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Detection of Sugarcane Mosaic Diseases Using Deep Learning Architecture to Avoid Annealing Temperature of PCR Primer in Laboratory Testing

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ABSTRACT

The sugarcane leaf diseases such as mosaic and streak mosaic are difficult to differentiate using Image processing techniques because both diseases show similar visual attributes such as pattern and color. To identify the type of diseases, we need to perform Polymerase Chain Reaction (PCR) testing which is used for the classification of diseases in laboratories. The accuracy of the PCR test depends on reaction mix preparation, reaction time, and DNA/RNA extraction. The major problem influencing the PCR test accuracy is the Annealing temperature of the primers and needs a standardized set of samples. In addition, it is a time-consuming process. In this paper, we proposed a Diversified Deep Learning Architecture (DDLA) which is developed with the input images after various pre-processing steps such as denoising using Discrete Wavelet Transform (DWT) and enhancing using histogram equalization in HSI color space to improve the similar pattern disease prediction accuracy. The performance of the proposed model is analyzed for a set of diseased leaves and the results are compared with the output of the popular pertained models such asVGG16, InceptionV3, ResNET50, Inception ResNET, and DenseNET201 with and without pre-processing. The training accuracy of the proposed model is 97% and the testing accuracy is 87%. The DDLA model produces ground truth test results with an accuracy of 88.7% for mosaic and 85.7% for streak mosaic with a less computational time of 152sec compared to the lab test duration of 6 hrs. The performance of the model is also measured in terms of Precision, F1 Score, Specificity, and Sensitivity. The Proposed DDLA model's F1 score is higher than the pre-trained models with a minimum test loss of 1.167. Moreover, the DDLA structure occupies less memory space when compared to the pertained models.

1. INTRODUCTION

In India, sugarcane is cultivated in all the regions of the country irrespective of climate and temperature. There are 50 varieties of sugarcane plants cultivated around the year. The sugarcane plant diseases are classified into 30 different types and they occur according to the climate, temperature, and soil type. Among the 30 varieties of diseases, few are visually identified, and few diseases are identified through lab tests. The major diseases affecting sugarcane production are Redrot, Smut, Wilt, Yellow leaf, Rust, Grassy shoot, Red Stripes, and Streak Mosaic. These diseases cause severe loss to the farmers due to improper identification of diseases and chronic in nature which leads the farmers to change crops often.

The characteristics of mosaic and streak mosaic diseases are shown in Table 1. These two sugarcane leaf diseases are similar in pattern, color, and texture that are marked with similar color circles. These diseases cannot be identified through visual interpretation.

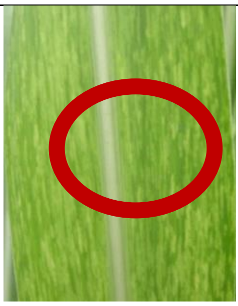
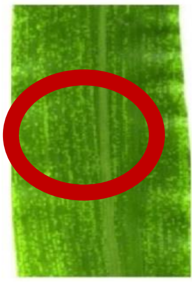
These viruses are identified using a laboratory-based technique known as Polymerase Chain Reaction (PCR) test. PCR is a molecular-based diagnosing method for leaf disease detection in laboratories. PCR test amplifies or creates millions of identical copies of a particular DNA sequence within a tiny reaction tube. PCR test is applicable only for the organism with known genome information/ Gene sequence. The accuracy of the PCR test depends on reaction time and DNA/RNA extraction.

Now, advanced PCR tests like single plex Reverse Transcription-PCR(RT-PCR) and Multiplex RT-PCR are used for the identification of sugarcane viruses in lab tests [1, 2]. Multiplex RT-PCR is used for simultaneous detection and identification of more than one sugarcane viruses. There are five different types of viruses such as Sugarcane mosaic virus (SCMV), Sorghum mosaic virus (SrMV), Sugarcane streak mosaic virus (SCSMV), Sugarcane yellow leaf virus (SCYLV), and Sugarcane bacilliform virus (SCBV), that are detected simultaneously with multiplex RT-PCR method. Different primers are used for amplifying the target virus DNAs and suitable assays [2].

The PCR test is performed because the morphological features of Sugarcane Mosaic Virus (SCMV) and Sugarcane Steak Mosaic virus (SCSMV) are similar. However, PCR is an expensive and time-consuming process. Hence, the researchers began to develop Image-processing based methods to identify the sugarcane leaf diseases.

Scientists have used a combination of various Digital Image Processing algorithms such as thresholding feature-based rules, etc., to classify various kinds of plant diseases [3]. These algorithms are more efficient and consume less amount of time for identifying the leaf diseases. However, due to various problems during image acquisition such as noise, lighting, the accuracy of Image-Processing models is majorly affected.

Table 1. Sugarcane mosaic diseases

S.No.	Disease	Symptoms	Type of Virus
1.	 **Sugarcane Mosaic**	• Contrasting dark green and light green shades noticed on the leaf lamina due to the varying levels of chlorophyll concentration on the leaf blade caused by the virus.	Sugarcane Mosaic Virus (SCMV)
2.	 **Sugarcane Streak Mosaic**	• Pale green symptoms on leaves of sugarcane.	Sugarcane Streak mosaic virus (SCSMV)

To overcome these problems, the input image must be preprocessed before the analysis. The pre-processing step involves filtering the noise and enhancing the critical features of the given input image which helps in improving the overall accuracy.

Nowadays, plant diseases are automatically detected using Deep Learning based methods in real-time. Convolution Neural Networks (CNN), a type of artificial neural network which is widely used in Image/object recognition and classification. This plays a significant role in the feature extraction and classification of the given leaf diseases sample. Since CNN provides an automatic feature extraction of the given image, the preprocessing step is generally skipped. However, due to the similar feature attributes of mosaic and streak mosaic leaf diseases, the model is unable to detect the type of mosaic disease. Therefore, we have developed an efficient CNN model with preprocessing which helps in the classification of sugarcane mosaic and sugarcane streak mosaic leaf disease based on disease pattern variations.

2. PROBLEMS

PCR testing is done for the presence of any living organism in Plants, Animals, Microbes etc. provided the genome information/ Gene sequence of the test organism is priorly known. In PCR test, the conditions/protocol needs optimization for each run, according to the program - number of cycles, the time of PCR reaction will vary accordingly. Moreover, the PCR test Accuracy depends on various parameters such as DNA/RNA extraction, PCR reaction mixture preparation, optimizing the protocol etc. Even after proper optimizing the PCR test can provide 90% accuracy. Still, sequencing the PCR product confirm the targeted gene/fragment and amplified by PCR. Furthermore, factors like Annealing temperature of the primers, Magnesium chloride concentration in the buffer, PCR running conditions/program, Number of cycles etc. needs to be standardized for a given set of samples. False positive control also a major problem in PCR testing due to the improper mixture of master mix and amplification of target nucleic acid from the organism of interest. PCR method is the only way to differentiate/confirm the mosaic and streak mosaic virus in plants. However, it is an expensive and time-consuming process.

The existing various image processing, Machine learning, deep learning-based disease classification methods are discussed in the relative work section. Even though Image processing-based methods are simple and less time-consuming, the appearance or image of similar pattern/symptom leaf diseases cannot be classified efficiently. Recently CNN based methods are commonly used to detect different types of plant diseases, however, the performance of the methods for similar pattern/color diseases still needs improvement. The related work section discusses a few CNN-based methods which were able to identify the sugarcane mosaic disease but are still unable to differentiate between sugarcane mosaic and sugarcane streak mosaic leaf diseases.

To overcome this problem, we have developed an efficient CNN structure called Diversified Deep Learning Architecture (DDLA), which pre-processes the image and extracts the disease pattern variations in the diseased leaves for disease classification.

3. CONTRIBUTION

This paper focus on the testing of similar pattern diseases using Convolution Neural Network. The proposed Diversified Deep Learning Architecture (DDLA) solves the problem of annealing temperature of the primers during mosaic and streak mosaic leaf disease detection.

1. To develop, (DDLA) architecture which consists of Discrete Wavelet transform (DWT) denoised images with color enhanced as the input for the training layers for sugarcane leaf disease identification such as mosaic and streak mosaic.
2. To evaluate, DDLA architecture for the different denoising images such as spatial and frequency domain filtering as training set and evaluated for the performance in disease identification.
3. To reduce, DDLA structure layers and occupies less memory space when compared to the pertained models such as VGG16, Inception V3, ResNet 50, DenseNET201 etc. The classification accuracy of sugarcane leaf disease is high with less number of layers.

4. RELATED WORKS

The plant disease detection methods as Serologic Method, Molecular Method, Image Processing Method, Fluorescence Imaging, Thermography based methods and Hyper spectral Imagery based methods are used [3, 4]. Among these, the molecular method approaches are suitable for identification of the diseases [5, 6]. The plant disease is diagnosed based on crop images of leaves, color, stems, and flowers through image processing-based techniques such as SVM, Fuzzy, K-means, GLCM, GA, PSO, and CNN. Plant disease severity is estimated by calculating the size of deformed or discolored pixels of a leaf or flower.

Barbedo et al. [7] discussed various plants diseases such as Sunflower, grapes, rice, cucumber using digital image processing algorithms such as thresholding, feature-based rules, fuzzy logic, and SVM. However, image acquisition needs proper environmental conditions such as lighting, angle of capture, and the distance between the object and capturing devices.

To overcome these problems, pre-processing of the acquired image is necessary for the accurate classification of diseases since the captured image has noise in the plant image and is never suitable for image analysis. The algorithms like Neural networks, SVM are used in classification for plant disease identification. Furthermore, Researchers use Deep learning, Machine learning, and Image processing combined techniques for plant disease detection [8].

To automate plant disease detection in real-time Deep learning-based methods play an important role in the earlier detection of diseases. Computer vision and Deep learning techniques provide a solution for the shortfalls in spatial image processing techniques. Deep Learning techniques especially Convolution Neural Networks provide a solution without pre-processing and feature extraction. The first CNN using Image-based classification was proposed by Moriya et al. in 2016 [9].

Xie et al. [10] proposed a method for Grape leaf diseases such as black rot, leaf blight disease detection through the pretrained Convolution neural networks and Adaptive CNN models. The three CNN models such as StridedNet, LeNet, and VGGNet are used for sugarcane diseases detection, and the model is fine-tuned by varying the dropout rates, and the number of iterations [11]. The author analyzed the presence of sugarcane disease in plants and not performed classification.

Malik et al. [12] analyzed five different sugarcane leaf diseases which can be interpreted visually and not similar diseases. Furthermore, the diseases detection accuracy is less compared to the RT-PCR test. The proposed CNN model identifies various diseases such as Helminthosporium Leaf Spot, Red Rot, Cercospora Leaf Spot, Rust, and Yellow Leaf Disease. VGG16, ResNet CNN structures were used, and also the performance of the network is analyzed with different learning rates such as differential learning rate and cyclic learning rate. Test time augmentation was also proposed to improve the performance of the CNN structures.

Wang et al. [13] used CNN for apple black rot disease analysis and disease severity is classified into four stages such as healthy, early, middle, and End. CNN is trained using transfer learning and training from scratch. Moreover, a series of deep convolution neural networks are trained and diagnose the severity of the disease. The performances of shallow networks trained from scratch and deep models fine-tuned by transfer learning are evaluated systemically to identify the diseases.

Sladojevic et al. [14] has developed a CNN model to recognize thirteen different types of plant diseases. Srivastava et al. [15] has used CNN networks such as VGG16, inceptionv3, and VGG19. Feature extraction and SVM for classification. The author had taken the sugarcane stem, color, and leaf of the plant for analysis and classified it as sugarcane disease. Agarwal et al. [16] proposed a CNN model with 3 Conv 3 max-pooling and 2 FC layers. The performance was better than the VGG16, Inception V3, and MobileNet and was used to classify Nine different diseases. However, the mosaic and streak mosaic diseases were not addressed in their studies.

Militante et al. [17] proposed a model to detect Sugarcane Disease using CNN and 9 diseases were detected including mosaic but not differentiated mosaic and streak mosaic diseases. Mohanty et al. [18] used CNN to detect 26 diseases detection from 14 different crop species. Furthermore, the author used to detect the mosaic virus in the tomato plant. Sharma et al. [19] discussed the advantages and limitations of CNN networks in plants disease identification [20]. The author discussed CNN-based disease detection techniques using various CNN models.

Even though the CNN networks were able to identify the disease, it suffers from poor generalization capabilities for unfamiliar datasets. Till now and then, disease detection techniques discussed are designed to detect diseases with visibly identified symptoms on sugarcane leaves and no techniques are proposed for the differentiation of mosaic and streak mosaic diseases.

5. MATERIALS AND METHODS

The conventional method for sugarcane leaf disease classification using CNN is shown in Figure 1. The raw image is given as an input to the CNN network. The CNN extracts features from the input image and based those features the disease is classified. In the proposed Diversified Deep Learning method, the input is preprocessed before passing it to the CNN for classification and is shown in Figure 2.

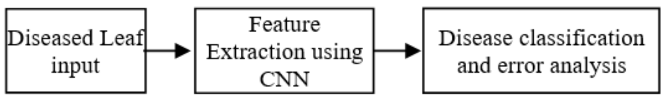


Figure 1. Conventional CNN method for disease classification

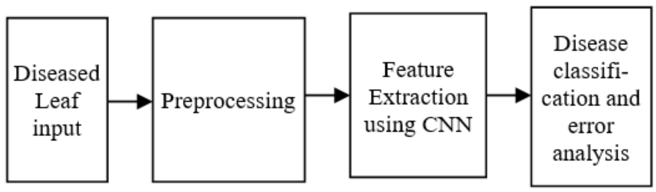


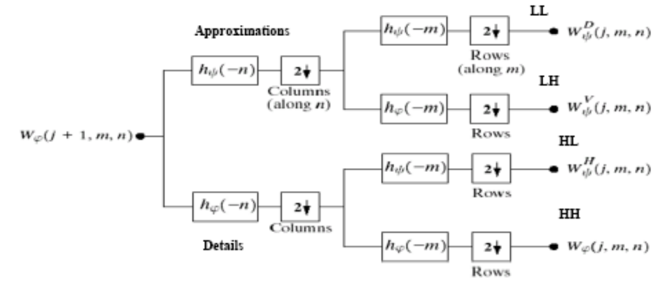
Figure 2. Proposed diversified deep learning architecture

Pre-Processing: In this paper, preprocessing steps such as Noise removal using DWT, Color space conversion-HSI, and Color histogram processing are included.

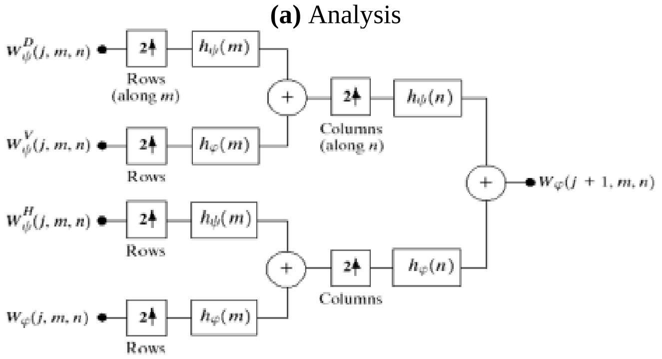
Figure 3. Pre-processing steps in proposed DDLA

The diseased sugarcane leaves are collected by humans and drones under different environmental conditions. The diseased pattern in the images is not clear due to environmental factors such as humidity, temperature, and illumination level. So, noise is added during capturing the images. Noise is a dominant factor that degrades the disease mosaic pattern in the diseased leaves. So, noise removal becomes necessary in preprocessing step before the leaf image is given to the CNN network. Figure 3 represents the pre-processing steps involved in DDLA.

Denoising using DWT: Denoising is done by using 2D Discrete Wavelet Transform (DWT) with a three-level decomposition of the input image as shown in Figure 4.a. using wavelet analysis filters. The decomposition is followed by down sampling. The DWT Synthesis filter bank is shown in Figure 4.b. The two level DWT decomposition results sub-bands as shown in Figure 5.



(a) Analysis



(b) Synthesis

Figure 4. DWT filter banks

Author [21] proposed an image denoising method using CNN embedded with DWT. The DWT process includes the network instead of the pooling layer in CNN [21]. In the proposed work, we used DWT for noise removal and it is used to remove white noise in the acquired image, which occurs due to ambient light and temperature conditions [21]. Compared with the classic algorithm, the proposed algorithm can improve the adaptability of image enhancement in images with low illumination and other issues. Overall brightness and contrast of an image while reducing the impact of uneven illumination. The enhanced images appear clear, bright, and natural.

RGB to HSI Color Space Conversion: The image enhancement is done using color histogram equalization and equalization is done in HSI (Hue Saturation Intensity) color space. The following expressions show the RGB to HSI color conversion process.

$$H = \begin{cases} \theta & if \;\; B \le G \\ 360 - \theta & if \;\; B > G \end{cases}$$

$$\theta = \cos^{-1}\left\{ \frac{1/2[(R-G)+(R-B)]}{[(R-G)^2+(R-B)(G-B)]^{1/2}} \right\}$$

$$I = \frac{1}{3}(R+G+B)$$

The H is called Hue, it represents the color of the image. It is represented in angle with respect to the red axis in the color circle. S-Saturation, it gives the percentage of color dilution with white color and I-represents the intensity of the image. The image enhancement is done by modifying the intensity value without altering the hue and saturation values.

Histogram Equalization: Histogram Equalization method is adopted to preprocess the original image to enhance the useful information. This process makes the intensity distribution among the pixels equally.

Proposed plant disease detection process: The detailed sugarcane leaf disease detection process is shown in Figure 6. The sugarcane leaf disease dataset (mosaic, streak mosaic, and healthy leaves) is prepared by collecting real-time sugarcane field leaf images and diseased images from a laboratory named Sugarcane Research Institute Coimbatore are added for validating the training results.

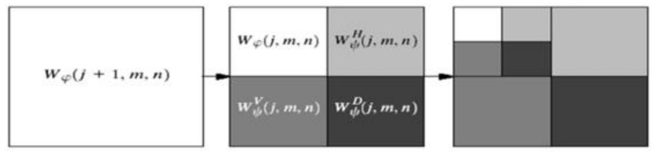


Figure 5. 2 level DWT decomposition sub bands

The dataset is preprocessed using DWT to remove the noise added while collecting the real-time sugarcane field images. And also, the duplicate images are removed by visualizing the captured images. Then the dataset is split into training and testing datasets. The training dataset is used for training and validation and the testing dataset is used for testing.

The training dataset is given to data augmentation for increasing the dataset size and reducing the overfitting problem of the CNN model during the training. The CNN model used for disease detection is built in two ways. One method is Transfer learning approach and another method is built from scratch. In Transfer learning approach, the pretrained CNN models like VGG16, InceptionV3 [22], ResNET50 [23], InceptionResNET [24] and DenseNET 201 are used to extract the features of the image and only the final layer is fine-tuned based on the data classes. In the second method, a CNN model with a smaller number of training parameters is built to detect the leaf diseases. Both the approach models are trained and their performance is measured using test dataset. The performance is evaluated by doing the error analysis.

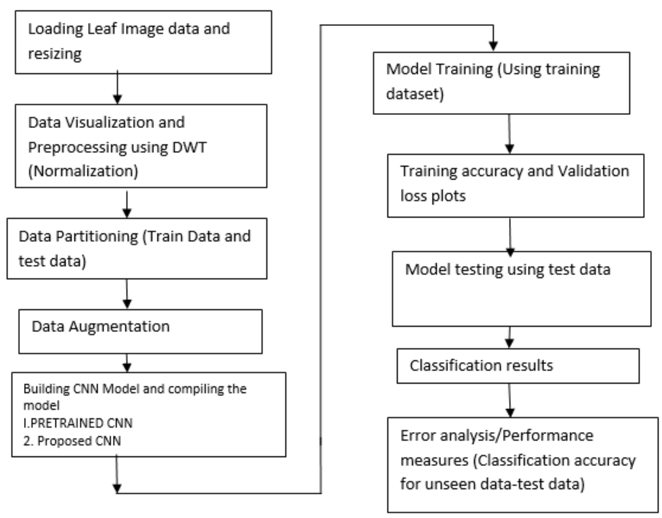


Figure 6. Proposed plant disease detection process

The first approach is shown in Figure 7. It consists of preprocessing steps and various pretrained models like VGG16, InceptionV3, ResNET50, InceptionResNET, DenseNET 201.The pretrained models were developed for ImageNET contest and made available in Keras applications platform. The networks were designed and trained to classify 1000 objects based on the images in the ImageNET dataset. Based on the transfer learning concept, these pretrained models can be used to classify images in small datasets. The fine tuning will be done in the output layer of these networks. The other layers in the network are used as fixed feature extractor for the new dataset. The output layer in the pretrained models is modified according to sugarcane disease classification.

The second approach is to start from scratch. We proposed a new CNN model instead of pretrained models. The proposed CNN consists of seven layers as shown in Figure 8, along with preprocessing. Two 2D convolution layers and two dense layers are arranged in sequential form. The two convolution layer's output feature maps are given to the Max pooling layers of size 2x2 in order to reduce the samples. The flattening layer makes the output of Conv layer into one dimensional.

In the proposed work, totally 1000, diseased images are taken for analysis. The images are collected into three classes as healthy, mosaic diseased and streak mosaic diseased images with different angles and different lighting levels.

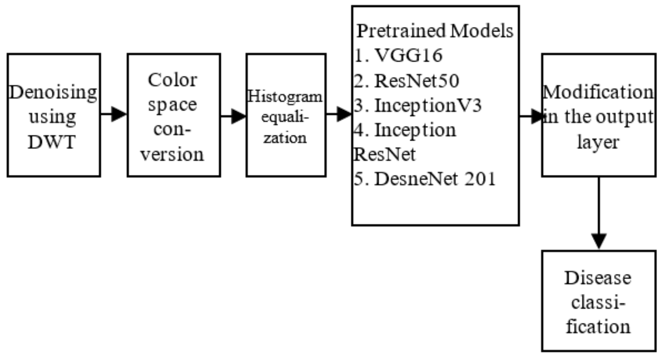


Figure 7. Proposed approach 1

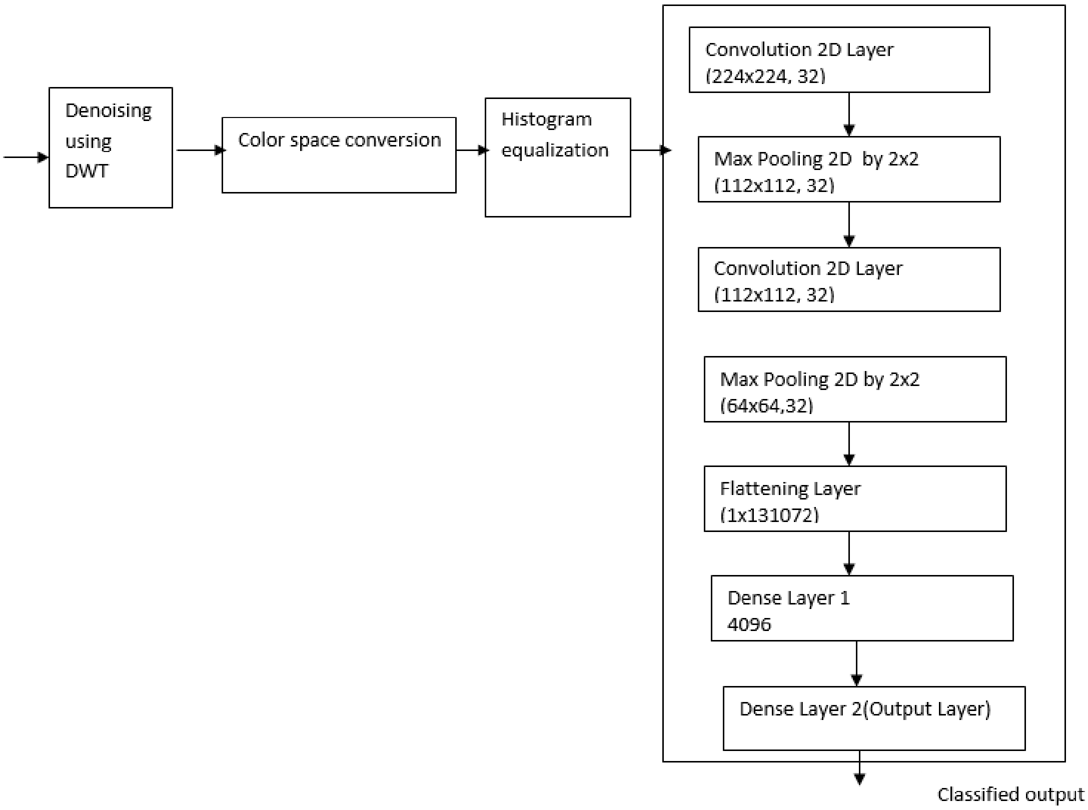


Figure 8. Proposed DDLA Model (Proposed metod-2)

6. RESULTS AND DISCUSSION

The sugarcane leaf disease dataset is about 1000 leaf images with different disease categories such as healthy (no disease) and mosaic (diseased category) and streak mosaic (diseased category). First, the leaf images are applied to pretrained models for classification in two conditions, such as with and without preprocessing. Next, the input leaf images are resized to 224x224 and given to the proposed DDLA model for classification. The data augmentation process in the DDLA improves accuracy and eliminates over fitting problem.

Sugarcane leaf samples are shown in Figure 9 and Figure 10 shows preprocessed leaf images.

The input leaf image and denoised image using DWT-wavelet db10 and after that the HSI color space shown in the Figures 10.a, 10.b, and 10.c. The histogram equalized HIS image and RGB converted image are shown in Figures 10.d and 10.e respectively. Similarly the Figures 11(a) to Figure 11(e) shows the streak mosaic diseased leaf images preprocessing outputs and Figures 12(a) to 12(e) illustrates mosaic diseased leaf image preprocessing outputs in sequence order. The histogram equalized, RGB image gives the difference in texture pattern and training of networks with these images results to increase model performance.

Figure 9. Input leaf images with mosaic and streak mosaic diseases and healthy leaves

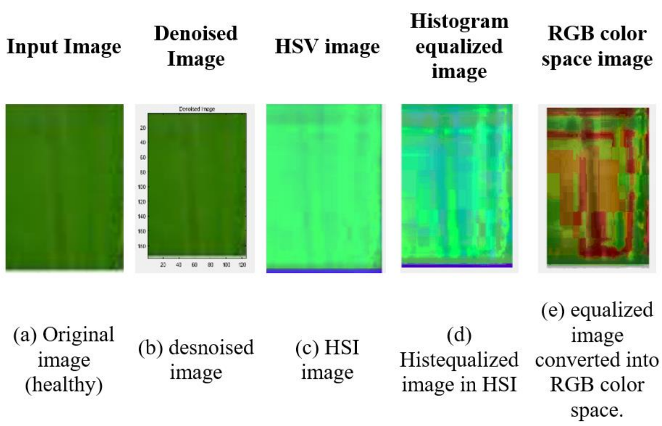


Figure 10. Preprocessing outputs (step by step) of the input leaf image (Healthy leaf)

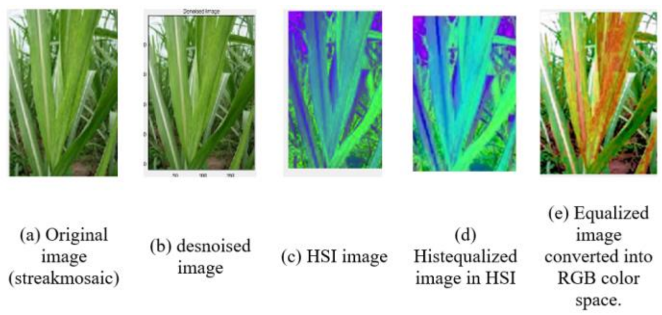


Figure 11. Preprocessing outputs (step by step) of the input leaf image (streak mosaic diseased)

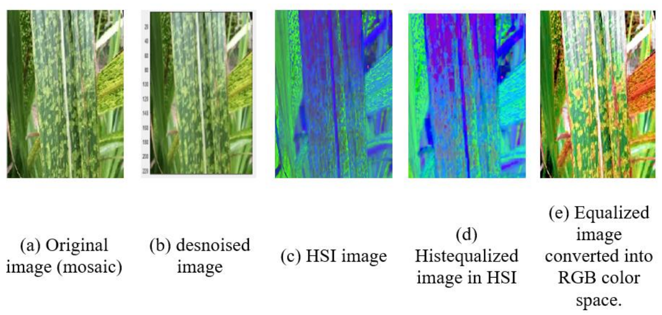


Figure 12. Preprocessing outputs (step by step) of the input leaf image (mosaic diseased)

Table 2. Pre-trained models with total number of parameters

Sl. No.	Pre trained model	Total No. of parameters	No. of trainable parameters
1	VGG16	14,764,866	50,178
2	InceptionV3	21,956,387	1,53,603
3	ResNet50	23,888,771	3,01,059
4.	InceptionResNET	54,336,736	54,276,192
5	DesnseNET201	1,232,340	1,232,340
6	Proposed CNN(DDLA)	5,319,075	5,319,075

The various pre-trained models and total number of parameters are given in Table 2. The VGG 16 has lower number of trainable parameters, when compared to the other pretrained models. The number of trainable parameters is approximately only 25%, when compared to ResNet50 and 50% with respect to InceptionV3. The total number of parameters is around 14 million in VGG16. The total number of parameters in ResNET 50 and inceptionV3 are around 21 million and 23 million respectively. The number of parameters in InceptionResNET50 is around 54 million. Inception-resnetV2, when compared to other models. So model required more memory space when compared to other models. The number of parameters in DenseNET 201 is less, when compared to the other pretrained models. The number of parameters in proposed DDLA is around 5 lakhs only.

Table 3 gives performance of the proposed DDLA model in two conditions such as without preprocessing and with preprocessing of input images. The model performance is measured for 20 epochs and are tabulated in Table 3. The processing DDLA is done in two conditions. With preprocessing and without preprocessing of input images. The performance of training and testing accuracy is less for all models, when compared to performance in with preprocessing inputs. It is around 3% less in both training and testing accuracies in the case of without preprocessing condition. The performance in with preprocessing condition is described as follows. The training accuracy of the VGG16 model is 96% and almost follows the validation accuracy. The training accuracy of InceptionV3 is slightly less than VGG16 and provides a small variation in training and validation accuracy. The accuracy of ResNet 50 is less, when compared to other models and validation loss also more and deviation is seen in validation accuracy and training accuracy. The accuracy of Inception ResNET is higher than ResNET50 and less than DenseNET201. The proposed DDLA training accuracy is slightly less than DenseNET201, still testing accuracy is higher than DenseNET by 6%.

The testing accuracy of DDLA model is higher than pretrained models and the testing accuracy is 97%. The algorithm is implemented using PC with AMD PRO A12 98008 R7 Processor frequency 2.7 GHz and 8GB RAM capacity.

Table 4 shows ground truth verification of proposed DDLA model for various sugarcane diseases such as Mosaic, streak mosaic. The DDLA model performance is compared with various pretrained models in two conditions such as with and without preprocessing. The DDLA Performance is compared with Lab test results and visual interpretation. The leaf disease detection using visual interpretation performs less and DDLA model in preprocessed condition is more than 12% for with preprocessing conditions of the pretrained models. The VGG16 and Inception V3 models produce test results of approximately 2%to 3% better accuracy in the preprocessed condition when compared to their performance in without preprocessing approach. The Resnet50 and Inception- ResNet provides an average of 65.4% and 71% in disease identification respectively. The performance of DenseNETt201 is better than pretrained models and produces test results with an accuracy of an average 74.96%. The accuracy of lab test using RT-PCR is 85 % to 90% for different diseases as shown in the Table 4 and laboratory test consumes 6 hours to detect disease. However, proposed DDLA model produces ground truth test results with an accuracy of 88.7% for mosaic and 85.7% for streak mosaic with less time period of 152sec. The model consumes less time for disease prediction and is almost 142 times better than the lab test duration time and 2% better than the other pretrained models detection time with an average classification accuracy improvement of 12%.

Table 3. Models training and validation accuracy (Mosaic and streak mosaic diseases classification)

	Without Preprocessing			With preprocessing (Proposed DDLA Model)		
Pre-trained CNN Model	**Training Accuracy**	**Validation Loss**	**Testing Accuracy**	**Training Accuracy**	**Validation Loss**	**Testing Accuracy**
VGG16	94.4%	0.612	22.4%	96%	0.6238	25%
InceptionV3	90.2%	0.492	28.3%	92%	0.527	31%
ResNet50	63.6%	1.326	42.2%	66%	1.419	44%
Inception ResNet	93.7%	1.246	67.4%	97%	1.39	69%
Dense Net201	96.8%	0.344	78.6%	**98%**	**0.266**	**81%**
Proposed DDLA model	92.9%	0.759	82.1%	**97%**	**0.8594**	**87%**

Table 4. Ground truth verification of the proposed model for sugarcane disease identification

		Disease Name/testing time.		
		Mosaic	**streak Mosaic**	
Lab test RT-PCR[ ]		85%	90%	Min 6 hrs
Pretrained CNN models without pre processing	VGG16	53%	60%	192 sec
	Inception V3	54.2%	61.3%	180sec
	ResNet50	67.5%	64.6%	300sec
	Inception ResNet	68%	66%	234sec
	DenseNet201,	74.5%	70%	312sec
Visual Interpretation		45%	50%	-
Pretrained CNN models with preprocessing	VGG16	55%	63%	195 sec
	Inception V3	55.4%	63.3%	184sec
	ResNet50	61.5%	62.6%	303sec
	Inception ResNet	70%	68%	237sec
	DenseNet201	76.2%	72.3%	315sec
Proposed DDLA Model		**88.7%**	**85.7%**	**152Sec**

Table 5. Confusion matrix for the three class problem (leaf disease classification)

Diseases Classification		**Actual**		
		Healthy	**Mosaic**	**Streak Mosaic**
Predicted	Healthy	$\text{True}_{\text{healthy}}$ (a)	$\text{False}_{\text{healthy}}$, (b) $\text{Actually}_{\text{Mosaic}}$	$\text{False}_{\text{healthy}}$, (c) $\text{Actually}_{\text{Streak Mosaic}}$
	Mosaic	$\text{False}_{\text{mosaic}}$, (d) $\text{Actually}_{\text{healthy}}$	$\text{True}_{\text{mosaic}}$ (e)	$\text{False}_{\text{mosaic}}$, (f) $\text{Actually}_{\text{Streak Mosaic}}$
	Streak Mosaic	$\text{False}_{\text{Streak Mosaic}}$, (g) $\text{Actually}_{\text{healthy}}$	$\text{False}_{\text{Streak Mosaic}}$ (h) $\text{Actually}_{\text{Mosaic}}$	$\text{True}_{\text{Streak Mosaic}}$ (i)

Table 6 shows performance of DDLA model in terms of sensitivity, specificity, F1 score, precision and accuracy from test set confusion matrix. The precision score of proposed CNN is high, when compared to the other pretrained CNN models. The proposed work classifies given input leaf image into healthy, mosaic diseased, streak mosaic diseased leaves.

For a multiclass problem, the sensitivity and specificity are calculated as follows.

The proposed work classifies the given input image into healthy, mosaic diseased, streak mosaic diseased leaves and is shown in Table 5. The sensitivity of the system for healthy leaf identification is given by

The sensitivity is defined as Sensitivity= $$\frac{TP}{TP+FN} \qquad (1)$$

and sensitivity for a multi class problem is calculated for each and every category. In this work, the sensitivity for healthy leaves, mosaic leaves and streak mosaic diseased leaves are calculated as follows.

Sensitivity of Healthy leaves $\text{Sensitivity}_{\text{healthy}}$

$$\frac{TP_{healthy}}{TP_{healthy}+FN_{healthy}} \qquad (2)$$

$$\text{Sensitivity}_{\text{Mosaic}}=\frac{TP_{Mosaic}}{TP_{Mosaic}+FN_{Mosaic}} \qquad (3)$$

$$\text{Sensitivity}_{\text{Streak Mosaic}}=\frac{TP_{\text{Streak Mosaic}}}{TP_{\text{Streak Mosaic}}+FN_{\text{Streak Mosaic}}} \qquad (4)$$

The confusion matrix of the sugarcane mosaic disease classification is shown in Table 5.

Table 6. Performance analysis of various techniques using confusion matrix

Pre-trained CNN Model	Sensitivity	Specificity	Precision	Recall	F1 score	Test loss	AUC
VGG16	0.33	0.583	0.4	0.43	0.41	4.547	0.698
InceptionV3	0.27	0.653	0.4	0.43	0.41	4.233	0.726
ResNet50	0.388	0.797	0.35	0.44	0.32	5.342	0.692
Inception ResNet	0.69	0.831	0.71	0.69	0.70	4.276	0.742
DenseNet201	0.81	0.91	0.83	0.81	0.82	1.457	0.864
Proposed DDLA	**0.77**	**0.86**	**0.88**	**0.81**	**0.82**	**1.167**	**0.892**

Let the conditions in the Confusion matrix are represented as follows

a=$True_{healthy}$, b= $False_{healthy}$, $Actually_{Mosaic}$
c=$False_{healthy}$, $Actually_{\mathbf{StreakMosaic}}$
d=$False_{Mosaic}$, $Actually_{healthy}$, e= $True_{Mosaic}$
f= $False_{Mosaic}$, $Actually_{\mathbf{StreakMosaic}}$
g= **False**$_{\mathbf{StreakMosaic}}$**, Actually** $_{healthy}$
h= **False**$_{\mathbf{StreakMosaic}}$**, Actually**$_{\mathbf{Mosaic}}$
i= $True_{\mathbf{StreakMosaic}}$
then

		Actual		
		Healthy	**Mosaic**	**StreakMosaic**
Predicted	**Healthy**	**a**	**b**	**c**
	Mosaic	**d**	**e**	**f**
	StreakMosaic	**g**	**h**	**i**

$$\textbf{Specificity(healthy)}=\frac{e+f+h+i}{e+f+h+i+b+c}$$

		Actual		
		Healthy	**Mosaic**	**StreakMosaic**
Predicted	**Healthy**	**a**	**b**	**c**
	Mosaic	**d**	**e**	**f**
	StreakMosaic	**g**	**h**	**i**

$$\textbf{Specificity (Mosaic)}=\frac{a+c+g+i}{a+c+g+i+d+f}$$

		Actual		
		Healthy	**Mosaic**	**StreakMosaic**
Predicted	**Healthy**	**a**	**b**	**c**
	Mosaic	**d**	**e**	**f**
	StreakMosaic	**g**	**h**	**i**

$$\textbf{Specificity (StreakMosaic)}=\frac{a+b+d+e}{a+b+d+e+g+h}$$

The Proposed DDLA model performance F1 score is higher than the other pretrained models. The model provides F1 score as 0.82 with test loss of 1.167. The DenseNET201 and proposed DDLA models performance are nearly equal. However, proposed model test loss is 0.3 less than DenseNet201.

The area under the curve is also one of the parameters that shows the classification performance of a model. It is a measure of the ability of a classifier to distinguish between classes. This is mostly applicable to binary-type classification problems. However, it can be calculated as an average value for multi-class type classification problems. The higher the AUC, the greater the ability of the model to distinguish between mosiac and streak mosaic diseased leaves. The average metric of AUC is calculated and given in Table 6 for all the pre-trained models and the proposed DDLA model. The proposed DDLA model produces a better AUC value when compared to the pre-trained.

7. CONCLUSIONS

The proposed CNN frame work-DDLA detects sugarcane leaf diseases with similar patterns, color, and texture effectively. The proposed (DDLA) architecture consists of DWT denoised images with colour enhanced as input for training layers for sugarcane leaf disease identification such as mosaic and streak mosaic. The model learns the features from preprocessed diseased leaves and improves classification accuracy. The model performance is analysed with pretrained CNN models in two conditions: without preprocessing and with preprocessing. The proposed DDLA model performance is better when compared to the Pretrained models, and the model's ground truth classification accuracy is around 12% higher when compared to the accuracy of pretrained models such as VGG16, InceptionV3, ResNet50, and InceptionResNet and Densnet201. The DDLA model produces ground truth test results with an accuracy of 88.7% for mosaic and 85.7% for streak mosaic with a time period of 152 seconds when compared to the PCR lab test duration of 6 hours. Also, DDLA model performance metric, F1, score, is higher than the pretrained models. The model provides an F1 score of 0.82 with a test loss of 1.167. The DenseNET201 and proposed DDLA models' performances are nearly equal. However, the proposed model test loss is 0.3 less than the DenseNET201. Moreover, the DDLA structure occupies less memory space when compared to the pertained models such as VGG16, InceptionV3, Resnet50, DenseNET201, etc. In the future, deep belief networks can be used to identify another type of similar sugarcane disease pattern, such as Red.

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