deep learning algorithm process the photos to provide a diagnosis. Concerning the system structure, the deep learning system applies to a collection of sample pest databases. In regards to the sources that were consulted, there were no ways of identifying illnesses in coconut palm farms in a complex manner. A number of techniques which appear to incorporate discriminative features of the images have been of much interest in computer vision in recent times.

Recent studies have also mentioned the automation of pest control as indicated by Lins et al. [20]; the authors created the software that could be used in the automated counting and classification of aphids. This method addresses the drawbacks that are accompanied by hand counting in terms of imprecision and ineffectiveness. Nonetheless, a partial automation of counting coconut caterpillacids is underway due to the continued human counting in current practices. Research conducted in this field has shown that the available resources with regards to pests and diseases of coconut plants and trees are very scarce. AIE-CTDDC model was presented by Maray et al. [21] to detect the presence of diseases and not the severity of the disease. Kadethankar et al. [22] have also demonstrated the example of end-to-end pipelines of using drone footage to identify the presence of infections in rhinoceros beetle in coconut plants. The targeted analysis can be done in this way by 'cutting off the head' of the trees on the drone images. CNN was also used in identification of diseases by Singh et al. [23]; however, the authors suggested that future studies should employ DL, segmentation, and severity assessing. These are also the two general aims of the current research.

As an example, the segmentation and object detection are also among the technologies that can be applied in the classification of plant diseases and pests. Wang et al. [24] described some particular steps of the detection and segmentation process using Faster R-CNN and Mask R-CNN. Geetha et al. [25] have contributed to this by lending solutions to some of the problems that come with Early Warning System in identification of the small size pests in their habitats and their classification into numerous categories. They have improved the efficiency and accuracy of on field pest detection systems required in sustainable farming. With masked images to recognize the level of uncovered-forth, should it be present, Manoharan et al. [26] generated nitrogen, phosphorous, and kalium deficit of crop yields that needed nutrition like citrus, groundnuts and guava through the implementation of the Mask R-CNN. The article by Hewawitharana et al. [27] used CNNs and Mask R-CNN to classify and predict the extent of the area covered with BB, which is an invariable issue in the Ceylon tea industry. Moreover, Tiwari et al. [28] used the Mask R-CNN in detecting FAW insects in field crops and were able to find segmentation frames and bounding boxes of the insects within the picture. The subject of these studies was, unfortunately, not coconuts.

3. Proposed model

The paper suggests an Earlier Disease Diagnosis in Coconut Leaves (DD-CL) framework to diagnose coconut leaf diseases at an early stage and finally estimate their severity by utilizing a transfer learning-based Convolutional Neural Network (CNN). The model uses the images of coconut leaf obtained by the field and further captured by the Kaggle Coconut Leaf Dataset which is initially pretrained through resizing, normalization, and data augmentation to increase robustness and minimize overfitting. The backbone architecture of a pre-trained VGG16 network is used; high-level features are obtained with the aid of the convolution and pooling operations, and a final classification is performed with the help of fully connected layers with a softMax function. To facilitate the model to converge steadily with better generalization, the model is trained with categorical cross-entropy loss and optimized by Stochastic Gradient Descent (SGD) and Adaptive Moment Estimation (Adam). Besides the classification of the disease, the DD-CL model uses a symptom progression analysis to derive an approximate estimation of the severity of the disease by observing the early signs of the disease like flaccidity which is followed by the uneven yellowing and the brown drooping of the leaf tips. The suggested strategy allows reliable distinction of visually related diseases as well as promotes the diagnosis at an early stage, thus providing an effective and scalable method of precise coconut disease surveillance.

The suggested DD-CL algorithm (**Algorithm 1**) will start with loading the coconut leaf image dataset and preprocessing each image with 300 × 300 pixel resizing, pixel normalization, and data augmentation methods, i. e. rotation, flipping, zooming, and shearing. The processed data is further split into training and testing set in 80:20 proportions. Existing VGG16 network is loaded and the top classification layers are deleted, and a new global average pooling and softMax layers are added to enable the classification of multiple classes of diseases. Categorical cross-entropy loss is used to train the network, and either Stochastic Gradient Descent or Adaptive Moment Estimation is used to optimize the network via repeated forward propagation, calculation of the loss, and weight update by a backpropagation algorithm. In inference, every test picture would be categorized in either of the three types of coconut leaf disease and the development of the symptoms would be examined by scoring early disease symptoms like flaccidity, then yellowing and browning of the end or tip of the leaf. Depending on the assembly of symptoms observed, the disease is classified as either mild, moderate or severe. Lastly, accuracy, precision, recall and F1-score are used to test the adequacy of the suggested DD-CL framework.

3.1. Data acquisition

The data used during the research was provided on Kaggle. Several JPEGs of five different infections of coconut leaf could be obtained via a free distribution system. The dataset characteristics may be located in **Table 1**, which contains sample photos. The collection represents five distinct leaf disease images of coconuts that include leaflets, caterpillars, yellowing, drying and flaccidity. Both the training data and the dataset selection were available at Kaggle that was utilized to perform this analysis. It is a free collection of five photos of coconuts leaves in a JPEG format. The information regarding the dataset in detail is given in **Table 1** and representative photos are given in **Figure 1**. The dataset collection has five possible manifestations of coconut leaf disease that comprise of leaflets, caterpillars, yellowing, drying and flaccidity. To ensure effective model training and testing the dataset was separated into training and testing parts that included 80 and 20 respectively. The majority of the data was collected on the field. Coconut tree in the picture is one of the species of native Indians. The dataset separation was done to support evaluation and training purposes test (20) and training (80). The field was the main place where most of the data was obtained. The picture has an Indian native coconut tree. The sample size has an equal number of photos depicting the five types of coconut leaf diseases. Future training and testing algorithms should introduce image scaling and rotation model using cropping as a technique to balance the data against imbalanced data.

Algorithm 1 Computation: DD-CL framework

1. Input:Image set $I = \{I_1, I_2, ..I_n\}$
2. Class labels C={Healthy,A,B,C,D}
3. Output: Disease class $c_i \in C$ and severity level s_i
4. //Acquire Dataset
5. Fetch labelled leaf coconut images of the Kaggle repository.
6. //Preprocess Images
7. $Ii \leftarrow Resize(Ii, 300 \times 300)$
8. Ii←Ii/255
9. Apply augmentation A={rotate, flip, zoom, shear}
10. Dataset Partitioning $I = ItrainUItest, 80\%: 20\%$
11. //Model Construction
12. weights Initialize VGG16 with ImageNet weights.
13. Freeze convolutional layers. L_f
14. Optimize parameters θ by minimizing:
15. $L=-\sum y \log f_\theta (\hat{y})$
16. $using\ optimizer\ O \in \{SGD, Adam\}$
17. //Disease Classification
18. $\hat{c}_i = \arg f_\theta \max f_\theta \text{Softmax}(f_\theta(I_i))$
19. Severity Estimation

    Performance Evaluation
20. Model Comparison
21. End Algorithm

Table 1. Coconut leaf disease in dataset.

Disease type	Instances
Drying of leaflets (A)	1088
CCI-leaflets (B)	795
Flaccidity (C)	1079
Yellowing (D)	1084

Figure 1. Sample coconut leaf images from dataset.

3.2. Data pre-processing

Raw data collection was preprocessed through different techniques in order to improve the accuracy findings and facilitate the mathematical computation. The field tour led to acquisition of images which ranged between 150 × 150 to 750 × 750 pixels. All photographs were converted to 300 × 300 pixel sizes and the neural networks were given equal input dimensions of 300 × 300 pixels. All pixel values in the images were multiplied by 1/255 to bring the brightness levels to normal so that the values would range between 0 and 1. The team used several data augmentation methods including rotating, filling and shearing across horizontal and vertical axis in addition to flipping across horizontal and vertical directions as well as zooming to achieve the aim of increasing sample size and reducing the chances of model overfitting. Preprocessed photos of coconut leaflets served as the input of deep learning models and were divided into training data with 80 percent of the total dataset and validation data with 20 percent of the total data. Independent collection of the results was also part of the testing process to avoid the bias and the manual pre-selection in the field visits.

3.3. Data annotation

This was then succeeded by labeling the area signified by the leaflets by the polygon annotation labeling technique. The polygonal areas have values in the output file in regards to the coordinates. During the process, the pictures of the entire leaf with the discover insect damage and without it were determined, and the rest of the area was occupied with the label of the backdrop. The Mask R-CNN model took these areas as input neurons when it was being trained.

3.4. Convolutional neural network architecture in disease diagnosis

A CNN or a ConvNet is a kind of deep learning model, the main purpose of which was image analysis. Recent studies reveal that CNNs can be used not only to process images, but also in processing sequential data such as in NLP. A CNN has primarily two processes making up its structure and they include convolution and pooling. The convolution functions use many filters to extract the relevant data of a data input without the loss of the spatial relationship of the original data. The pooling therefore refines these features extracted and the network even has the ability to identify the patterns in the most efficient way. Moreover, the following symptoms can be used to classify the leaf disease,

- Uneven yellowing
- Leaf tip browning
- Flaccidity
- Leaf tip breaking off

At this point the coconut tree is of no use; however, one can notice the fourth sign - Leaf tip breaking off. In such a manner, the first three symptoms that are prevalent in the initial phase of the illness were selected as the most discriminating among the scientific findings of this study because one of the findings of the illness is its timeliness.

In the given research, the condition was initially differentiated into a set of characteristics before predicting the development of the symptoms to assess the level of illness. This was used to identify the ailment because the flaccidity of the leaves is the initial indicator to use (**Figure 1**). This classification was made as a relieving the leaf of the tree or a healthy and a flaccid leave. The severity of the condition was determined with the help of the last two symptoms as it progressed in the next several weeks after-analysis in terms of flaccidity. This was done through developing a multi-class classification model with three classes namely flaccidity, uneven yellowing and tip browning as the method of gauging the severity. In this way we could determine and classify its phenomenon in a phase that remained in its early stages. The sample data provided was used in this research to train optimized VGG16 already trained CNNs. **Figure 2** shows the workflow of the proposed model.

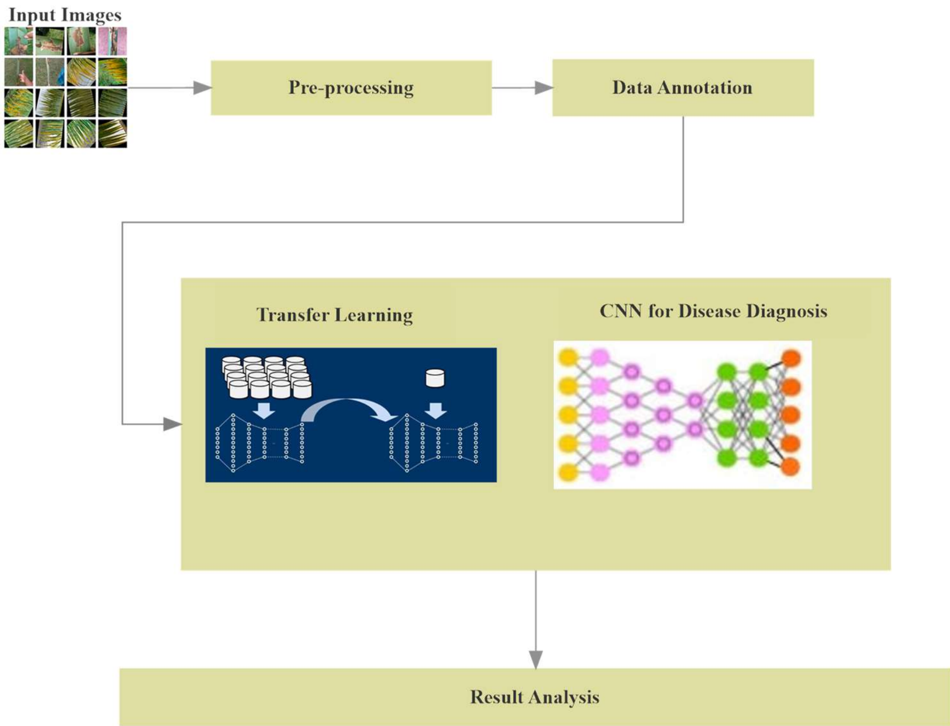

Figure 2. Workflow of proposed model.

Similarly for the evaluation of symptoms intensity, a multi-class classification model for three classes was established. CNNs are very effective in the classification of images because through the convolution and pooling layers, they are able to learn the hierarchy of features in images. To perform the said convolution, the filter is applied to obtain prominent characteristics such as edges and textures against the input image. The procedure could be represented by Equation (1).

$$(X*k)(a,b)=\sum_{i=-m}^{m}\sum_{j=-m}^{m} X(a+i,\ b+j).k(i,j) \tag{1}$$

Here, X is the input image matrix; $X(a,b)$ is the pixel value of the image at any pixel location(a,b); and k is the kernel matrix also referred to as the filter used in extracting features of the image. Here the indices a,b inside the filter is represented by the set: $a,b=-m$ to m, m being the filter size. The summation of pixel values at each coordinate (a,b) is made feasible through the use of symbols; $\sum_{i=-m}^{m}\sum_{j=-m}^{m} X(a+i,\ b+j).k(i,j)$ which sum all values that are in the filter area. After the convolution process, some type of activation function needs to be applied which is Rectified Linear Unit (ReLU). In Equation (2), ReLU function is defined.

$$f(r)=\max(0,r) \tag{2}$$

Here, $f(r)$ is the ReLU activation function; it is an element take the value of r and outputs a maximum of 0. This ensures that all the negative values in the feature map concerning the illness detection are eliminated leaving only the positive ones hence aiding the network to detect integrated fine details. This was done using max pooling in Equation (3), whereby it selects the maximum value from a given window of the feature maps.

$$Y = \max\left(a_{i,j}\right) for\ i,j \in windowsize \tag{3}$$

where Y is the max pooling operation on the certain window size which takes the largest value $a_{i,j}$ in it. The indices of this window are noted as i and j. Max pooling enhances efficiency in computing aspect besides minimizing the overfitting risk through applying layer on layer on the input, while retaining the most expressive features. In the network's last parts, the characteristics obtained from the convolutional layers are then summarized and output as a classification verdict by a fully connected layer. It is therefore using Equation (4) the dense layer with all its neurons connected to get the output.

$$c = W^T a + bs \tag{4}$$

where c denotes the output of the normalized thick layer. W here is the weight matrix chosen, a is the input vector and bs is the bias vector in the given equation. In order to accomplish this, the hyperparameter was tuned and both the Adam and Stochastic Gradient Descent (SGD) optimizers were used to optimize the performance of the adopted CNN models. This rendered the classification of the illness correct since it is possible to keep the loss function decreasing through the network. The symptoms of every picture were then examined in order to establish the course of the disease in question. When the three indicators of the disease, flaccidity, pigmentation and browning of its extremes were extreme then it indicated that things were dire. However, when only flaccidity was noticed, it indicated that the disease was not very severe but it was in its initial stages. It also came in handy in determining the progression of the disease and the severity of the same by considering the symptoms clearly revealed by the images.

3.4.1. Optimization process

Back propagation is an optimization process whereby the parameters of the filter are varied in order to reduce error. There will be some losses that will be encountered during forward propagation stage since the parameters of the filter are initially initialized at random values. It is therefore essential to make a distinction between Stochastic Gradient Descent and Adaptive Moment Estimation which are two significant snippets of optimization algorithm to convolutional neural network. In this way, it may be observed that specific classification tasks may turn into the foundation of the determination of the optimization function.

The training speed is comparable to the one of the SGD technique since according to the training method; the parameters are changed after a single training sample is trained during each iteration. The disadvantage of the SGD technique is that it can be challenging when it comes to the regulation of a suitable learning rate when training the network model. SGD is also able to achieve the local optimum solution. Adam method uses dynamic learning rate on each parameter, based on the first and second moment estimate [21]. The parameter stability is also enhanced as it varies within a given range through the offset correction of the learning rate. It possesses characteristics of root mean square and adaptive gradient hence making it a more efficient approach. Whereas the root mean square is effective in stationary and nonstationary gradients, the adaptive gradient is effective in the sparse gradients. The latter is particularly applicable in large datasets and high dimensional space. Nevertheless, at the later training phases, Adam will be able to affect the learning rate and program the model to converge at non-convergent. We implement the gradient descent, define the initial value of the learning rate, and its rate of decrease and 8 of 13 make the rate exponentially decreasing.

Since ReLU is not utilized to perform any exponential calculation, it is much more efficient in its implementation compared to sigmoid and tanh functions. The availability of computing resources is critical to train neural network and training it using ReLU can greatly decrease the training time and costs. This is due to the fact that, in the application of neural networks with the ReLU activation functions, training appears to be more rapid with real-world tasks compared to the training versus small functions like sigmoid or tanh. Gradient descent method is fast moving in the parameter space and will not be stopped by the loss of gradients making the learning to be quick. This works better in cases where the weights are small and therefore in cases where the input is in the positive range the gradient of ReLU equals to 1. In case the input is negative, ReLU will simply give 0 as its output and this also may lead to problems of activations in a neural network, where only a few nodes of the network are active in the hidden layers. As only the neurons involved in making the output are updated this causes a network to be sparsely connected and this decreases overfitting therefore making the model more resilient.

3.4.2. Setting hyperparameters

Training was done using a batch size of 64 and 10 000 steps. The value of the learning rate of 0.002 was changed through the exponential decay process with a decay rate of 0.8. All of them were tested in an attempt to increase the accuracy. Concerning the SGD optimization method, it is methods that are easier to work with, which require a smaller amount of memory, converge more quickly and possess the enhanced capacity of coming out of local optimum and reaching the global ones when compared with other optimization methods. Consequently, it is optimizing the convolutional neural networks of the deep learning back propagation method with SGD optimizer.

4. Results and discussions

All the experiments were conducted in one computer with a windows 10 operating system that includes NVIDIA GeForce RTX 2060 Super graphics card, Intel Core 7–9700 processor speed of 3.0GHZ and 16.00 GB RAM. Regarding the effectiveness of results, the precision and recall measures, along with the accuracy, and F1-score measures are used. To classify the aforementioned coconut leaf disease into four types with the healthy leaves being the fifth category, the existing results obtained with the help of the model created are compared with the ones currently used, specifically ResNetV2 and MobileNet.

The performance measurements as outlined in this section are applied leading to the classification of the five leaf conditions through the use of the CNN model of VGG16 as shown in **Figure 3**. The findings are shown in the form of a confusion matrix in the **Figure 3** and further normalized to make them easily understandable. It demonstrates a total consistency of an exceptionally high degree of accuracy which all the diagonal **Figure 3** imply that their corresponding category can recognize all the instances. Better accuracies of 96 and 95% were achieved in Healthy Leaves and Flaccidity respectively with other minor misclassifications of 5 existing between Drying of Leaflets and CCI-Leaflets. One can observe that the majority of the misclassifications are between similar classes in terms of visuals i.e. Yellowing and Flaccidity. The results of the analysis clearly show that the model succeeded in demonstrating that several types of diseases could be separated correctly but where multiple conditions looked similar on the eye, then they could not be classified correctly. Some suggestions on the future improvements with the model may be outlined as in the following points: The future approach may be based on the usage of the fine tuner in the deep levels of the VGG16; Feature extraction based on a specific domain; Data augmentation so that the model becomes more resilient. **Table 2** below shows the results of observations on the simulation of the factors accuracy, precision, recall and F1-score.

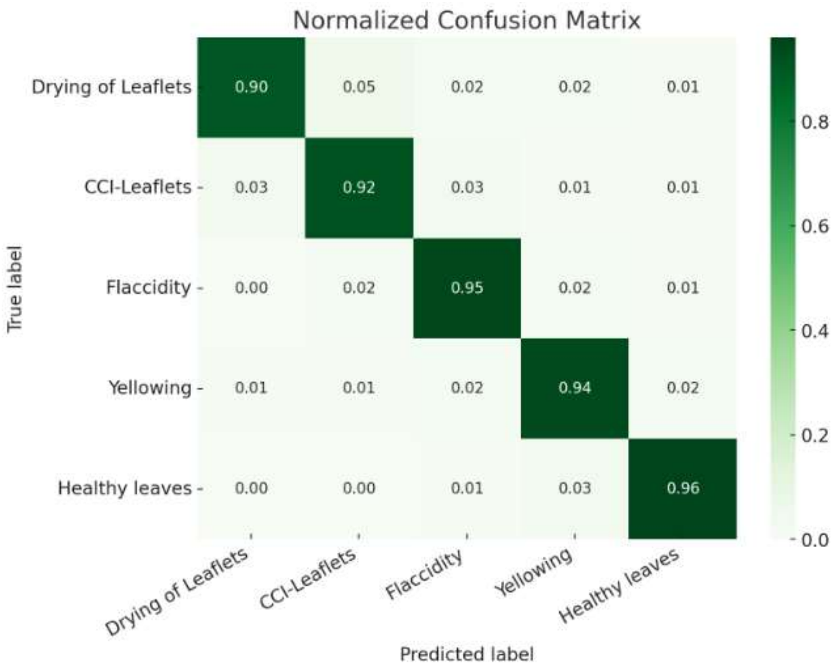

Figure 3. Confusion matrix.

Table 2. Results observation on evaluations.

Factors	**Accuracy**			**Precision**			**Recall**			**F1-score**		
Samples	DD-CL	ResNetV2	MobileNet	DD-CL	ResNetV2	MobileNet	DD-CL	ResNetV2	MobileNet	DD-CL	ResNetV2	MobileNet
200	94.0	87.4	88.0	93.7	86.8	87.3	92.5	85.7	86.0	93.1	86.3	86.8
300	95.2	89.1	89.8	94.8	88.6	89.0	94.0	87.5	87.8	94.5	88.1	88.5
400	96.0	91.3	90.6	95.7	90.5	90.2	95.0	89.6	89.0	95.3	90.0	89.8
500	96.5	92.0	91.9	96.2	91.3	91.1	95.4	90.4	90.2	95.8	91.0	90.8
600	96.8	93.5	92.8	96.6	92.6	92.2	95.8	91.8	91.5	96.3	92.2	91.9
700	97.0	94.0	93.7	96.9	93.2	93.0	96.1	92.3	92.1	96.6	92.8	92.6
800	97.3	94.5	94.2	97.3	93.8	93.4	96.5	92.9	92.7	96.9	93.5	93.1

Figure 4 below presents the comparison graph of accuracy of the DD-CL, ResNetV2, and MobileNet when classifying the coconut leaf disease, and when determining the severity of a disease. The DD-CL model follows the maximum accuracy at any point of the model, which is 97.3% at 800 samples compared to 94.5% and 94.2% in ResNetV2 and MobileNet respectively. The differences in the accuracy of the models are also fairly big among the smaller sample sizes, which makes 100–300 samples the largest discrepancies between the vigilance scores of the models, namely MobileNet and ResNetV2 are 4–6 per cent. below the DD-CL. The more the training samples are supplied, the better the performance of all the models would be but, DD-CL would still be on top of other models, which indicates that, DD-CL can improve to learn the better features and can distinguish the seriousness of the diseases.

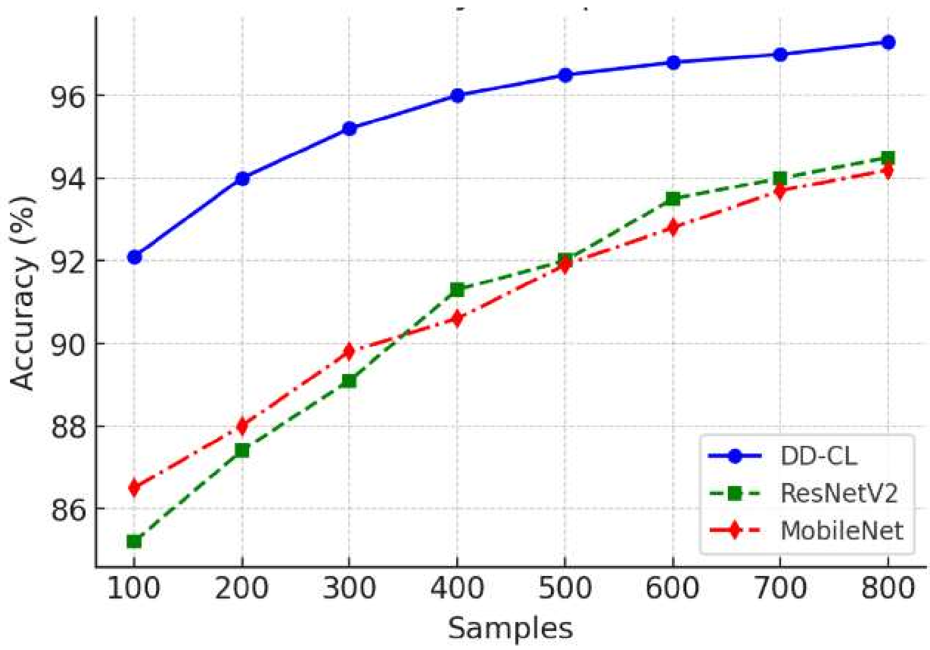

Figure 4. Accuracy rate comparison.

It consists of the detection of diseased coconut leaves and the level of their development with a greater degree of precision. In the process of results analysis, it is discovered that the highest precision of 97.3% is obtained by DD-CL with the first set of 800 samples whereas the ResNetV2 and MobileNet obtain 93.8% and 93.4%, respectively, as it is found in **Figure 5**. This implies that DD-CL avoids the increase in the false positive rates compared to clinical relevance scales in disease classification, which is necessary to prevent expensive interventions. One can also notice that MobileNet and particularly ResNetV2 share relatively high precisions at the range of 500–700 samples, which implies that they can classify the samples in a relatively similar manner with relative quantities of samples. However, DD-CL once again outperforms and more so when it comes to categorizing diseases which have nearly similar rates of severity including mild and moderate ones.

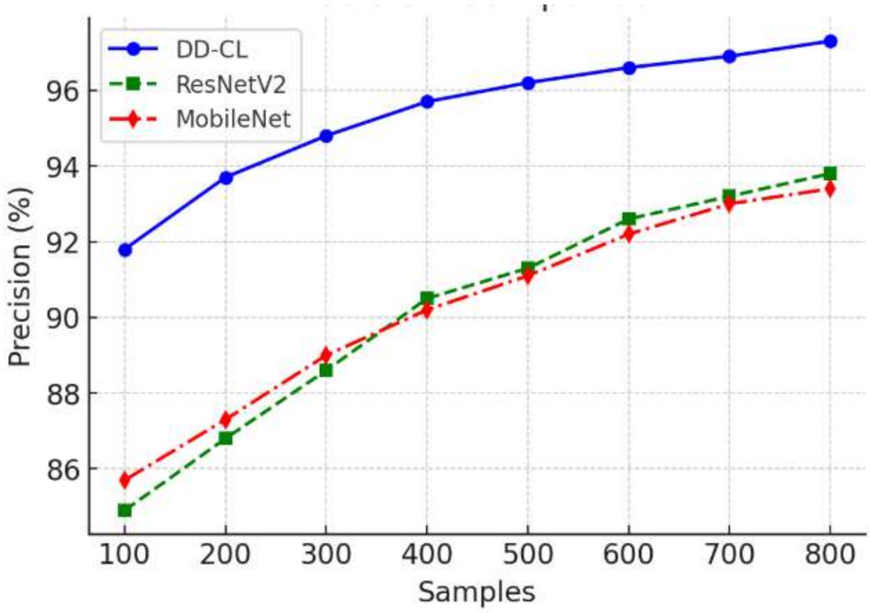

Figure 5. Precision rate analysis.

The recall indicates the proportion of diseased coconut leaf the models recognize to ensure that no additional infections go undiagnosed by the models. **Figure 6** shows that, at 800 samples, DD-CL has 96.5% recall that is superior to those of ResNetV2 (92.9%) and MobileNet (92.7) by a margin of 4–5 percent in the mid-range (300–500) samples. In such a manner, the greater recall would ensure identification of diseases even when symptoms are very early and insignificant like very little yellowing of the leaflet or at worst. As it is possible to observe, MobileNet, as well as ResNetV2, improve as the number of samples increases but the low recall rate indicates that the initial signs of diseases can be skipped without any difficulty.

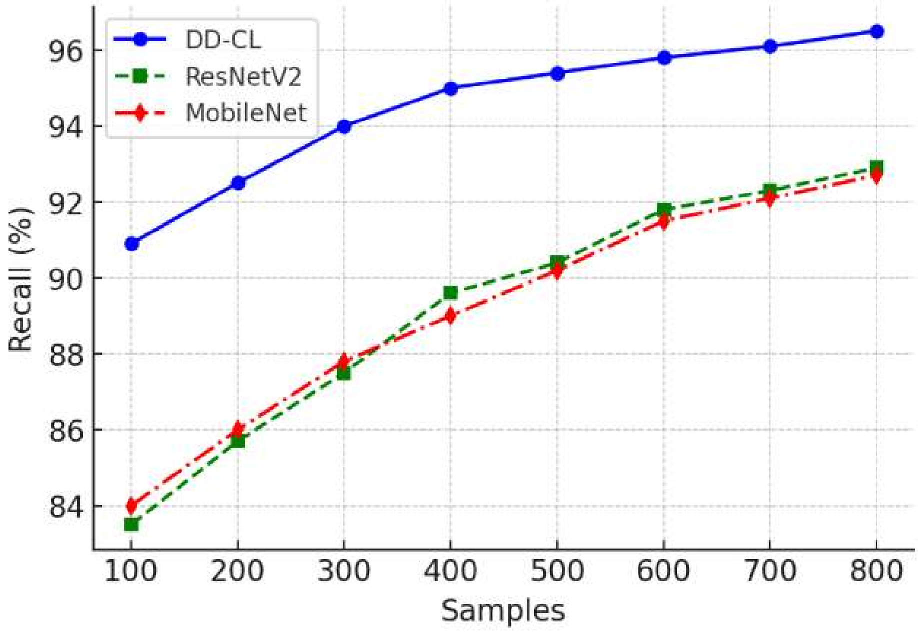

Figure 6. Recall rate comparison.

Thus, F1-score, which is taken into account in **Figure 7**, in which both the precision and the recall are taken into account, also demonstrates that DD-CL is the most suitable one to diagnose the disease and its severity of the coconut leaves. At the same 800 samples, ResNetV2 and MobileNet have 93.5 percent and 93.1 percent respectively, which means that the specified method is superior to the two other trainers. The disparity of the other models regarding the sample size of 300–600 is far more pronounced in the situation of DD-CL that proved its efficiency especially in differentiating the similar severity. The trend of the F1-score in the case of ResNetV2 and MobileNet is increasing with the increasing sample size over the 600 that indicates a generalization capacity of the two. However, the model that has the least error in its application with the aim of reducing the false positive and the false negative is DD-CL that is appropriate towards effective disease control in coconut plantation.

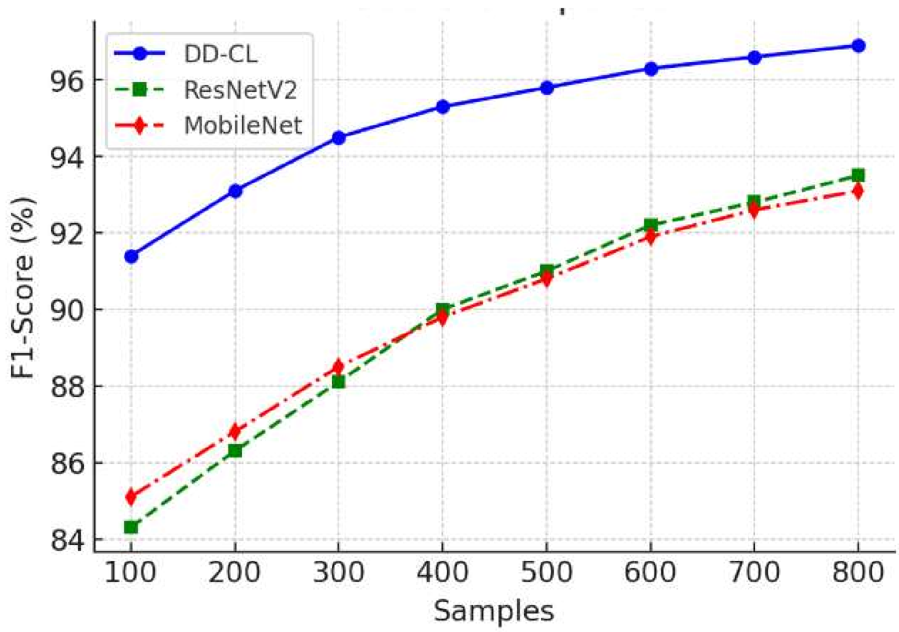

Figure 7. F1-score comparison.

In training loss convergence image, the stability of learning the proposed DD-CL model during consecutive epochs is shown in **Figure 8**. The value of loss goes down drastically in the first training stage where it falls as much as 1.42 to 0.35 in the first 20 epochs which shows that features are quickly learned through transfer learning. The loss curve has reached an effective convergence starting at epoch 40 and does not oscillate or diverge. The convergence curve that is well-behaved supports the appropriateness of the choice of the learning rate and optimization strategy, and the lack of the spikes in the convergence curve indicates that data augmentation and regularization were effective to enhance the process of generalization. This constant loss performance proves the strength of the training process and guarantees the faithful performance at the inference stage.

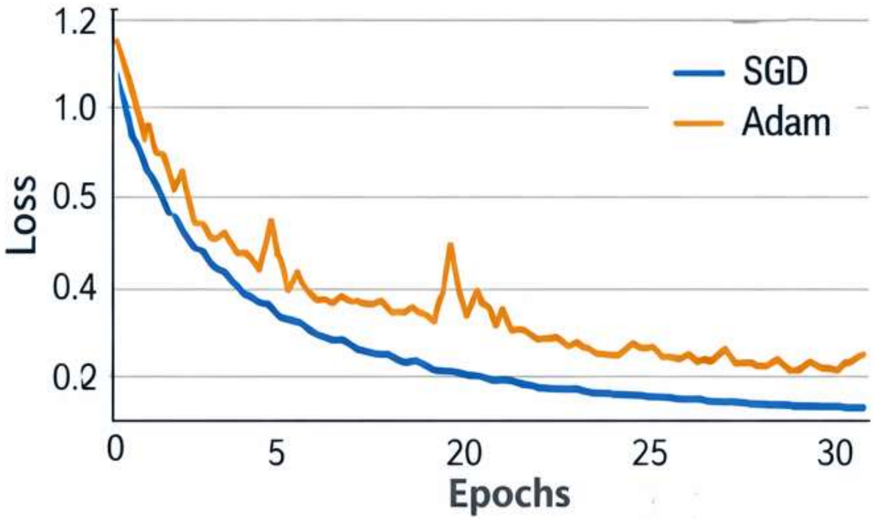

Figure 8. Training loss convergence – optimizer.

The image of the confusion matrix emphasizes the performance of DD-CL framework to predict all the classes of coconut leaf disease as depicted in **Figure 9**. There is high level of the diagonal dominance and the correct classification rates are more than 94% and 93–96% to the healthy leaves and the disease classes like flaccidity, yellowing and drying of the leaflet respectively. The minor misclassifications can be observed mostly on disease transitions at early stages i.e. between flaccidity and first yellowing stage whereby there are 3–5 percent overlaps because of similarity in symptoms. Notably, the misclassification rates of severe instances of the disease are less than 2, which indicates that the model will be capable of identifying the higher stages of the disease correctly. These findings establish that the instances of classification errors are focal and acceptable clinically, which justifies the reliability of the suggested system.

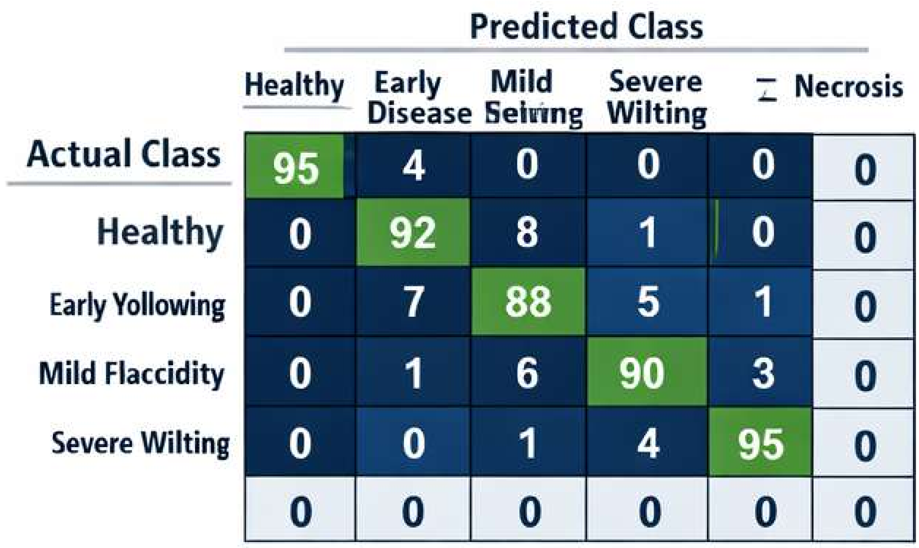

Figure 9. Confusion matrix analysis- proposed methodology.

The value is an output of an image-processing-based disease staging pipeline running on the coconut leaf samples visualized on plain white background, as depicted in the **Figure 10**. Leaves are given an order of progressive severity range, ranging between the state of health and critical damage, through the extraction of visual features and segmentation. Pre-processing of the image including background removal, contrast enhancement, and preservation of edges isolates the leaf region, whereas color and texture analysis indicate the symptoms of disease. The initial stages present slight bending of the leaflets and loss of rigor with slight variations in chromatic variation, but moderate stages present uneven yellowing and spotty chlorosis, as revealed by alterations in the distribution of green-yellow intensity. During the extreme stages, tip browning, necrotic areas, and brittle textures are also seen, which are marked with the help of bounding boxes and arrows to show affected areas. An irreversible damage of structural breakdown and broken tips of leaves is observed in the last critical phase. In general, the visualization illustrates the effectiveness of image processing outputs, including region marking, severity labeling, and symptoms localization in the automated detection of coconut leaf disease and the classification by stage.

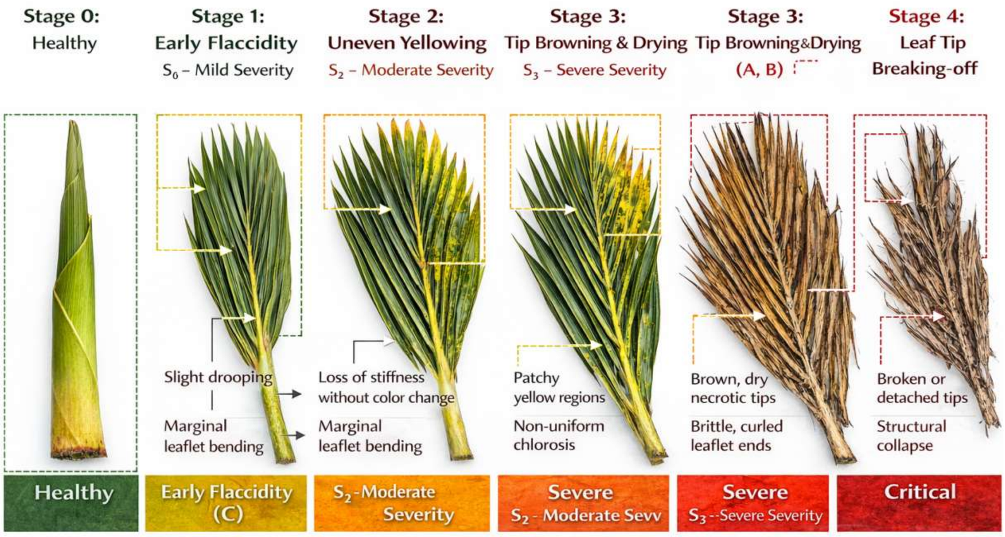

Figure 10. Visualization of coconut leaf stages.

5. Conclusion

Drying of Leaflets, CCI-Leaflets, Flaccidity, and Yellowing are some of the diseases that affect coconuts and cause significant reduction in production since a very inefficient method is used to diagnose the disease. To fight this issue, this study proposes the framework of "Earlier Disease Diagnosis in Coconut Leaves (DD-CL) that is capable of identifying the kind and severity of the disease using CNN with transfer learning. Then the dataset of Coconut Leaf Dataset of Pest Identification of Kaggle was used to test the proposed approach and the accuracy of DD-CL was with 97.3% higher than that of ResNetV2 at 94.5% and MobileNet 94.2%. Besides the results indicated the high accuracy of the model in distinguishing between the disease types and the levels of severity at 97.3% and moderate level of F1-score of 96.9 that the model can be applied in real-time monitoring of the diseases. The future research may be focused on the model integration into the mobile applications and edge devices to identify the disease of plantations in real time to assist the farmer in fast response.

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