

**SUGARCANE DISEASE DIAGNOSIS UTILIZING A  
COMBINED RESNET-INCEPTION DEEP LEARNING  
TECHNIQUE AND A WEB APPLICATION**

**A. Anitha rani<sup>1</sup>, Karthikeyini Chockaian<sup>2</sup>, C. Reshma Ravi<sup>3\*</sup>**

<sup>1</sup>Assistant Professor, Department of Electronics and Communication  
Engineering, Excel Engineering College, Namakkal,  
aanitharani.eec@excelcolleges.com

**Orcid: 0009-0000-7911-9124**

<sup>2</sup>Professor, Department of Electronics and Communication Engineering,  
Excel Engineering College, Namakkal, ckarthiraja@gmail.com

**Orcid: 0000-0002-0134-4855**

<sup>3\*</sup>Research Scholar, Excel Engineering College, Namakkal,  
reshma.bme@gmail.com

**Orcid: 0009-0003-3214-3233**

\*Corresponding Author: C.Reshma Ravi, Mail: reshma.bme@gmail.com

**Abstract**

Biotic factors such as plant diseases have often been a thorn in the progress of plant growth and crop production all over the world, thereby limiting the food humans consume. The best-coordinated branch of farming is the production of sugarcane. Due to these perfect growing conditions, it has become the favorite crop form among farmers. It is directly linked to the sugar industry and is notable enough to have an influence on particular countries such as Brazil, India, and China. Although it ranks twenty-fifth among the world's most commercially grown crops, sugarcane has the most significant output value of all crops grown for commercial purposes. On the other hand, several diseases threaten agricultural productivity and produce quality. Some of them farmers can see with their naked eyes when they inspect leaves on the plant. But many infections remain undetected, and farmers are overwhelmed by gigantic losses. Consequently, it is essential to identify the kind of infestation in a bid to reduce loss. The current research work develops a novel deep-learning architecture that identifies unhealthy sugarcane plants based on their leaves, stems, colors, etc. The work presents three cases where hybrid feature extractors involve two features, namely LBP and GLCM, which extract texture and shape-based features. The fused model of ResNet-Inception performed better than other deep learning approaches, such as GoogLeNet and AdaBoost, in the study. Some of the diseases include Yellow leaf disease, Cercospora leaf spot, Rust spots, Helminthosporium leaf spot, and red rot. Specifically, the proposed model achieved 98% accuracy, 97% precision, 95% recall, and 96% F1 score.

**Keywords:** ResNet-Inspection, Google net, Adaboost, Deep Learning, GLCM

## **1. Introduction**

The health of sugarcane has a direct influence on agricultural production and the sugar industry, making it an essential crop. They suggest a method utilizing deep learning techniques to tackle the difficulties related to disease identification in sugarcane. Our approach uses image analysis and deep learning (DL) model to precisely detect and categorize a range of sugarcane illnesses [1]. In order to handle the increasing difficulties on farms and agricultural settings brought on by climate change, a lack of resources and experience, and other factors, DL is attracting the attention of farmers, specialists, and decision makers [2]. The rising incidence of these illnesses and farmers' ignorance of how to recognize and treat them served as the driving forces behind the education. In command to solve this difficulty, ML more especially, computer vision employing deep learning techniques was used. A DL model was built and evaluated using a dataset of photos of sugarcane leaves, both healthy and damaged [3].

The aim to intend a robust approach that utilize the LBP and feature extraction for extract the GLCM based texture and shape-based features. In order to evaluate and categorize objects inside pictures, texture and shape-based characteristics are frequently employed in image processing, computer vision, and pattern recognition. The distribution and spatial organization of pixel intensities inside a sugarcane leaf picture is referred to as texture. It records a region's surface characteristics or patterns [4]. Combining the advantages of both architectures to enhance performance is known as fusing deep learning models, such as ResNet-Inception. Inception employs well-thought-out modules to effectively capture texture and form characteristics, whereas ResNet concentrates on residual learning to solve the disappearing gradient issue [5]. Python language is used to determine a number of statistical metrics, including specificity, AUC, accuracy, precision, and sensitivity. The scenario with the best accuracy is selected. To evaluate accuracy, the receiver operating characteristic curve is calculated [6].

### **Objectives**

- To Design and implement a combined ResNet (Residual Networks) and Inception model for accurate image-based sugarcane disease detection.
- To Collect and annotate a diverse dataset of sugarcane leaf images that covers a range of diseases, including bacterial, fungal, and viral infections.
- To design and implement a web-based interface where users (farmers, agricultural experts, etc.) can upload sugarcane leaf images for automated disease diagnosis.

The following is a description of the main sections that make up the remainder of the article: Studies on Diagnosing Sugarcane Disease with a Web Application and a Resnet Inception Deep Learning Method that have been finished by different Authors are included in section II.

## **2. Related Work**

**W. Shafik et al., (2023)** For instance, the majority of these strategies employ DL, ML, or vision-based artificial intelligence techniques and models to offer illness detection solutions. Compared with conventional classifiers, Support Vector Machines and Logistic Regression classifiers achieved higher accuracy in trials.y. Currently, there is an increase in the number of

cognitive CNNs that employ transfer learning and attention processes. However, there has been no standard way of evaluating the performance of the models, even though most of the models use the F1 Score, a confusion matrix, accuracy, recall, and precision.

**Margesh Keshkar et al., (2023)** creates an innovative hybrid deep-spatio temporal textural feature learning model for the identification of diseases in medicinal plants. that is powered by evolutionary computing and ROI-specific. It then used the Alex Net transferable network and GLCM to maximize the potential deep spatiotemporal textural properties. According to a depth performance evaluation, the suggested model produces results with an F-measure = 99.15%, and equal error rate = 1.03%, accuracy = 98.97%, precision = 99.42%, recall = 98.89%, indicating its resilience to real-time Identification and categorization of diseases in medicinal plants

**Pavan Sharma et al., (2022)** To get a greater rate of production growth and less crop damage, it becomes the primary responsibility to accurately monitor the plants, identify illnesses comprehensively, and identify strategies for monitoring or managing these plant disease pests. It could be feasible to create a trustworthy illness detection system by utilizing machine vision, DL techniques, and tools for feature extraction and classification the bar graph shows the accuracy of plant diagnoses made using different techniques. With an accuracy of 99.80%, EfficientNetB7 is the most accurate of these algorithms. DenseNet and ResNet50 placed second and third, respectively, with accuracy rates of 99.75 and 99.70 percent.

**Mr. Kathan Gohil et al., (2022)** This article compares and contrasts five different machine learning classification methods for plant disease identification. When compared to other classifiers, several writers employ the SVM classifier to classify illnesses. The outcome demonstrates that CNN classifiers are highly accurate in detecting a greater range of illnesses. Other categorization methods in the future Naïve Bayes classifiers in machine learning, such as decision trees, may be used to detect plant illnesses and to assist farmers in automatically identifying all kinds of agricultural diseases.

**Wasswa Shafik et al., (2023)** For example, to provide sickness detection solutions, most of these tactics use deep learning, machine learning, or vision-based artificial intelligence techniques and models. However, present issues need to be considered and fixed before AI is applied. a thorough study of the literature in this work and offer a detailed analysis of the findings utilizing publically accessible datasets and data gathering methods. The specified research topics are addressed in this part by outlining the contributions of the 176 researchers who worked on each study.

**Haider, K. et al. (2023)** consequently, the growth of the economy depends heavily on the quality of crop output. The largest threats to crop productivity in the agriculture sector are pests and plant diseases. Therefore, it is crucial to create a technique for precisely identifying these diseases so that the right actions may be done to cure them, improving crop quality and yield. Combining computer vision or image processing methods that use deep learning with tools for categorizing and extracting information might result in a dependable illness detection system. Different methods for diagnosing plant diseases have be proposed by a variety of researchers.

**Tej Bahadur Shahi et al., (2023)** focus on ML and DL approaches utilizing UAV-based remote sensing, this paper attempts to assess the real advancements in crop disease identification. Initially, outline the significance of various sensors and image-processing methods for use UAV images to improve agricultural disease estimates. Second, we provide a taxonomy to compile and group the current research on using UAV photography to identify agricultural diseases. Third, we evaluate and compile the results of many DL and ML techniques for agricultural disease diagnosis. Lastly, we highlight the difficulties, possibilities, and future prospects of UAV-based remote sensing for the identification of agricultural diseases.

**X. Leong et al., (2023)** shows a cutting-edge wearable device that integrates a retrained convolution neural network, a camera module, and a Raspberry Pi into a pair of elegant eyeglasses. These glasses give real-time haptic or audible input by detecting objects and determining their distance from the wearer. Using machine learning methods for object classification and integrating camera and sensor technology into a lightweight, user-friendly frame were both part of the challenging development process. Numerous quantitative indicators were used to assess the system's performance, demonstrating its accuracy, speed, and usefulness

**Abhinav Agarwal et al., (2023)** uses DL techniques to classify the different plant diseases. The convolution neural network architecture for plant sickness is used because of its high success rate in image-based classifications. The DL models are faster and more accurate than manual leaf observation exact. In this study, the PD CNN architecture is trained using the Plant Pathology 2020 FGVC7 data set. The model has the highest accuracy of any of them, at 95%.

**Daphal SD et al., (2024)** outlines a method for a smart farming system to use image processing and soft computing to meet the needs of Indian sugarcane farmers. The study includes four sugarcane diseases as well as three characteristics: color, shape, and texture. Neuro-Fuzzy, Artificial Neural Network and Case-Based Reasoning algorithms were trained on pictures to evaluate the feature extraction approach's specificity, F1 score, sensitivity and accuracy.

Using the YOLO algorithm, the author **Mostafizur Rahman Komol et al., (2023)** suggests a method for identifying three categories of sugarcane illnesses. The YOLO version 8 model reached a maximum accuracy = 96.67% after being trained and evaluated on a dataset of images of sugarcane illnesses. This far above the ground accuracy shows how our suggested approach may be used to diagnose and treat afflicted plants early on. Our suggested method can increase the efficacy and efficiency of disease control in sugarcane by utilizing the YOLO algorithm, a deep learning technique.

"CNN" stands for Convolution Neural Networks, and this Paper **Dr. Mahesh Gowda N M et al., (2023)** "Sugarcane Disease Recognition Using Deep Learning" explains what they are. The organization of the animal visual system serves as the model for the connection structure of CNN, a form of feed-forward ANN. Cortex Convolution Neural Networks, one type of DL model, have demonstrated encouraging outcomes in picture recognition tasks, such as the identification of plant diseases. Consequently, this study makes a recommendation for applying deep learning algorithms to help farmers recognize and classify illnesses in sugarcane.

**Midhunrajetal., (2024)** The frequency of bacterial, fungal, and viral diseases is one of these important variables lowering agricultural productivity. In order to detect plant illnesses, researchers developed and tested a variety of ML and DL technique. Consequently, the many research conducted in the field of plant disease detection utilizing ML and DL-based approaches are thoroughly analyzed in this study. Numerous datasets pertaining to plant diseases are also carefully analyzed. It also discusses the problems and challenges with the existing systems.

Author	Dataset	Algorithms	Result Achieved
Swapnil Dadabhau Daphal at el., (2024)	Test Dataset	XceptionNet, VGG19, ResNet50, and EfficientNet_B7	accuracy = 86.53%
Akshara Avinash Sarode at el., (2023)		Alexnet, VGG 16, DL, CNN, Transfer Learning, Adam's Optimizer, epoch	ResNet101, outperformed other models, demonstrating the excellent accuracy and performance of the suggested model
Ismail Kunduracioglu at el., (2024)	Sugarcane Leaf Dataset	EfficientNet-b6 and InceptionV	Accuracy rates of 93.39% and 93.10%.
Anas Ansari, at el., (2024)		Deep Learning, Convolution Neural Networks	accuracy of 95%
Ms. Riya Walia at el., (2023)		Machine Learning and Deep Learning	A sizable dataset gathered from sugarcane farms in various geographical locations is used to assess the model's performance.
Daphal SD et al., (2024)	For sugarcane leaf disease.	ResNet50, XceptionNet, VGG19, and EfficientNet_B7	accuracy = 86.53%

### 3. Proposed Methodology

As depicted in Figure 1, a process pipeline with four key components was developed: collecting the data set, extracting features from the collected image set, generating a fused model from the collected image dataset, and designing a webpage interface for getting the output of the test image. Images are getting from the dataset from Kaggle dataset includes five categories: healthy, mosaic, red rot, rust and yellow illness. The images are preprocessed to extract samples with crucial texture and shape-based features and then labelled. The dataset image split as train and test with help of keras library. The saata were supplied to fused deep learning algorithm for model creation and created model is saved in the working directory. The webpage is created with help of flask library then created model imported for the prediction of test image. the attractive user interface gives the option for load the test image and prediction for that. The performance metrics of proposed fused model compared with other deep learning model such as Adaboost and google net.

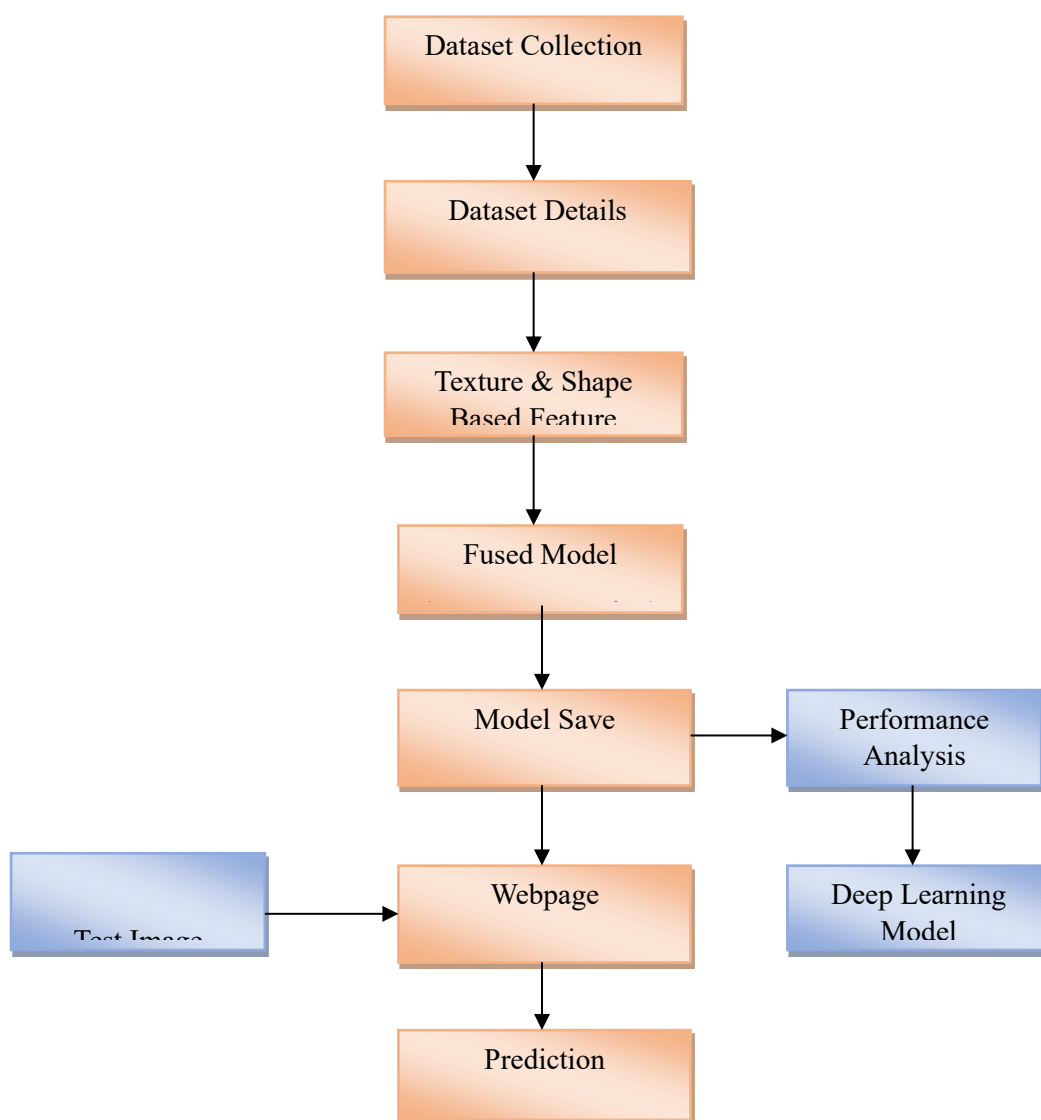


Figure 1. Step-By-Step Procedure of Proposed Work

### 3.1 Dataset Details

Five primary categories comprise this personally collected picture collection of sugarcane leaf disease: mosaic, rust, redrot, yellow illness, and healthy. To preserve diversity, the dataset was taken with smart phones of different configurations, and it includes 2569 images total, including all categories. The database was gathered in Maharashtra, India, and is well-balanced and has a good variety. The sizes of the images vary because they come from different capturing devices, and all of the images are in RGB format. The figure 2 depicts the sample image present in the dataset is tableted in the table 1.

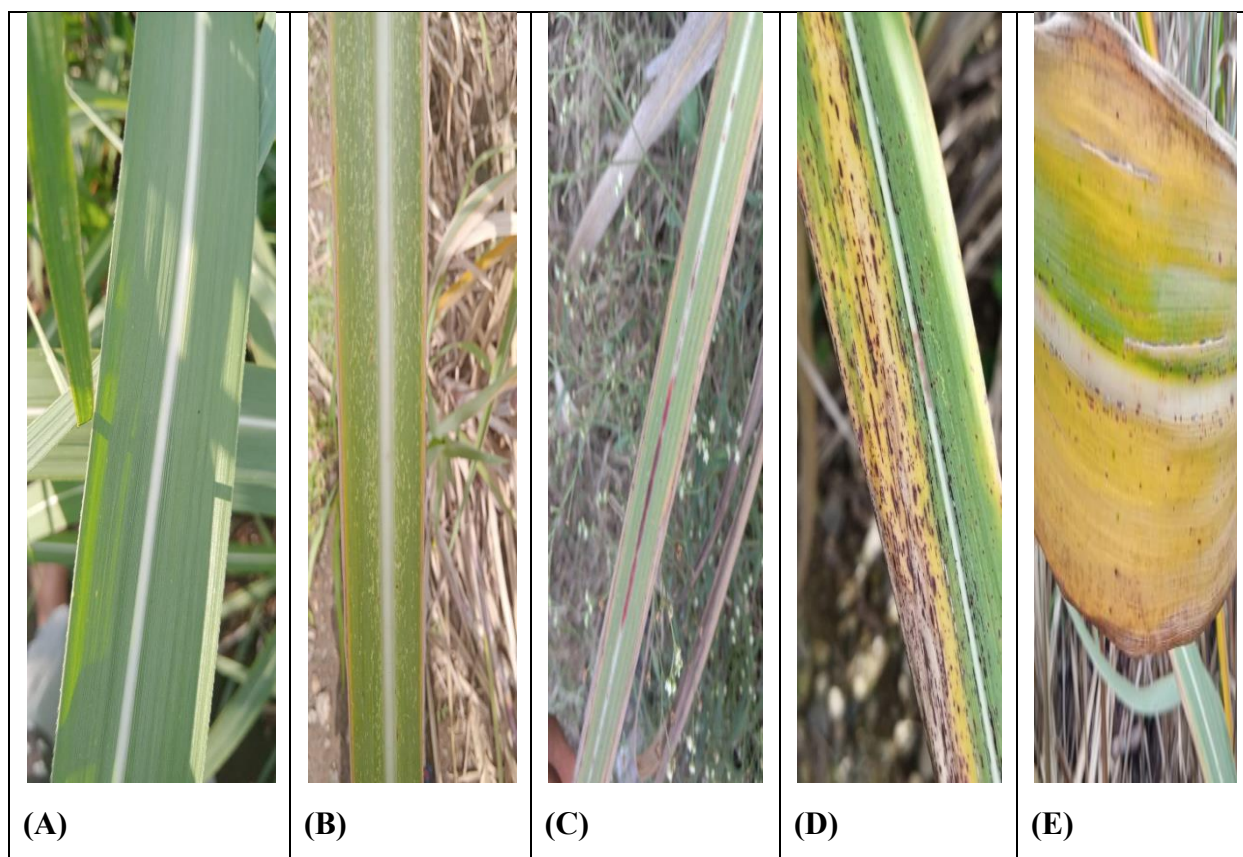


Figure 2. Image present in the dataset (A) Healthy (B) Mosaic (C) Red Rot (D) Rust (E) Yellow

Table 1: Image class and number of image present in the dataset

S. No	Class of Prediction	Number of Images
1	Healthy	522
2	Mosaic	462
3	Red Rot	518
4	Rust	514

5	Yellow	505
---	--------	-----

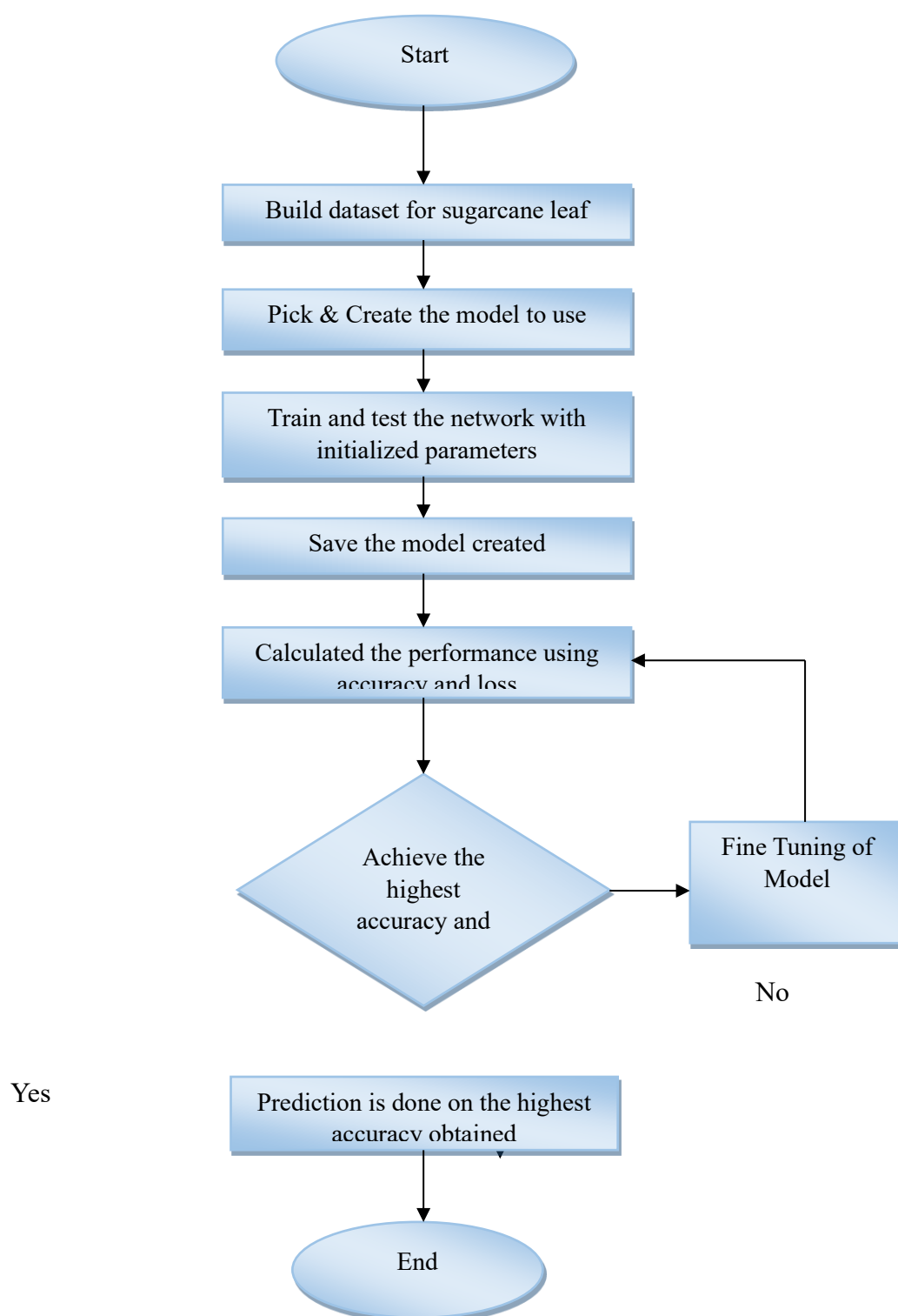


Figure 3. Workflow diagram for the prediction model

### 3.2 Feature Extraction

#### Gray Level Co-occurrence Matrix

The GLCM provides unique texturing-related mathematical information. The number of rows and columns in the square GLCM matrix is exactly the same.  $N$  is the number of gray levels in an image, and the GLCM matrix is an  $N \times N$  matrix.

#### Mean

The average value for the whole set of data is called the mean. A mathematical expression for the mean value is provided.

$$\mu = \frac{\sum_{x=0}^{N-1} \sum_{y=0}^{N-1} f(x,y)}{N \times N} \quad (1)$$

Whereas,

$\mu$  – Mean,

$f(x, y)$  – Input image pixels,

$N$  – Number of samples.

#### Variance

Heterogeneity is analyzed using this statistic, which has a strong correlation with first-order statistical variables such as standard deviation. The following is a mathematical representation of the variance.

$$\text{Variance}(V) = \sum_{x=0}^{N-1} \sum_{y=0}^{N-1} (x - \mu)^2 f \quad (2)$$

#### Standard deviation

The variance squared separated by the total number of samples is one way to define the standard deviation. The definition of the mathematical form is

$$\text{Standard Deviation}(SD) = \sqrt{\frac{\sum |x - \mu|^2}{N}} \quad (3)$$

#### Entropy

Entropy quantifies a picture's disorder or complexity. It manifests when the texture of a picture is complex and varied. High entropy is associated with low energy, and vice versa, due to the inverse relationship between entropy and energy.

$$\text{Entropy}(E) = \sum_{x=0}^{N-1} \sum_{y=0}^{N-1} f(x, y) * \log(f(x, y)) \quad (4)$$

#### Contrast

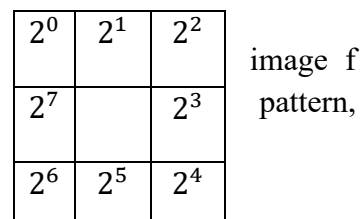
A picture's spatial frequency and unique GLCM moments are quantified by contrast. It is the variation between a set of pixels' highest and lowest values.

$$\text{Contrast}(C) = \sum_{x=0}^{N-1} \sum_{y=0}^{N-1} (x - y)^2 f(x, y) \quad (5)$$

**Homogeneity**

The term "homogeneity" describes how consistently an input (x, y) is organized. If an input image's layout exhibits a consistent it is deemed homogenous.

$$Homogeneity(H) = \sum_{x=0}^{N-1} \sum_{y=0}^{N-1} \frac{f(x,y)}{1+|x-y|^2} \tag{6}$$



**Maximum probability**

This corresponds to the strongest reaction and is effectively the largest item in the matrix. This might be the overall maximum or the maximum in any one of the matrices.

$$C_m = \max P(f(x, y)) \tag{7}$$

**Local Binary Patterns**

A feature extraction approach called Local Binary Patterns is used to extract structural and statistical information from picture texture characteristics. Timo Ojala was the first to introduce the LBP approach. The LBP operator compares the gray levels of nearby pixels to determine how to operate. Patterns of Local Binary are a rotation-invariant technique for extracting texture features. The thresholding method yields the LBP value, which is subsequently multiplied by the binary weight. In the simplest version of LBP, the worth of the central pixel serves as a threshold at 3x3 neighboring pixels. The texture character will be represented by a binary pattern produced by the threshold operation [26].

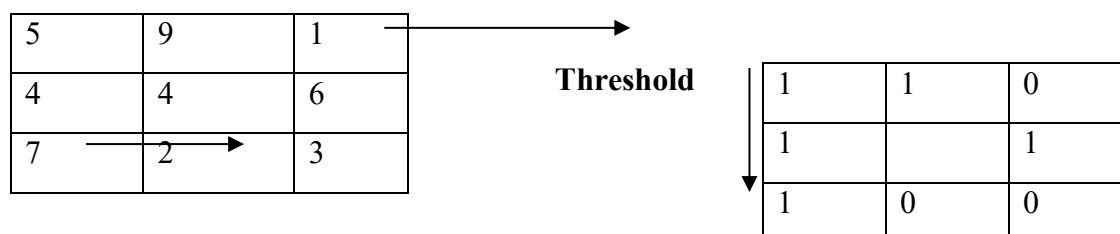


Figure 4. Example of a Basic Operator for LBP Feature Extraction

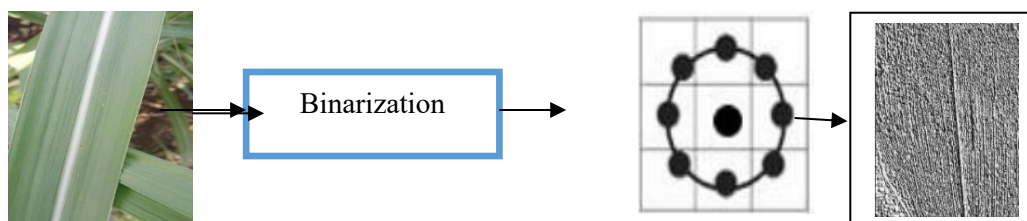


Figure 5. Examples of images taken both before and after the LBP procedure

The Algorithms ladder for manipulative LBP

- The input is a 300 by 300 picture that have already be resized and processed in grayscale.
- Calculate the neighbor intensity value of 8 and the radius value of 1.
- The weight value will be multiplied by the outcomes of the preceding step.
- decimal with the weights rotating in a clockwise manner from lowest to greatest

### 3.3 Deep Learning Techniques

#### 3.3.1 ResNet

The deeper CNNs are challenging to train and need a large dataset. Furthermore, training deep networks takes a long time. In 2015, researchers created residual networks to solve these problems. Compared to VGG-19, ResNet is eight times deeper. It includes Layers: 152, 101, or 50. There are 26 million trainable parameters in ResNet-50, 60 million in ResNet-101, and 90 million in ResNet-152. ResNet-50 has a small space and time complication, as shown by the number of parameters, whereas ResNet-152 has the maximum space and time complication. Instead of employing unreferenced learning, the residual networks use residual functions to learn. The residual relations offer answer to the disappearance gradient issue, much like the ReLu activation function. A low error rate = 3.57% was recorded by this model. It had a 0.1% lower error rate than Inception-v3. Training ResNet models takes a long period. As a result, using them to resolve issues in real time where a prompt decision is needed becomes challenging [27].

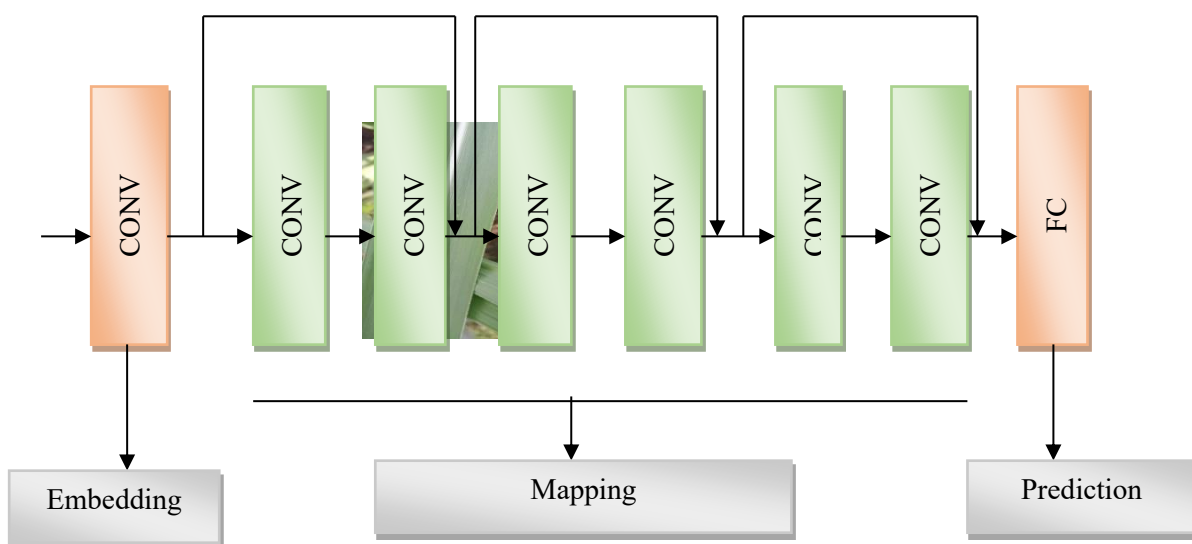


Figure 6. ResNet Architecture

#### 3.3.2 Google Net

In addition to improving computational resource usage, GoogleNet outperformed AlexNet by 8.63%, achieving a top-five test error rate = 6.67% in the ILSVRC-2014

competition. The model's performance is improved by using global average pooling rather than fully linked layers. Can be enhanced by raising its divergence limit [27].

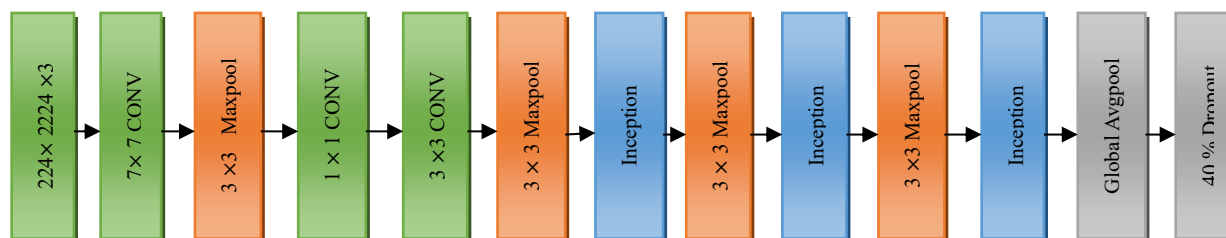


Figure 7. Google net Architecture

### 3.3.3 AlexNet

In 2012, the AlexNet model with 3-FC and 5-Conv layers was presented. Using data augmentation and regularization, the AlexNet variation with the convolution layers Conv-1 and Conv-2, normalization, and a pooling layer obtained a top-five test error rate = 15.3% and accuracy = 93.8% on a maize dataset. Techniques. The representation may be used in a numeral of domains, including medical image processing, NLP, and plant disease identification [27].

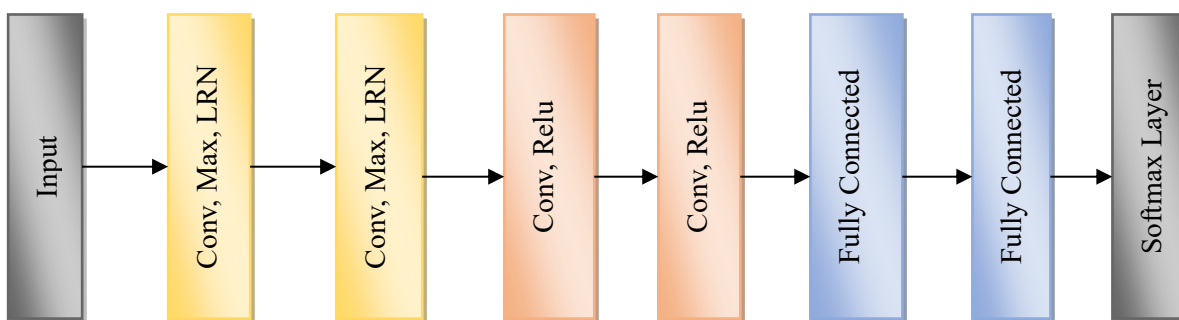


Figure 8. AlexNet Architecture

### 3.3.4 Combined model of ResNet-Inception model

Contrary to the current deep learning techniques, the new approach to the CNN model is a new model that uses and integrates the fundamentals of both the deep residual network ResNet model and the Inception model. The Inception model has shown that it is possible to scale up thousands of layers, and deep residual networks have provided better performance and efficiency. The feature of the residual networks is that there are a large number of residual blocks built with identity mapping. The inception model is an intense convolutional network that is constituted of multiple convolutional Networks. So, in this study, we present a deep hypernetwork system that can be trained to extract the texture and shape-based characteristics of an input picture of a sugarcane leaf without much pre-processing or using a large amount of data augmentation. The last hybrid deep ResNetInception network design proposal is presented in Fig 9. The construction of two remaining blocks forms the suggested construction, as is seen in Fig 10. Each convolutional layer is followed by ReLU activation, and there is only one average pooling layer in the network. The outputs of one layer are used as the inputs for the

subsequent layers. As observed in Figure 9, the network has only one cascaded residual block with a complete connection. The networks of every convolutional layer in this residual model come from every convolutional layer that precedes it. In this study, we deployed three convolutional layers regarding our empirical assessment of the number of convolutional layers. The feeding data is given to the classifier after the final layer of the convolution layer applies average pooling to the data after convolution has been done.

The C1 and C2 layers both convolve an input and then pass the data through a rectified linear unit (ReLU) operation: convolutional layers 1 and 3 produce 9 feature maps, each with 9 filters. The operation of each kernel (filter) is defined in equation (8) to calculate four essential features of an image.

$$X^i = \varphi(W^i * X^{i-1} + \beta^i) \quad (8)$$

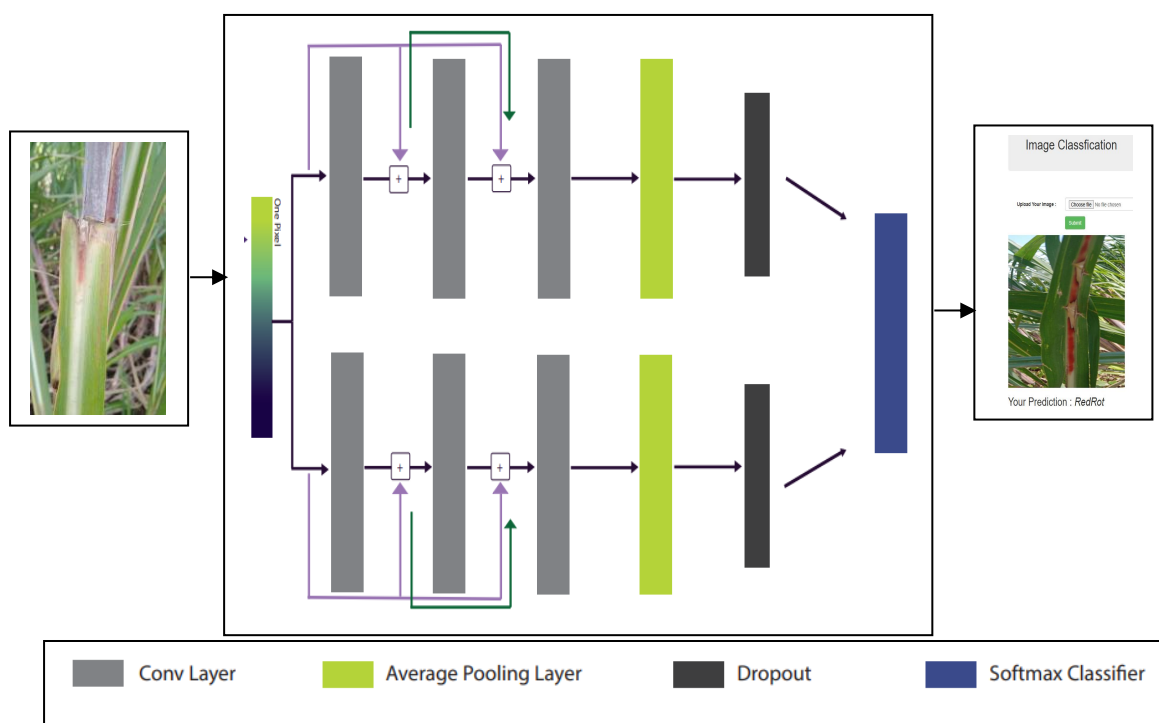


Figure 9. Architecture of ResNet Inception model

Where  $*$  is the convolution operator that applies the rectifier function  $\phi$ , adds the bias term  $\beta$  to the filter  $W^i$  to convolve the input data  $X^{i-1}$ , and generates the feature map  $X^i$ . In our proposed model, the number of units in each convolutional filter (or 1D convolution window) is 16, and the number of layers is 9 filters. Each filter applies its output dimensions so as to equal that of the input tensor in order to produce the output. This has two aspects: the convolution stride length. Convolutional layers are weights (kernels) initialized using the Glorot uniform (Xavier) weight initialization method. Equation 9 defines the elementwise action that the ReLU activation function  $\phi$  performs on the input data  $x$ :

$$\varphi(x) = \max(x, 0) \quad (9)$$

Since each pixel and its band are represented as a single vector with a single label in the sugarcane image data, 1D convolutional kernels are more suited for this structure than 2D or 3D kernels. Two residual models that are eventually related are part of our model. Equation 10 defines how the higher residual model operates: and the lower residual model is defined in equation 11.

$$\begin{aligned} X^1 &= \varphi(W^1 * X^0 + \beta^1) \\ X^2 &= \varphi(W^2 * (X^0 + X^1) + \beta^2) \\ X^3 &= \varphi(W^3 * (X^0 + X^1 + X^2) + \beta^3) \\ X^4 &= \text{AvgP}(X^3) \end{aligned} \quad (10)$$

$$\begin{aligned} X'^1 &= \varphi(W'^1 * X^0 + \beta^1) \\ X'^2 &= \varphi(W'^2 * (X'^0 + X'^1) + \beta^2) \\ X'^3 &= \varphi(W'^3 * (X'^0 + X'^1 + X'^2) + \beta^3) \\ X'^4 &= \text{AvgP}(X'^3) \end{aligned} \quad (11)$$

We utilize the Inception module's parallelism feature, which was inspired by it, to ensure that the upper and lower residual models operate in tandem and are eventually coupled. Each of the first three lines. equation displays the data's convolution procedure. Next, we use the dropout approach after feeding the average pooling layer with the outputs of the third convolutional layers, X3 and X03. The next section goes into further information about the dropout and average pooling techniques.

$$X^i = \text{AvgP}(X^{i-1}) \quad (12)$$

In this case, AvgP stands for the average pooling operation, while  $X^{i-1}$  represents the input data from the prior convolutional layer.

Immediately following the average pooling layer at the end, we use a dropout approach with a probability of 0.25. The soft-max classifier is then used to classify the output data. Therefore, except from the soft-max classifier, we don't have any completely linked layers. There are 153 trainable parameters in the first convolutional layer.

#### 4. Result and discussion

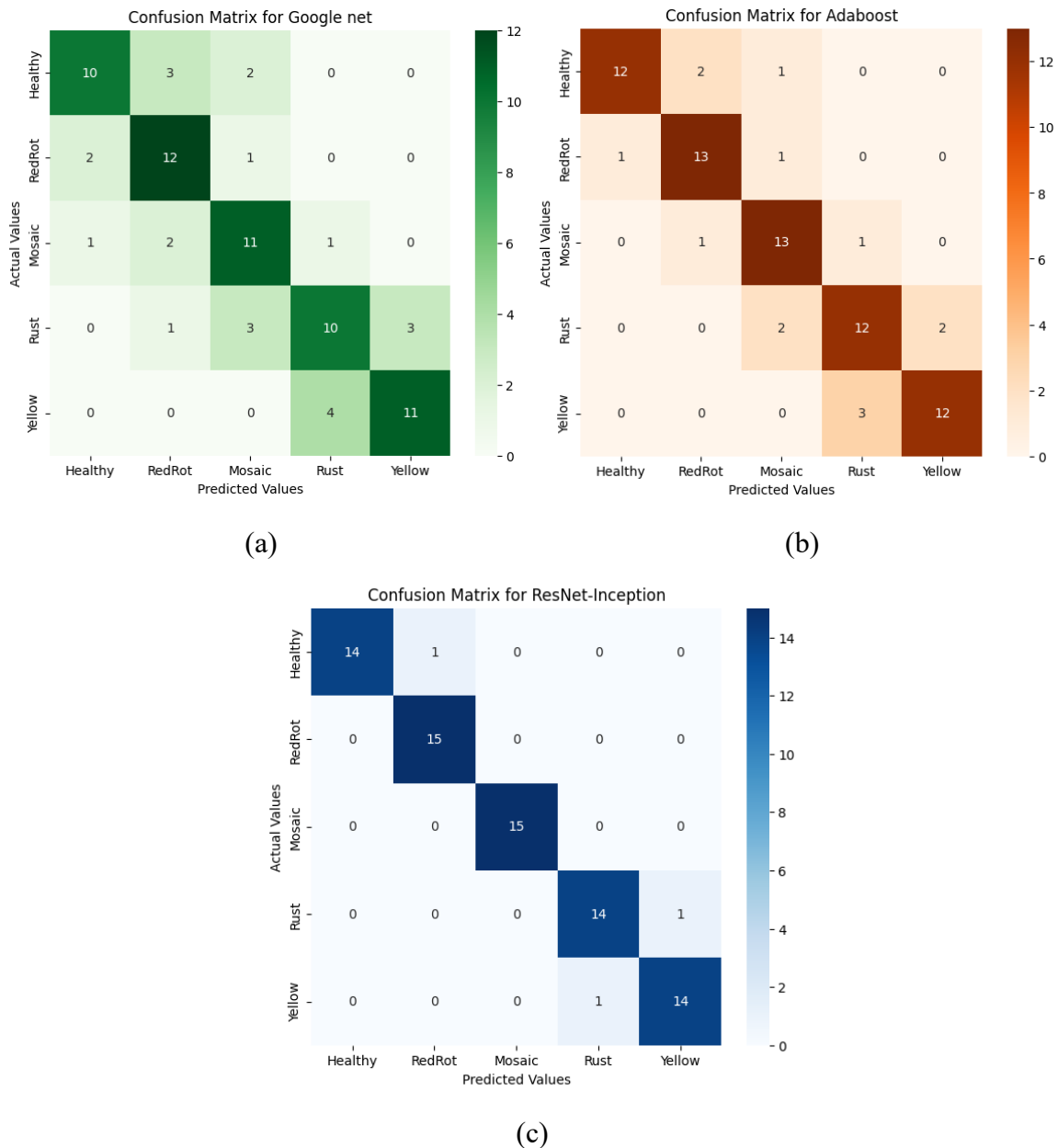


Figure 10. Image present confusion matrix (A) Google net (B) Adaboost (C) ResNet-Inception

The comparison evaluates three models—Google Net, AdaBoost, and ResNet-Inception—for sugarcane disease prediction across five categories: Healthy, Red Rot, Mosaic, Rust, and Yellow. As shown in the figure 10, Google Net identifies 12 Red Rot and 11 Mosaic instances correctly but struggles with similar diseases, showing 10 true positives for Rust with 7 false positives (3 misclassified as Yellow) and 11 true positives for Yellow with 4 misclassifications from Rust. AdaBoost improves accuracy, predicting 13 Red Rot and Mosaic cases correctly, 12 Healthy with 3 errors, 12 Rust with 4 misclassifications, and 12 Yellow with 3 misclassifications from Rust. ResNet-Inception outperforms both, with negligible errors—misclassifying only one Healthy sample as Red Rot and one Yellow sample as Rust—demonstrating superior accuracy and reliability. The findings, illustrated in the figure, highlight

ResNet-Inception’s minimal misclassification and emphasize the importance of model selection and fine-tuning for accurate agricultural disease prediction.

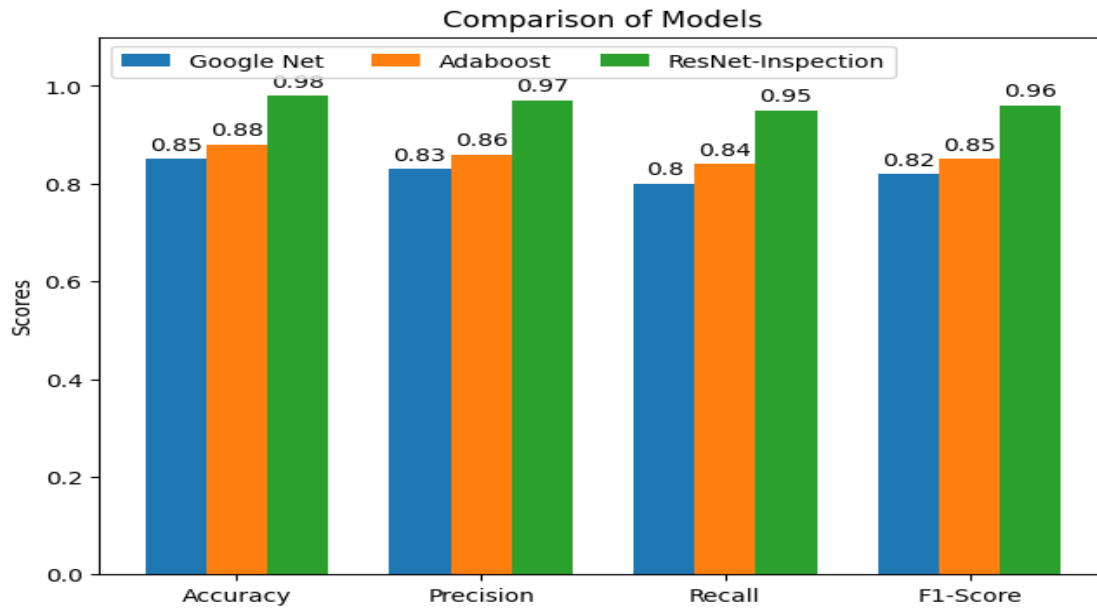


Figure 11. Comparison of model

The figures 11 include Google Net, Adaboost, and ResNet-Inspection. Google Net had measured an acceptable accuracy, precision, recall, and F1-score of 85%, 83%, 80%, and 82%, respectively. Adaboost was slightly better at an overall accuracy of 88 %, precision of 86%, recall of 84%, and F1-score of 85%. However, ResNet-Inspection revealed a higher accuracy level than both models. It performed the best across the performance indicators, with an accuracy of 98%, precision, recall, and F1-score of 97%, respectively. The findings demonstrate that ResNet-Inspection outperforms other models in recognizing sugarcane diseases and distinguishing patterns and types of diseases most accurately. Higher precision and recall also show that the proposed model could eliminate false positive and false negative cases, which makes it more reliable in diagnosing diseases that affect agricultural systems.

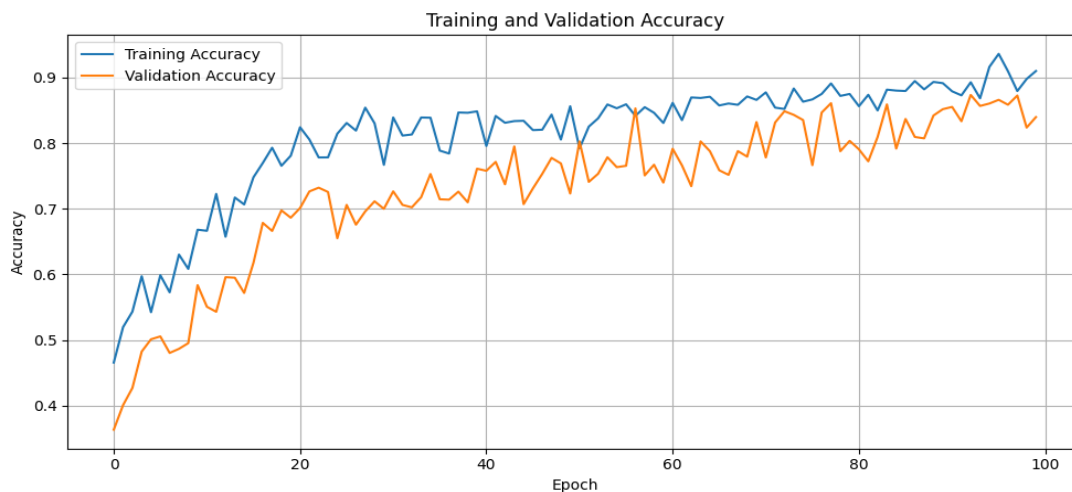


Figure 12. Training and validation accuracy of a model

This illustrates how far the training and validation accuracy of a model, which is probably used for sugarcane disease prediction, has reached 100 epochs. First, training and validation accuracy increases sharply, and this means the model has been trained well. The two accuracy outcomes of every training cycle show that the training accuracy is always higher than the validation accuracy since the model is trained on the training data. However, if the difference between the two lines is high, a model might overfit, and it might make more wrong predictions. Consequently, especially after the 40th epoch, the accuracy of training keeps climbing, though at a slightly declining rate. The validation accuracy is on the decline and may also fluctuate slightly, proving that the model begins to learn the training data by heart. This overfitting is an observation on its own. This implies that methods like regularization, dropout, or early stopping could be helpful in making the model perform better on new sugarcane diseases. The best validation accuracy is obtained around epoch 70-80.

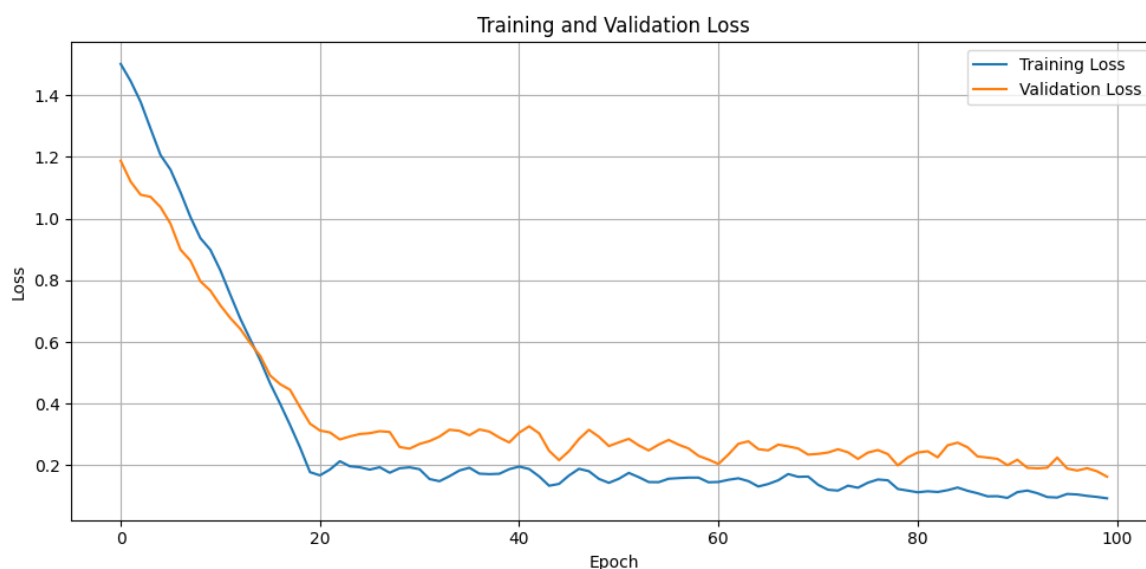


Figure 13. Training and validation loss of a model

The figure 13 shows the training and validation loss of a sugarcane disease prediction model, and the data used is for 100 epochs. Firstly, both losses reduce sharply at the beginning, indicating a fast learning rate, which means that the chosen model increasingly captures patterns in the training data. Since the 20th epoch, however, a shift is observed – while the training loss keeps decreasing more gently than in the previous epochs, validation loss starts to level off, fluctuating around a specific value. This skewness indicates overfitting, in which machine learning models tend to learn by heart; that is, they begin to learn unique characteristics that apply to specific training data but are not likely to work well on new data. Inspiringly, training and validation losses should be reduced in a similar manner. The observed trend indicates that regularization, dropout, or early stopping mechanisms need to be employed to minimize overfitting and to optimize the model for correctly predicting sugarcane diseases on new datasets. In addition, the still near zero validation loss after 20 epochs meant that training can only maximize profits and leads to further degradation of the generalization performance due to overtraining. The figure 14 shows the webpage-based sugarcane’s leaf

disease prediction system.the page is created with help of python programming language and flask module.

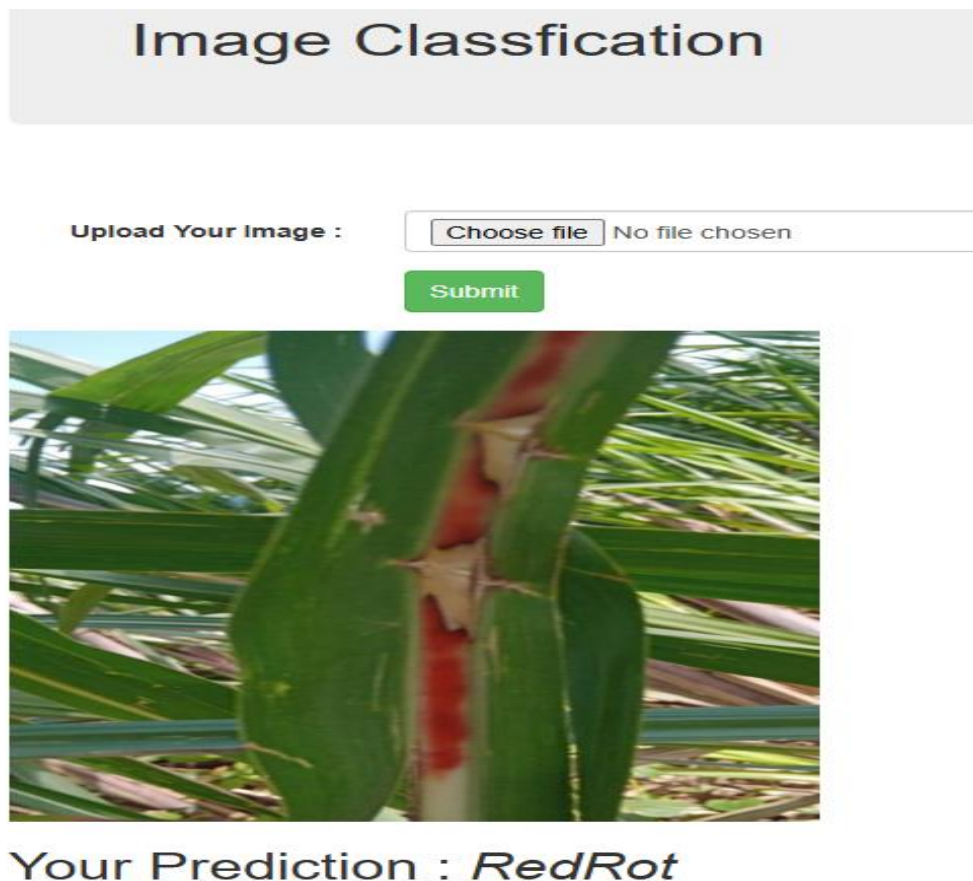


Figure 14. Webpage based sugarcane image prediction system

## 5. Conclusion

This research utilized a combination of deep learning to identify sugarcane leaf disease with high accuracy and increased speed. Each image had a high resolution, and multispectral imagery and pixel-by-pixel classification were used to classify the disease accurately and to get quantitative features. Using the Flask, a web application that enables real-time prediction and live visualizations was created. In the study, the classification performance of deep learning models, including ResNet, AdaBoost, GoogleNet, and a combined model of ResNet and Inception, was assessed for both pixel-level and plant-level analysis. The ResNet-Inception introduced in this study performed the best, achieving high levels of recognition of infection areas and a high level of agreement with the obtained density maps with the ground truth density maps. The advantages of ResNet and Inception, the model was able to categorize each pixel into one of the five categories of diseases so as to provide detailed predictions. Experimental outcomes confirmed the credibility of the hybrid model, which yielded an overall accuracy of 98%, preciseness, recall, and F1-score of 97% and 95%, respectively. These precision statistics show that the model can effectively identify diseases affecting sugarcane leaves without producing excessive false alerts or overlooking possible infections. Thus, this

work is a breakthrough in plant disease diagnosis since the proposed hybrid deep learning provides a practical and precise solution.

### References

1. Mr. Kumar K, N Keerthana, Sahana R, "A Survey on Deep Learning Technique for Sugarcane Disease Detection", *Ijrasnet Journal for Research in Applied Science and Engineering Technology*, ISSN :2321-9653,2023.
2. Akhter, R., & Sofi, S. A. et al., "Precision agriculture using IoT data analytics and machine learning", *Journal of King Saud University-Computer and Information Sciences*,2021.
3. Anas Ansari, Adarsh Borde, et al., "Sugarcane Disease Identification Using Deep Learning", *IOSR Journal of Computer Engineering (IOSR-JCE)* e-ISSN: 2278-0661, p-ISSN: 2278-8727, Volume 26, Issue 2,2024.
4. Santhrupth B C, Devaraj Verma et al., "Enhancing Sugarcane Leaf Disease Diagnosis with USEM: A Hybrid Approach Using U-Net and Stacked Ensemble Learning", *Frontiers in Health Informatics*, Vol. 13 No. 3 (2024).
5. Thamarai Muthusamy, Gomathi Eswaran, "Detection of Sugarcane Mosaic Diseases Using Deep Learning Architecture to Avoid Annealing Temperature of PCR Primer in Laboratory Testing", *IETA*, Vol 39,2022.
6. Sakshi Srivastava,Prince Kumar, "A Novel Deep Learning Framework Approach for Sugarcane Disease Detection",*SN Computer Science* , Vol1(2):87,2020.
7. W. Shafik, A. Tufail, A. Namoun, L. C. De Silva and R. A. A. H. M. Apong, "A Systematic Literature Review on Plant Disease Detection: Motivations, Classification Techniques, Datasets, Challenges, and Future Trends," in *IEEE Access*, vol. 11, pp. 59174-59203, 2023.
8. Margesh Keskar, Dhananjay D. Maktedar, "Hybrid deep-spatio textural feature model for medicinal plant disease classification", *Indonesian Journal of Electrical Engineering and Computer Science*, Vol. 30, ISSN: 2502-4752,2023.
9. Pavan Sharma, Rakesh Kumar Yadav and Dilipkumar Jang Bahadur Saini, "A Survey on the State of Art Approaches for Disease Detection in Plants", *International Journal on Recent and Innovation Trends in Computing and Communication*, ISSN: 2321-8169, Vol: 10, Issue: 11,2022.
10. Mr. Kathan Gohil, Prof. Amita Tailor, Prof. Anjali Solanki "A Comprehensive Survey on Plant Diseseses Detection", *International Journal for Research in Applied Science & Engineering Technology*, ISSN: 2321-9653, Vol 10,2022.
11. WASSWA SHAFIK, ALI TUFAIL, "A Systematic Literature Review on Plant Disease Detection: Motivations, Classification Techniques, Datasets, Challenges, and Future Trends", *IEEE Access*,2023.
12. Haider, K. et al. (2023). A Comprehensive Study of Plant Disease Detection Using Deep Learning Methods. In: Shaw, R.N., Paprzycki, M., Ghosh, A. (eds) *Advanced Communication and Intelligent Systems. ICACIS 2022. Communications in Computer and Information Science*, vol 1749. Springer.
13. Tej Bahadur Shahi, Cheng-Yuan Xu, "Recent Advances in Crop Disease Detection Using UAV and Deep Learning Techniques", *MDPI*, Vol 15,2023.

14. X. Leong and R. K. Ramasamy, "Obstacle Detection and Distance Estimation for Visually Impaired People," in *IEEE Access*, vol. 11, pp. 136609-136629, 2023, doi: 10.1109/ACCESS.2023.
15. Abhinav Agarwal, D.K. Agarwal, "Plants Disease Detection Using Deep Learning Plant Disease CNN Models for Image Segmentation", *FLORA AND FAUNA*, Vol 28,2022.
16. Athiraja Atheeswaran · Raghavender K.Vm, "Expert system for smart farming for diagnosis of sugarcane diseases using machine learning", *Computers and Electrical Engineering*, Vol 109,2023.
17. Midhunraj, P.K., Thivya, K.S. & Anand, M., "An Analysis of Plant Diseases on Detection and Classification: From Machine Learning to Deep Learning Techniques", *Multimed Tools Appl* 83, 48659–48682 (2024).
18. Swapnil Dadabhau Daphal, Sanjay M. Koli, "Enhanced deep learning technique for sugarcane leaf disease classification and mobile application integration", *HELIYON*, Vol 10, Issue 8,2024.
19. Akshara Avinash Sarode, Sufyain Salim Posharkar, "Enhanced Sugarcane Disease Diagnosis through Transfer Learning & Deep Convolutional Networks", *International Journal of Innovative Science and Research Technology*, ISSNNo: -2456-2165, Vol8, Issue 6,2023.
20. Ismail Kunduracioglu, Ishak Pacal, "Deep Learning-Based Disease Detection in Sugarcane Leaves: Evaluating EfficientNet Models", *Journal of Operations Intelligence*, Volume 2, Issue 1 (2024).
21. Anas Ansari, Adarsh Borde, "Sugarcane Disease Identification Using Deep Learning", *IOSR Journal of Computer Engineering (IOSR-JCE)* e- ISSN:2278-0661, p-ISSN: 2278-8727, Volume 26, Issue 2,2024.
22. Ms. Riya Walia, Dr. Satender kumar, "Advancing Sugarcane Disease Detection through CNN-Based Deep Learning", *International Journal of Membrane Science and Technology*, Vol 10,2023.
23. Daphal SD, Koli SM, "Enhanced deep learning technique for sugarcane leaf disease classification and mobile application integration", *Heliyon*, 2024.
24. Mostafizur Rahman Komol, M., Sabid Hasan, M., Ali, S. (2023). Sugarcane Diseases Identification and Detection via Machine Learning. In: Bansal, J.C., Uddin, M.S. (eds) *Computer Vision and Machine Learning in Agriculture*, Volume 3. Algorithms for Intelligent Systems. Springer, 2023.
25. Dr. Mahesh Gowda N M, Rajeshwari Machra, "Sugarcane Disease Recognition using Deep Learning", *International Journal of Advanced Research in Science, Communication and Technology*, Volume 3, Issue 1, 2023.
26. Aeri Rachmad, Mohammad Syarief, et al., "Corn Leaf Disease Classification Using Local Binary Patterns (LBP) Feature Extraction", *Journal of Physics: Conference Series*, 2406 (2022).
27. Vijaypal Singh Dhaka, Nidhi Kundu, "Role of Internet of Things and Deep Learning Techniques in Plant Disease Detection and Classification", *MDPI, Sensors* Vol 23,2023.