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Artificial Intelligence Framework for Sugarcane Diseases Classification using Convolutional neural Network

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Abstract - In many regions of the world, plant disorders have long been a threat to crop development and agricultural production, negatively affecting the availability of food for people. The best organised sector of agriculture is sugarcane cultivation. It is the first crop that farmers grow because of the ideal conditions for its development. It is closely related to the sugar sector and has a significant impact on the economy of several countries. Of all the crops grown for commercial purposes, sugarcane has the highest production value. In contrast, a different type of diseases can affect the quality and productivity of the crop. Growers can detect some of them by visual inspection of the leaves. Unfortunately, the majority of infections go undetected, causing farmers to suffer significant losses. To reduce the damage caused by an infestation, it is important to determine the type of infestation. So, we proposed a Deep Learning (DL) model that uses images of diseased leaves to train the model to recognise a specific disease affecting the sugarcane plant. In this work, we have used bacterial blight, red rot, red rust and healthy leaf images. The method used two convolutional neural networks to classify the 851 sugarcane leaf images. As a result, Resnet50 achieved the highest accuracy of and 99.70% for binary classification (normal and abnormal images). The trained model achieved its goal by identifying photos of sugarcane and classifying them into classes of healthy and diseased leaves. As a result, this research provides a proposal for using deep learning algorithms to help farmers detect and categorise sugarcane infections. Finally, we have applied an DL visualization technique such as gradient class activation map, occlusion sensitivity, and local interpretable model-agnostic to differentiate and understanding the classification process by highlighting area that is more used for the classification.

Keywords-rust, CNN, bacterial blight, red rot, sucrose

I.Introduction

Sugarcane lot of sucrose, a kind of sugar. Jaggery, white sugar, and various by-products including bagasse and molasses may all be produced using it. 75% of the world's sugar is produced with the aid of sugarcane. India is the second-biggest agriculture-based sector in the world [1]. Since sugarcane juice is naturally alkaline, using it helps prevent both breast and prostate cancer. Also, it is good for the proper functioning of the liver and kidneys as well as for keeping the blood pressure within normal ranges. The sugarcane plant, however, has seen illness outbreaks that result in crop destruction [2]. Sugarcane that has been infected severely damages crop productivity. It is important to monitor illness and health for effective crop production. For diagnosing a sick stem, leaf, colour fruit, diseased size, shape, and area of leaves, etc., deep learning (DL) based methods are used [3]. As sugarcane takes longer to grow (10–16 months), illnesses may commonly infect it. For example: Several diseases caused by bacteria, fungus, viruses, phytoplasma, or protozoans affect the sugarcane plant. Just a few sugarcane diseases, such red rot, bacterial blight, and rust are mosaic diseases [4].

Diseases are spread primarily via soil and infected setts, whereas they are spread secondarily by the air, rain splash, and soil. Bacterial blight affects young and middle-aged leaves. Between the midrib and base of leaf blades, long, thin, watery-green stripes initially appear. Later stages of the illness cause stripes to cover the whole leaf, merge, and change colour from light to dark red. The wilting, rotting, and pungent stench of leaves is unpleasant. Large voids develop within the inter-nodes as the rotting spreads towards the stem. Inflorescences and tops usually break off and fall to the ground as a result of top rot, which is a sign of the illness later on in its course. Leaf wilting, rotting, a weaker root system, and stunted growth are all symptoms of this disease, which is illustrated by the watery-green stripes and reddish stripes on the whole leaf.

Red rot may harm any of the sugarcane plant's vegetative components, although it is most important as a disease of the planted seedlings and standing stalks. The midribs of the leaf often make it quite clear. Standing stalks are the only outward sign of red rot in its early stages, with the exception of pale-colored stalks that sometimes have a reddish to purple rind discoloration. Only by slicing the stalk lengthwise can diagnostic signs be seen. The environment and the sugarcane variety's sensitivity determine the speed and scope of virus propagation within the stalk. The damaged tissues quickly take on a distinctive, somewhat acidic, starchy smell and become dull red, sometimes with white spots that are extended at an angle to the main axis of the stalk. These white spots are distinctive to the illness and are important for diagnosing red rot in order to separate it from other stalk rots. They come in a variety of sizes and numbers, and sometimes they are so abundant that the tissues seem mottled. Compared to susceptible types, they are less obvious in resistant variants. Reddened vascular bundles move through the reddened regions, expanding into the healthy tissues and often moving through the nodes into adhering inter nodes.

Elongated yellowish leaf patches that are 1-4 mm long are the first signs of sugarcane common rust or red rust. The spots become longer parallel to the leaf venation as the illness progresses (particularly on the lower leaf surface). They grow one to three times wider and up to 20 mm longer. Moreover, they change into specks of orange-brown or red-brown colour with a faint but distinct chlorotic halo. The rust pustules eventually merge. As a result, the leaf epidermis ruptures and develops necrotic patches. Typically, lesions are more numerous closer to the leaf tip and less near the base. The primary signs of this are Long, yellowish leaf spots are the first signs; spots eventually become reddish-brown, and severely damaged leaves may become necrotic.

Farmers, specialists, and decision-makers are becoming more interested in using machine learning to handle the rising issues in farms and agricultural settings brought on by climate change as well as a lack of knowledge and resources. The application of machine learning for difficult agricultural processes: crop characterisation, crop health monitoring, soil monitoring, disease identification, and grading has been established in earlier works [5]. In addition to other technologies, machine learning is utilised with sensors, drones, GPS, and other technologies [6]. As a result, it helps farmers ensure profitability, maximise crop health, and increase agricultural output.

DL has been applied for several illness categorization tasks more recently. Crop losses in terms of quantity and quality are mostly caused by diseases [7]. Machine learning-based methods for illness categorization are still hard to come by, however. Disease outbreaks can have a varied impact on livelihood and food security. As a result, reliable disease detection and categorization are required to assist farmers, specialists, and novice farmers alike. Now, deep learning advancements provide the door to improved disease categorization while fulfilling the demand for early disease monitoring to safeguard crops as early as possible [8].

In the Philippines and the rest of the globe, sugarcane is regarded as a commodity. The Department of Science and Technology (DOST) has highlighted sugarcane in the Harmonized National Research and Development Agenda 2022 [9]. More than 70 billion pesos were generated by the sugarcane sector in the Philippines in 2017 [10]. While many sectors depend on sugarcane and its products, disease and pest infestation are affecting sugarcane output because of growing environmental concerns and climate change. Also, the Philippines lacks knowledge and study about the growth of sugarcane. As a result, it was chosen as one of the crops in the DOST research agenda. However, there are just a few DL - based techniques that may be employed locally for early illness detection. The main contributions of the work are

- We have used Resnet50 and Densenet201 CNNs for the classification and also suggesting which model classify the leaf diseases efficiently.
- We have done binary class classification.
- We have used the hyper-parameters to tune the network models.
- We have calculated ten performance evaluation metrics.
- Finally, we applied gradient class activation map(GCAM), occlusion sensitivity(OS), and local interpretable model-agnostic (LIME)to visualize the area that is most suitable for classification.
- miss classification analysis have done.

II.Related Work

Depending solely on the illness's severity, crop loss due to disease may range from 10% to 50% [11]. Accurate and prompt diagnosis will undoubtedly decrease crop loss in sugar beet fields. Thus, illness signs must be promptly diagnosed and suitable actions must be done right away to avoid the development or spread of the infections [12]. Precision agriculture and the accuracy of plant protection practises may both be improved and expanded by advances in computer vision [13]. For the purpose of identifying and categorising sugarcane illnesses, numerous research presented the method known as image processing. The feature was extracted from an image using an image processing approach, and its infection status was then determined [14]. By the use of direct image processing, it is feasible to analyse the colour and form characteristics of diseased leaf pictures in order to identify the infected regions and classify the disease's severity. Instead, the support vector machine (SVM) and K-means clustering were used to categorise diseases using machine learning (ML)

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techniques. Similarly, convolutional neural networks(CNN) and artificial neural networks (ANN) were used in the illness classification process using deep learning (DL) techniques. The use of DL methods for plant pest and disease detection has received much research in recent years [15]. Even though a number of methods and strategies have been developed, there is still potential for development [16].

To achieve the highest accuracy rate in identifying and diagnosing illnesses, Militante and Gerardo [17] sought to combine several CNN frameworks of DL methods. A maximum accuracy rate of 95.40% was achieved by the model, which was trained to identify illnesses using 14,725 images of sugarcane leaves infected with disease and healthy sugarcane leaves. LeNet, VGGNet, and StridedNet are components of the CNN architecture, and they have been used to recognise and identify illnesses. A portable device that uses SVM to identify the yellow spot disease on sugarcane leaves was created by Padilla et al. [18]. The work focuses on creating a model that, using image processing, records and displays pictures of sugarcane leaves integrated with a single unit system. By recognizing a yellow spot on the leaf, authors trained the model for describing and categorizing the variation among leaves that are healthy or unhealthy. DL-NN framework was provided by Hemalatha et al. [19] in which the various agricultural diseases are predicted by training the system on a picture of a diseased leaf. The following diseases are distinguished: helmanthospura leaf spot, Cercospora leaf spot, red rot, and yellow leaf disease. A CNN that has been trained for image classification is used in the procedure. By changing a CNN parameter, Ozguven et al. [20] created an improved Fast RCNN framework, and they have since published Fast RCNN architectures for automatically identifying the sugar beet leaf disease. Thilagavathi et al. [21] concentrated on recognising the various illnesses in a sugarcane leaf and created a web application for the farmer to discern the major diseases of sugarcane [21]. The plan captures the leaf picture and applies adoptive histogram equalisation, followed by segmentation using the k-means clustering technique. The statistical properties, including skewness, variance, mean, covariance, and standard deviation, are retrieved using PCA and GLCM. Finally, SVM is used to do the classification and detection. For the sugarcane white leaf, Quoc et al. developed a loopmediated isothermal amplification (LAMP) as an alternative approach for the effective and speedy detection of the SCWL phytoplasma within thirty minutes [22]. The 16SrXI SCWL phytoplasma has been detected using the three LAMP primer sets. The control was the plant cytochrome oxidase LAMP prime, which enhances a plant housekeeping gene. For monitoring the two sugarcane field experiments with nitrogen (N) fertiliser input from the wet tropic area of Australia, Shendryk et al. used a UAV mounted LiDAR and multi spectral image sensor [23]. We examined crop output in terms of vegetation, height, and density indices from the six experiments that were applied at forty-two-day intervals. Reverse transcription LAMP (RT-LAMP) for SCSMV diagnosis was created by Wang et al. [24]. Four SCSMV primers, including P2-F3, P2B3, P2-FIP, and P2-BIP, have been tested and created through a panel of sugarcane viruses in accordance with the conserved poly-protein gene nucleotide sequences of SCSMV isolated that differed from sorghum mosaic virus and sugarcane mosaic virus. Dhaka et al. [25] used deep CNN to conduct a thorough study on plant leaf diseases in 2021. The benefit of this work is that it offers a very thorough overview of plant leaf diseases, which is highly helpful; nevertheless, the work's main disadvantage is that it mostly employs basic conventional procedures and little DL approaches. For the detection of cassava disease, OlusolaOluwakemiAbayomi-Alliet al.[26] discovered a more effective method. It makes use of the colour transformation approach for picture preparation. This study has the advantage of successfully classifying photos using the augmentation approach, but it has the disadvantage of having poor illness detection accuracy. Almadhor et al. [27] implemented the project in 2021 to use machine learning methods to identify illnesses of guava plants. This initiative offers precise disease identification findings for guava plants. This work needs to be expanded using contemporary DL or ML approaches. With the MASK RCNN approach, Rehman et al. [28] classified the apple leaf diseases. Region-based CNN, or RCNN, is used here. For the purpose of identifying illnesses of apple leaves, this model provides effective results. The requirement to train the many photos is the problem in this endeavour.

The aforementioned existing studies all use various approaches to concentrate on disease detection in sugarcane leaves. The provided current efforts were limited in scope, varied by area, and weren't very helpful in precisely identifying and categorising the illnesses of sugarcane leaves. As a result, the suggested study activity requires precise detection and classification algorithms.

Table 1: Datasets used for the Classification

Disease	Train	Test	Total
Abnormal	210	139	349
Healthy	301	201	502
Total	**511**	**340**	**851**

Figure 1: Sugarcane Leaf Diseases

The main objective of the proposed research is more precise diagnosis and classification of sugarcane leaf diseases.

III. Datasets

In this, we have collected two different datasets that are publically available in kaggle [29, 30]. This [29] dataset contains the three classes of sugarcane diseases such as bacterial blight, normal, red rust where as [30] consists of three classes such as red rot, red rust, and normal images. In

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this work, we have done binary classification; normal and abnormal classes. This combined dataset consists of 851 images, all are in .jpg, .png, .jpeg format. The detailed dataset distribution listed in the table 1 and sample images are presented in the figure 1. All these images are resized to fit input of CNN. Then images are divided into 60% for training and 40% for testing and validation. Then data augmentation is used for only training images. In this, we have used Random X reflection and random X and Y translation. After augmentation the training images are increased to 2044. Figure 2 gives the illustration of the data augmentation.

IV. Method

The classification of sugarcane leaf diseases from digital leaf images that are publically available in kaggle. The proposed model of classification of sugarcane leaf diseases is shown in the figure 3. In this, images are collected from various databases and given these images are undergone the image pre-processing. In pre-processing all images are resized to respective input size of CNN models listed in the table 2. After resizing normalization of images is processed. In normalization, images are scaled to

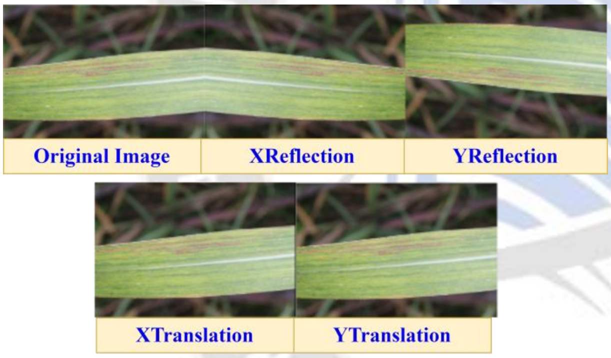

Figure 2: Image Augmentation

Table 2: Input size of all used Pre-trained CNNs [31]

CNN	Input Size
Resnet50	224 X 224
Dense201	224 X 224

Table 3: Network Training Options

Function	Value
Epochs	50
Optimizer	Adam
Verbose Frequency	40
Initial Learn Rate	0.0001
MiniBatchSize	32
Validation Frequency	40

the pixel value [0 1]. All images are splitted into training and testing with ratio of 6:4 after pre-processing [31]. Then, data augmentation is used for training images with random scaling value [-30 30], random X-reflection, random X and Y translation. After augmentation the trained images are updated to 1864 for abnormal class and 180 for normal case. Fallowed by the augmentation training of CNN model takes place. In training, each CNN model is trained by using hyper-parameters: 50 epochs, 1e-4 constant learn rate, 32 batch size, validation frequency of 40 and cross entropy regularization with ADAM optimizer. Testing of each CNN model is done with test set of images after completion of the training. Basic architecture of the CNN is shown in the figure 4 and architectures used in this work are shown in the figures 5 and 6. The steps of classification of the sugercane diseases are

- Collection Datasets.
- Image pre-processing.
- Data augmentation for training Images.
- Designing CNN model and defining hyper parameters.
- Train each CNN model.
- Test each CNN model using test sets.

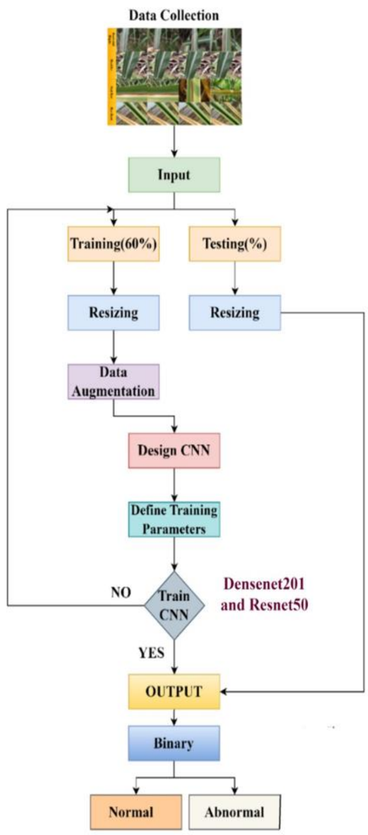

Figure 3: Proposed Model for classification of sugarcane leaf diseases

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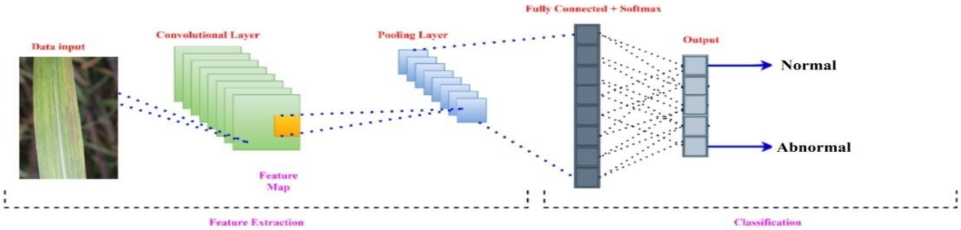

Figure 4: Architecture of Basic CNN

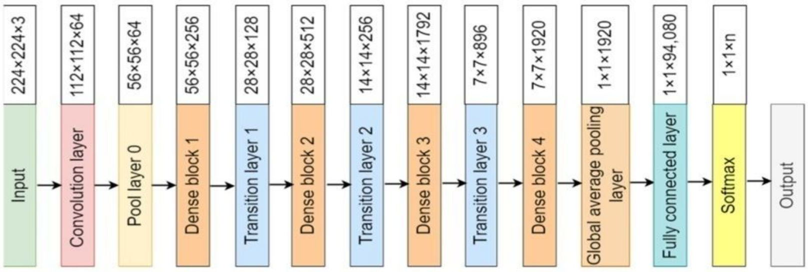

Figure 5: Architecture of Densenet201

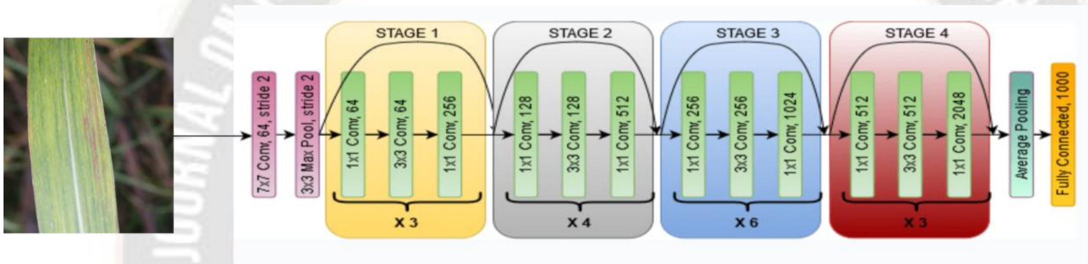

Figure 6: Architecture of Resnet50

- Repeat steps from 3 if training is not done.
- Calculate the performance metrics.

IV.1. Convolutional Neural Network(CNN)

A CNN is currently widely used in a variety of fields such as artificial intelligence, medical image processing, image categorization, etc. CNNs deliver higher results for bigger datasets. In neural networks, there are a thousand different categories that CNNs can distinguish between [32]. We utilised Resnet50 and Densenet-201 for this. In CNN, data is processed through four layers as shown in the figure 4.

The architecture of general CNN is defined mathematically as $i(\hat{\ }x) = sign(2\sigma softmax(H3\sigma relu(H2\sigma relu(H1+l1)+l2)+l3)-1$

(1)

where, $i(\hat{\ }x)$ is the output of CNN $\sigma_{softmax}$andσ_{relu}areSoftmax and RelU activation functions respectively. H_1,H_2,H_3 are the hidden Layers. l_1,l_2,l_3 are bias length or number of neurons in rectangle grid.

i. Convolutional Layer: A convolution layer consists of a rectangular grid of neurons. An identical rectangular grid of neurons must exist in the layer above. There are the same section weights for all neurons in this layer, since eachneuron receives input from a layer above. The convolutional filter is therefore simply a convolution of the previous layer's output, with the weights defining its parameters. This convolution is given as

$$y_i,j^l = \sum_{a=1}^{N}\sum_{b=1}^{N} K_{a\,b}\, x(i+a)(j+b)^l$$
(2)

Where, $_{yi,j}{}^{l}$is the output $_{m}\times_{n}$matrix, i=1, 2, 3,......., m. and j=1, 2, 3,...., n. $x_{(i+a)(j+b)}{}^{l}$ is input $m \times n$ input matrix, k is the kernel weight $_{N\times N}$ matrix Above equation shows the convolution of two functions. The convolutional layer's non-linearity is then used. The nonlinearity of the convolutional layer is then exploited. The Rectified Linear Unit (ReLU) is responsible for these non-linearities. When compared to other activation functions, the performance of the ReLU function is excellent. And the output of this is given as

$$f(x) = max(0,x) \qquad (3)$$

The input data—known as the feature map—is mapped by the convolutional layer and ReLU function. The pooling layer processes the data after the convolutional layer.

ii. Pooling Layer: Pooling layers reduces the number of parameters when the pictures are too huge. Spatial pooling, sometimes referred to as sub-sampling or downsampling, reduces each map's dimensionality while retaining essential data. There are three basic types of pooling layers; maximum pooling layers are straightforward and don't require any

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learning. It uses the highest value for the ReLU-mapped element. The average pooling layer can also accept the largest value of the feature map. The total of all elements on the map is known as sum pooling.

iii. Fully Connected Layers: This layer is also known as FC-layer. This layer closely resembles the layers of a typical neural network. This layer converts the input from the convolutional and pooling layers from the preceding layers into vectors. The categorization of leaf diseases into normal and abnormal is done by using the softmax activation function. The sole applications of this softmax function are multi-class classifications.

iv. Softmax: Several sigmoid functions are mixed to form softmax. Softmax activation is advantageous for multi-class classification applications since it returns probabilities for each individual data point. The number of neurons in the output layer must match the number of classes in order to construct a network for a multi-class issue. This function is represented mathematically as

$$\sigma(Z)_j = e^{z_j} / \sum_{s=1}^{S} e^{Z_s} \tag{4}$$

for j=1, 2, ..., K.

v. Experimental Results and Discussion

We have implemented proposed model using Python in 32GB RAM and 1TB SSD with NIVIDIA GTX. In this, we have classified the diseased images in two different scenarios as binary classification and four-class classification. After classification performance evaluation metrics: Accuracy(ACC), Specificity, precision, recall, F-score, Error rate($_{Erate}$), false positive rate(FPR), Mattew Correlation Co-efficient(MCC) are calculated using the equations from (1) to (8)

$$Acc = \frac{(TP+TN)}{(TP+TN+FP+FN)} \tag{5}$$

$$Specificity = \frac{TN}{(FP+TN)} \tag{6}$$

$$Precision = \frac{TP}{(TP+FP)} \tag{7}$$

$$Recall = \frac{TP}{(TP+FN)} \tag{8}$$

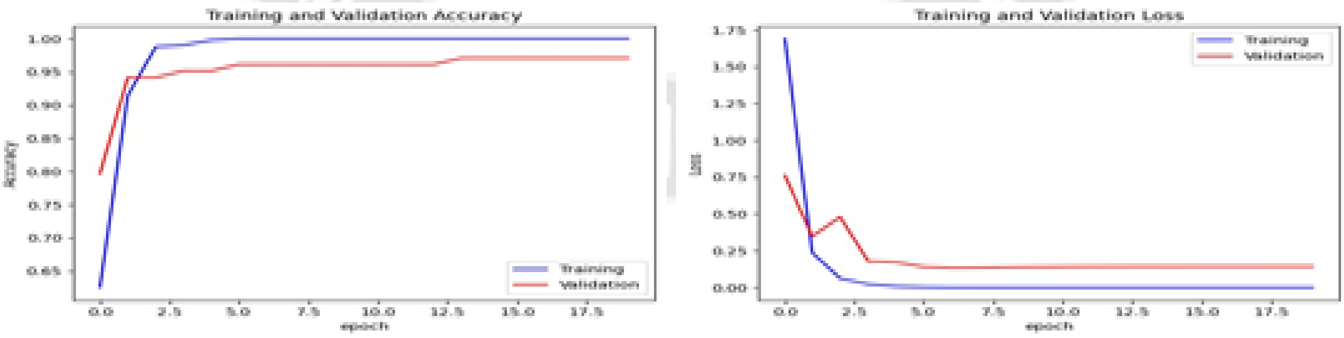
$$F1 - Score = 2 \times \frac{TP}{(2*TP+FP+FN)} \tag{9}$$

$$E\ Rate = 1 - Acc \tag{10}$$

FPR = 1- Precision (11)

$$MCC = \frac{TP.TN - FP.FN}{\sqrt{(TP+FP).(TP+FN).(TN+FP).(TN+FN)}} \tag{12}$$

Where, TP is true positive, TN is true negative, FP is false positive, and FN is false negative. The accuracy and loss curves shown in the figure 7 Figure 8 shows the confusion



(a) Accuracy Curve of Resnet50 (b) Loss Curve of Resnet50

Figure 7: Accuracy and Loss curves of Resnet50

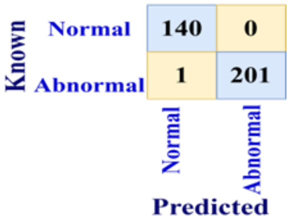


Figure 8: Confusion Matrix of Resnet50

matrix of Resnet50. The performance evaluation parameters are calculated and tabulated in the table 4. In this, we have tabulated the performance of the two pre-trained CNN models.

From table 4 resnet50 network achieved the more accuracy of 98.98%, precision of 96.61%, 96.65% of f-score, 96.11% of MCC value, 97.02% of recall or aka sensitivity, 99.32% of specificity, and error rate of 1.02% classification of sugarcane leaf diseases into red rot, red rust, bacterial blight and normal images. Also, we have conducted the binary classification making two classes normal and abnormal. Abnormal images consists of red rot, red rust, and bacterial blight images. We used resnet50 for binary classification that achieved the highest accuracy for multi-class classification. So, resnet50 achieved the highest accuracy of 99.70%, 99.75% of precision, 99.69% of f-score, 99.39% of MCC, 99.69% of recall or aka sensitivity, and 99.40% of specificity.

V.1Deep Learning Based Visualization Techniques

In order to comprehend the region of the image that the network model will find most useful for making decisions, the various types of classes must be visualized, distinguished, and understood. In order to illustrate the various

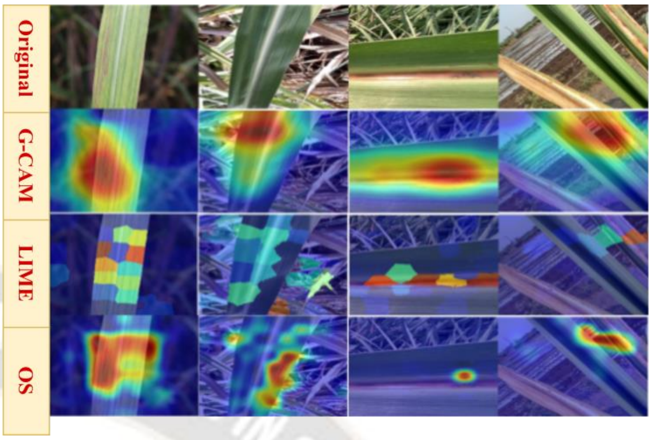


Figure 9: Visualization Techniques Applied to Distinguish the Classes

classes, we used G-CAM, OS, and LIME, as shown in the figure. The darker red and red hues used by the G-CAM and OS methods indicate greater values, suggesting that the characteristics in the area are those of the appropriate class. Indicating that feature extraction is prohibited, the remaining hues indicate lesser values. Additionally, if the network consistently mis-classifies some images, OS is used to identify the specific aspects of the images that are perplexing the network design. Similar to LIME, the hue blue denotes that no features were extracted, while the colours yellowish, orange, and the remaining ones denote that features were extracted for a specific class.

Table 4: Performance Evaluation Metrics of CNNs

CNN Model	Accuracy (%)	Precision (%)	F-score (%)	MCC (%)	Recall (%)	Specificity (%)	Sensitivity (%)
Densenet201	97.94	94.02	94.3	92.66	94.16	98.51	94.16
Resnet50	**99.7**	**99.75**	**99.69**	**99.39**	**99.69**	**99.4**	**99.69**

V.2Miss-Classification Analysis

This section describes the detailed analysis image misclassification. Table 5 shows number number of misclassified images of all CNNs used in thin this work. From this table Resnet has the less miss-classification with only

Table 5: Miss Classified Images

CNN Model	NMCI
Densenet201	11
Resnet50	7

*NMCI: No. of Miss Classified Images

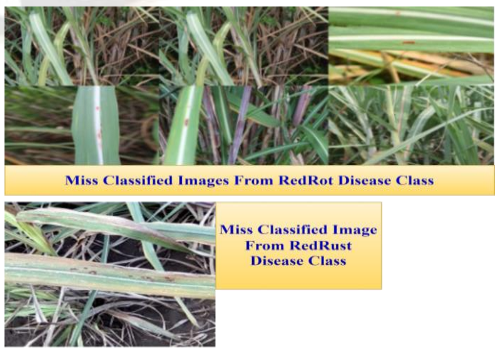


Figure 10: Common Images that are Miss Classified by each Network

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7 images and EfficientnetB0 has more misclassification images of 85. Figure 10 shows miss-classified images that are common for all networks. This miss-classification can be reduced using feature extraction, optimization, image preprocessing, and hyper-parameter tuning. This can be taken care in the future works.

V.3Comparison of Proposed Method with Previous State of-the-art Method

For the categorization of Sugarcane diseases, deep learning models including CNNs, recurrent neural networks (RNNs), and hybrid models have been utilized. On a number of datasets, including publicly accessible datasets sugarcane leaf disease dataset 1 and 2, these models have demonstrated encouraging results. Deep learning models have produced excellent accuracy and efficiency in the categorization of sugarcane diseases, which can result in enhanced yields and reduced loss. Table 6 shows the comparison of proposed method with previous state-of-the-art method. In this, previous models are classified the sugarcane leaf diseases using deep learning as well as deep learning and achieved better accuracies. But our proposed model achieved the highest accuracy of 98.98% for the classification of sugarcane leaf diseases into red rot, bacterial blight, red rust, and healthy images.

Table 6: Comparison of Proposed Method with Previous State-of the-art Methods

Method	**Accuracy(%)**
DCNN	96.00
CNN	95.00
GLCM+SVM	80.00
Traingle Thresholding	98.60
VGGNet	95.40
MobilenetV3	99.00
SVM	95.00
SVM	96.00
D-Neural networks (CNN, FFNN, RBNN)	97.00
Resnet50	**99.70**

*DCCN: Deep CNN;
GLCM: Gray-Level Co-Occurrence Matric;
SVM: Support Vector Machine;
FFNN: Feed Forward Neural Network
RBNN: Radial Basis Neural Network.

vi. Conclusion

The most important advancements in image classification have been made possible by deep learning, and these advancements have served as the foundation for detecting and treating plant illnesses by leveraging technology to detect images as the basis for recognizing a number of crop diseases. This comparison technique can effectively categorize sugarcane leaf diseases into abnormal and normal as well as binary classification using leaf images. Using Densenet201, and Resnet50. The performance of several classifiers in this experimental study's categorization of leaf diseases is compared. Pre-processing and data augmentation techniques improve the accuracy of classification models when the size of the dataset is minimal. Resnet50 obtained the greatest accuracy of 99.70% for binary classification. In the future, the optimization technique may also be utilized to identify the key characteristics from the Extraction section in order to improve accuracy.

Conflict of Interests There is no conflict of interests.

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