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# AUGMENTING SMART FARMING: SEVERITY-CENTRIC BLAST PADDY LEAVES ASSESSMENT

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**Abstract**
Paddy leaf rice blast disease is a devastating rice disease which causes severe yield losses and threatening rice production globally. Rice blast caused by the fungus Magnaporthe oryzae, pose a threat to both the above and below-ground parts of paddy plants. It's crucial to identify signs of disease, like rice blast severity and understand its effective management strategies. Deep learning (DL) methods have shown to be successful in solving this problem for intricate prediction problems. The study presents a unique Spatial Stacked Deep Convolutional Neural Network (SS-DCNN) method for forecasting the impact of a rice blast severity that utilizes DL principles. Using a prominent disease dataset from Kaggle, it was implemented a three-step preprocessing methodology, including k-means based segmentation, high-pass filtering, and bicubic interpolation, to ensure data quality and enhance images. To extract meaningful features, it employs two methods, Histogram of Oriented Gradients (HOG) and Accelerated-KAZE (AKAZE), which aid in reducing dimensionality while retaining essential features. The proposed model is applied to finish the classification task, naturally accounting for temporal correlations in the data. This is especially important for estimating the intensity of the rice blast severity, as past trends have a big impact on results. The study, which focuses on rice blast severity forecasting, is carried out with the help of Python tools. Several measures of accuracy are used to evaluate the suggested model's efficiency. Their all-encompassing strategy seeks to improve rice blast severity prediction measures relative to current approaches.
***Keywords:***Python, Paddy Leaf disease prediction, Dataset, Spatial Stacked Deep neural Network (SS-DNN), k-means based segmentation, High pass filter, Bi-cubic interpolation, Histogram of Oriented Gradients (HOG), Accelerated-KAZE (AKAZE)

## 1. Introduction

In the world, the three main food crops are paddy, wheat, and maize.The most area is planted with paddy among them.The production of paddy has been severely impacted by paddy diseases.Diseases that spoil the rice which have a significant impact on crop productivity. Among these, rice blast plant diseases account for a 10–15% reduction in rice yield [1].Many symptoms, including as lesions, colour changes, damaged leaves, stem damage, and abnormal development of the bud, stem,flower,leaf, and root, can be used to diagnose leaf diseases. The two main causes of the decline in agricultural productivity are diseases and pest infestations. Applying appropriate preventive and protective measures is aided by accurate and timely prediction of rice blast severity. It therefore helps to increase agricultural productivity and enhance the quality of the harvest [2].

Diseases that cause damage to rice plants include sheathing rot, brown spot, bacteria blight, leaves blast, and leaf smog. Segmentation is used to group together the healthy and diseased sections of the leaves [3]. Additionally, rice blast severity is an important concern for rice grower globally. Farmers are facing difficulties as a result of crop illnesses because of industrial agriculture, reduced yield, and financial losses. Therefore, the need to be defined as appropriate is the main emphasis of disease identification and rice blast severity [4]. Farmers can prevent the agricultural land from being harmed or destroyed by detecting plant diseases. To distinguish between the wholesome and dangerous regions, hue value-based historical past exclusion is used [5].Additionally, rice blast severity can be detected and addressed directly to reduce its outcomes on crop yield. Due to their lack of knowledge of the ailment, farmers apply useless pesticides in the wrong quantities, which lowers crop great and also degrades the soil and different environmental factors [6].Using images of infected plants to forecast and classify severity levels primarily based on the quantity of impacted leaf area, a hybrid prediction version for early detection of blast ailment rice blast severity in paddy flora is being evolved. The main objective is to help farmers allocate resources in a timely manner and avoid widespread pollution in the field.

## 2. Related works

Study [7] recognized paddy leaf disease in real time using a faster region-based convolutional neural network (Faster R-CNN). According to the results, the Faster R-CNN model offers a very effective method for detecting infections on paddy leaves, with the ability to quickly and more precisely diagnose the most common paddy illnesses. This paper [8] produced the greatest results for paddy leaf disease identification by automating the process and achieving the maximum level of accuracy achievable using deep learning CNN models. This method is better than the laborious, antiquated manual illness diagnosis procedure, which also has very dubious accuracy. After analysing many of their models, including Xception, “Inception-Resnet-V2,ResNet-101, and VGG-19,” the findings indicate that “Inception-ResNet-V2” has a greater accuracy of 92.68%.

Study [9] used a Residual Neural Network (RNN) for the purpose of categorising the photos into the appropriate illness classifications. This technique has been found to be quick and very effective, and Comparing it to other classifiers, like Support Vector Machines (SVM) and plain Convolutional Neural Networks (CNN), it yields superior results, because it prevents the model from becoming saturated with larger data sets or deeper networks. On the dataset, obtained an accuracy of roughly 95.83%. Study [10] introduced a CNN based AlexNet model is contrasted with two other CNN models (VGG-16 and Lenet-5); it becomes clear that their Alex Net model is superior in terms of accuracy. Study [11] outlined an automated diagnostic method was developed and integrated into a smartphone application. This innovative approach utilized deep learning techniques on an extensive dataset comprising 33,026 images, each portraying one of six distinct paddy diseases. It has been determined that the diagnostic system's methodology and execution are quite adequate for handling the challenges involved in identifying and categorizing different paddy plant illnesses.

Study [12] created a deep learning method using convolutional neural networks (CNNs) to automatically recognise three distinct paddy leaf diseases. The CNN system was able to distinguish among healthy and morbid leaves of rice with 94% accuracy by automatically extracting pertinent information from raw pictures. Study [13], was to identify nine paddy leaf diseases, six CNN-based ensemble and transfer learning models were employed.Three CNN architectures were given they weighted voting in a new ensemble framework. Research [14], determined the recommended approach uses mask R-CNN and quicker R-CNN algorithms to distinguish distinctive paddy plant leaf pictures and come across disease. R-CNN is the excellent masks for his or her experimental records analysis as it could understand and discover several paddy blast ailments, which includes blast (96%), brown spot (95%), and sheath blight (94.5%). The findings endorse that it's far possible to identify diseases via live leaf photograph capture and boom accuracy via using several regions to forestall the unfold of paddy blast disorder.The intention of the study [15] utilized the "Visual Geometry Group Network-sixteen (VGG16)" by way of the usage of Image NET's pre-education version for alternative and switch mastering.The VGG16 model system was able to classify healthy and damaged leaves from rice with 94% accuracy by automatically obtaining relevant data from unprocessed images.

The purpose of this study [16]aimed to recognize and classify diseases in images using CNNs. The examination focused on six primary paddy illnesses: bacterial leaf blight, narrow brown spot,blast, brown spot, bacterial leaf streak, and paddy ragged stunt viral disease.The popular pre-trained models in the study were compared in terms of detection performance: Mask RCNN, Retina Net, YOLOv3, and Faster R-CNN. Study [17-18] attempts to analyze the thermal images of paddy leaves to build a Modified Lemurs Optimization Algorithm as a filter-based feature conversion technique with the goal of improving the accuracy of paddy disease detection via machine learning techniques.

## 3. Proposed Methodologies

Capture the images of rice blast severity plants diseases using the digital camera. Pre-processing improves the characteristics of the captured picture, enhancing the processing information. Image segmentation makes analysis easier by grouping pre-processed images according to comparable characteristics.From the segmented images, features are extracted using criteria such as forms, colours, and textures, moreover, features are classified as different illnesses affecting rice plants. Procedures for diagnosing rice blast severity are shown in Figure 1.

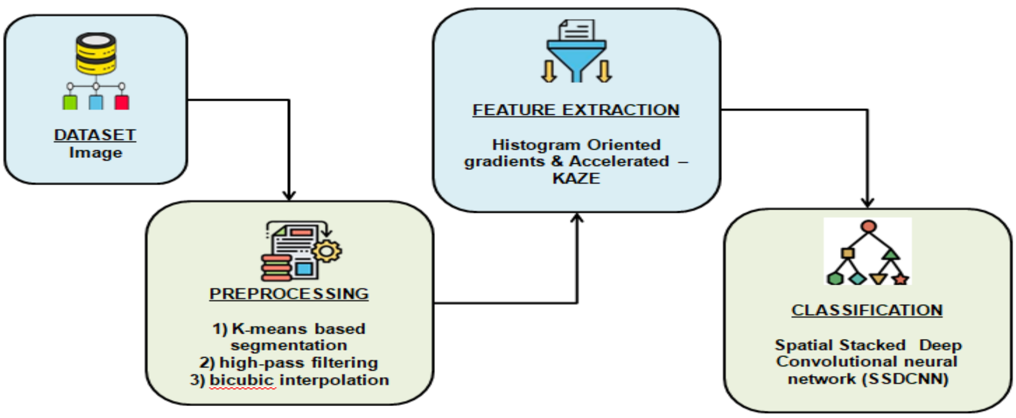


**Figure 1: Components of the proposed method**

### 3.1 Dataset

Images for the dataset were gathered from the Kaggle website. A different folder contains these disease datasets. Rice blast severity was assessed. Seventy percent of the dataset was utilized for training, while thirty percent was utilized for validation. As a result, the dataset had 84 test images and 157 training images. Figure 2 depicts the sample dataset.


**Figure 2: Dataset samples**

#### 3.1.1 Diseases

The bacteria "Xanthomonas Oryzae" is the primary cause of bacterial leaf blight, a kind of monsoon season sickness known as kharif. Water-soaked leaves that start at the margins and spread to the base of the leaf are one of the disease's symptoms. Brown spots are mostly found during the kharif season and are caused by the fungus "Helminthosporium oryzae." Small brown patches on leaves that eventually take the shape of round or oval brown spots are the signs of these illnesses. Rice blast severity is a fungal disease that causes elliptical blotches with a bright Centre and reddish rims. It occurs throughout the kharif and Rabi season, which runs from November to February.Figure 3 represents the types of diseases affected by Paddy leaves which rice blast severity is one of them.


**Figure 3: Types of diseases affected by Paddy leaves**

The research examined four rice blast severity levels: average, mild and severe were denoted by the characters Sy1, Sy2 and Sy3, respectively. The region of the infected plant leaf impacted by the illness determined these rice blast severity categories. When the percentage of a leaf's total area afflicted by the disease fell between 1-33%, the leaf was considered to have moderate disease. Similarly regions between 34-63 %, and 64-100% of the total area were categorized as mild and severe, respectively.

### 3.2 Pre-processing

#### 3.2.1 K-means Based Segmentation

The method of K-means clustering is applied. Clustering is the process of grouping an image into clusters. Because of this clustering, the afflicted area can be more easily illustrious.When applying this gather to a leaf image, the sections that are sick and those that are not should group together. This method is used on the hue part of the background-removed picture's HSV (hue, saturation, value) model. The hue component lacks brightness and darkness but includes the pure colour. To solve the cluster's unpredictability issue, the centroid value of the hue component histogram is fed to create ideal segments. In addition, the unwelcome green portion of the group of ill components is eliminated.

The image with the backdrop removed is used to create a rice blast severity components histogram is to establish a threshold value that can be utilised to distinguish between the healthy and diseased sections of an image, the histogram and the affected region are consulted.Both, the normal and sick portions' hue values are kept in two different arrays.The below Figure 4 displays the image clustered from the hue portion image.

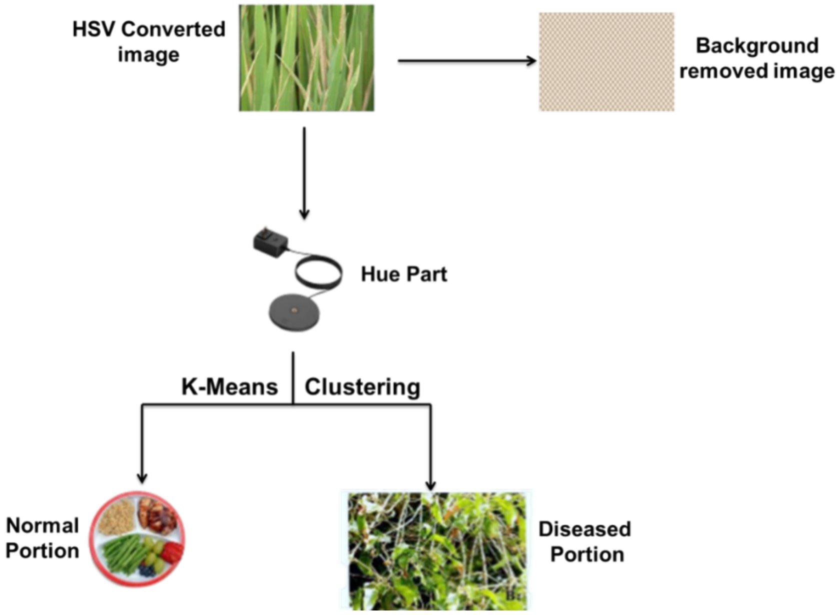


**Figure 4:Clustered image from the hue part**

#### 3.2.2 High-Pass Filter

Electronic filters that allow sounds above a specific cutoff frequency and attenuate signals below it are called High-Pass Filter (HPF).An EQ curve called a HPF is used to eliminate low-frequency noise from an audio source.The filter's design determines the cutoff frequency value.HPF enhances the high-frequency components of animage, highlighting its edges and tiny details. Two examples are the Laplacian filter and the unsharp mask filter.A linear time-invariant system is typically used to simulate a high-pass filter.In contrast to low-pass filters, high-pass filters are utilized when it is intended to transmit higher-frequency signals while blocking lower-frequency ones.

#### 3.2.3 Bicubic Interpolation Method

The bi-cubic interpolation technique uses a third-order polynomial function to attempt to create a surface between its corner points. The intensity values, as well as the diagonal, vertical, and horizontal derivatives for each of the corresponding corner locations, must be supplied to carry out bi-cubic interpolation.The third order polynomial $e\_j\ (w, z)$, which characterises the interpolated surface, is provided by

$$e_j(w, z) = \sum_{j=0}^{3} \sum_{i=0}^{3} b_{ji}\, w^j z^i \tag{1}$$

To calculate the function, 16 coefficients$(bji)$ thecoefficients include information that is necessary for precisely fitting a surface between the corner points. They are fundamental to the bi-cubic interpolation approach outlined in the preceding equation.

**3.3 Feature Extraction**

At this stage, the leaf's key features are extracted to be classified at the recognition stage. This step crucial since it lowers misclassification and increases recognition rate when it operates well.

**3.3.1 Histogram Oriented Gradient (HOG)**

It was, first developed by Dalal and Triggs for human body identification, is a widely used descriptor in pattern recognition and computer vision applications. This paper presents a feature extraction method for leaf image identification based on HOG.Here is a description of the procedures involved in calculating HOG characteristics for easy reference. To simplify the computation of HOG descriptors, a 16x16 pixel image is taken into consideration.Pixel values on the grey scale range from 0 (black) to 255 (white), representing the image. For the pixels that surround the pixel of interest $(x, y)$, arbitrary values are assumed. An image is first divided into blocks and cells. They use the assumption that a cell in this computation is 8 by 8 pixels in size. Moreover, it is expected that the block size is 2x2 cells.In mathematics, it is expressed as

$$\nabla e(w, z) = \begin{bmatrix} h_w \\ h_z \end{bmatrix} = \begin{bmatrix} \frac{\delta e(w,z)}{\delta w} \\ \frac{\delta e(w,z)}{\delta z} \end{bmatrix} \tag{2}$$

In the example under consideration, the gradient vector is calculated as

$$\nabla e(w, z) = \begin{bmatrix} e(w, z+1) - e(w, z-1) \\ e(w+1, z) - e(w-1, z) \end{bmatrix} \tag{3}$$

The gradient vector's magnitude and direction are its two characteristics. Equations (4) and (5) provide this, respectively.

$$|\nabla e| = \sqrt{h_w^2 + h_z^2} \tag{4}$$

$$\theta = tan^{-1}\left(\frac{h_z}{h_w}\right) \tag{5}$$

$$\nabla e(w, z) = \begin{bmatrix} e(w, z+1) - e(w, z-1) \\ e(w+1, z) - e(w-1, z) \end{bmatrix} = \begin{bmatrix} 105 - 55 \\ 95 - 45 \end{bmatrix}$$

$$\nabla e(w, z) = \begin{bmatrix} 50 \\ 50 \end{bmatrix}$$

$$|\nabla e| = \sqrt{50^2 + 50^2} = 70.71 \tag{6}$$

$$\theta = tan^{-1}\begin{bmatrix} 50 \\ 50 \end{bmatrix} = 45^o \tag{7}$$

All of the pixels in a cell have their magnitude and direction determined in a similar manner.

**3.3.2 Accelerated KAZE**

The description of features in a non-linear scale space, KAZE finds and describes 2D picture characteristics using the Hessian matrix. This feature descriptor uses an anisotropic diffusion-based non-linear scale space in its accelerated form, called AKAZE. Feature detectors and descriptors were created using both the KAZE and AKAZE approaches. By using the fast explicit diffusion (FED) approach, AKAZE's 2D feature detector and descriptor create a fine and coarse pyramid framework that builds a non-linear scale space. By using this method, many filtered pictures are produced, which aids in the development of a complete non-linear scale space.

**3.4 Classification**

The process of classifying a given collection of rice blast severity data into several classifications is known as classification. By following the extraction of each feature, a feature vector is concatenated and categorized in the classification stage.

**3.4.1 Spatial Stacked Deep Convolutional Neural Network**

A stacking-based deep learning model called a spatially stacked deep convolutional neural network (SSDCNN) is utilized to accurately and efficiently identify rice blast severity of the illnesses of paddy leaves.SSDCNN is used for image classification.SSDCNN are powerful identification techniques that have gained a lot of interest recently. With extensive verification, CNN has emerged as one of the most effective techniques for pattern classification. It has also been applied more often in the field of image processing, where it can outperform more conventional techniques.DCNN are very successful because of their powerful feature learning capabilities.It could be learned layer-by-layer by stacking linear and non-linear processing units at various abstraction levels. By stacking these scale-specific representations, a classifier can make use of each.

If the input data consists of RGB true-colour images, then the format of the input data is given by:$nh \times nw \times 3$;If the data are grayscale images, the format of the input data is given by: $\mathrm{nh} \times \mathrm{nw} \times 1$ Additionally, the image′s size and the amount of data channels should be constant, and the input layer′s input data should be normalised. The convolution operation procedure is then illustrated in the below Equation (8),

$$z_{j,i}^{s} = \sum_{q=0}^{n=1} \sum_{t=0}^{e-1} \sum_{s=0}^{e-1} X_{t,s}^{(q,s)} \, w_{j+t,i+s}^{k-1} + a^{k} \quad (8)$$

Every convolution kernel is visited once according to the first-level summation formula. According to the second- and third-layer summation formulae, the input data is exposed to a convolution processwith a convolution kernel of size $(\mathrm{CKS}) \times \mathrm{f}$ , here $W$ stands for weight and $b$ for bias. In the output layer, where $U, j$ denote the image's position as shown by Equation (9)

$$j = 1,2 \ldots .(m_g - e)$$

$$i = 1,2 \ldots .(m_\omega - e) \quad (9)$$

Utilize the Sigmoid activation function, as shown by Equation (10).

$$Sigmoid(w) = \frac{1}{1+f^{-w}} \quad (10)$$

A pooling layer, also known as a down-sampling layer, is a crucial stage in a convolutional neural network. Its dimensions are typically equal to those of a square window. Equation (11) depicts the pooling process.

$$z_{j,i}^{k} = \max_{0 \le t,s \le e} \left[ ReLU\left(\sum_{q=0}^{n-1} \sum_{t=0}^{e-1} \sum_{s=0}^{e-1} X_{t,s}^{(q,k)} \, w_{j+t,i+s}^{k-1} + a^{k}\right)\right] \quad (11)$$

Based on the degree of haze, the completely connected layer is divided into six groups, each with a matching label: $(0\ 0\ 0\ 0\ 0\ 1), (0\ 0\ 0\ 0\ 0\ 1\ 0), \ldots, (0\ 1\ 0\ 0\ 0\ 0\ 0\ 0)$. Among them, data that are obscured by information, like clouds, and are hence unidentifiable, are designated with $p$ position 1, or $1\ 0\ 0\ 0\ 0\ 0\ 0$.The classification procedure (SoftMax classification layer) determines the likelihood that this vector falls into each category; the classification outcome is represented by the category with the highest probability, as indicated by Equation (12)

$$g_{\theta}(w_j^{k-1} = \begin{bmatrix} o\left(z_j = 1 \middle| w_j^{k-1}; \theta\right) \\ o\left(z_j = 2 \middle| w_j^{k-1}; \theta\right) \\ \vdots \\ o\left(z_j = m \middle| w_j^{k-1}; \theta\right) \end{bmatrix} = \frac{1}{\sum_{i=0}^{m} f^{\theta_i^S} w_j} \begin{bmatrix} f^{\theta_1^S} w_1 \\ f^{\theta_2^S} w_2 \\ \vdots \\ f^{\theta_m^S} w_m \end{bmatrix} \quad (12)$$

Where $\mathrm{p(yi = n|xl - 1i; \theta)}$shows the classification function's probability estimation for the data's nth category and $\theta$ denotes the parameters of the model.The normalised version of the probability is represented by the equation's rightmost formula, which ensures that the total of all the probabilities equals 1. Algorithm 1 depicts the SSDCNN.

**Algorithm 1:**Spatial Stacked Deep Convolutional Neural Network (SSDCNN)

```
inputnumpy as np
inputthe tensor as tf
fromtf.keras input layers, models
        SSDCNN planning
defbuild_ssdcnn(input_form, number_classes):
        model = form. Chronological()
form.add(coating.MaxiPooling2D((2, 2)))
form.add(coating.Conv2D(64, (3, 3), creation='relu'))
form.add(coating.MaxiPooling2D((2, 2)))
form.add(coating.Conv2D(128, (3, 3), activation='relu'))
form.add(coating.MaxiPooling2D((2, 2)))
form.add(coating. compress())
form.add(coating.thick(512, activation='relu'))
form.add(coating.thick(num_classes, activation='softmax'))
        returnform
input_shape = (224, 224, 3)
num_classes = 10
ssdcnn_form= build_ssdcnn(input_shape, num_classes)
ssdcnn_form.compile(optimizer='adam',
loss='categorical_crossentropy',
metrics=['efficiency']
ssdcnn_form.summary()
```

This algorithmic and architectural method highlights the use of deep learning that is, SSDCNN in the paddy leaf disease classification, highlighting the latter's capacity to handle challenging problems in the field of image-based classification.

## 4. Results and discussion

This section explains the way to recognize, assess and categorize the rice blast severity of leaf disease. Pytorch 2.0, which is compatible with Python 3.11, was used in the experimental configuration on a Windows 10 computer. The accuracy, precision, F1 score and recall are the performance measures used to evaluate the process.

### i. Accuracy

Accuracy is the proportion of accurately identified instances among all occurrences and is a statistic used to evaluate the degree to which a system or model is performing. Accuracy is measured using the following equation (13) and is commonly expressed as a percentage in the context of data analysis:

$$Accuracy \rightarrow \frac{TP+TN}{TP+FP+FN+TN} \tag{13}$$

### ii. Precision

Precision describes the degree of refinement, exactness, or accuracy that is achieved in the process of carrying out a procedure. Additionally, it places an emphasis on the capability of achieving consistent and predictable outcomes with a limited amount of variability or departure.

$$Precision \rightarrow \frac{TP}{TP+FP} \tag{14}$$

### iii. F1-Score

Binary classification uses a metric called the F1-Score. Accuracy and recall are combined into a single score in this statistic. The formula (15)that is used to compute it is as follows:

$$F1 - score \rightarrow 2 * \frac{(Precision \times Recall)}{(Precision + Recall)} \tag{15}$$

### iv. Recall

It also known as sensitivity or TP rate, is a statistic that measures how well a model can detect all pertinent occurrences out of all the real positive cases. It is a statistic in binary classification that shows up. The calculation is done using the following formula (16):

$$Recall \rightarrow \frac{TP}{TP+FN} \tag{16}$$

Figure 5and 6depict the outcomes of the classification.

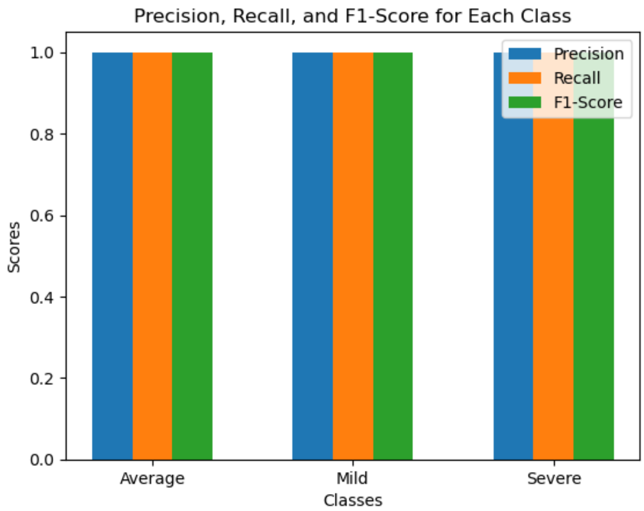


**Figure 5: Outcomes of metrics**

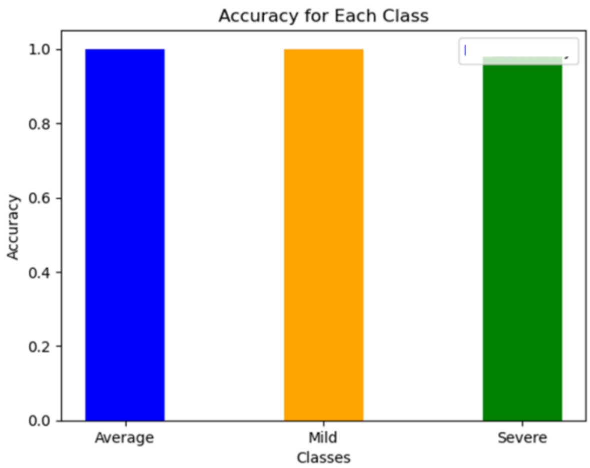


**Figure 6: Outcome of accuracy**

The overall accuracy of the proposed method is 97.70%.The efficiency of the suggested approach is contrasted with the current models such as Deep Convolutional Neural Network (DCNN), Artificial Neural Networks (ANN) and Convolutional Neural Network (CNN) methods. The comparison based on the achieved accuracy for different algorithms is shown in Figure 7.

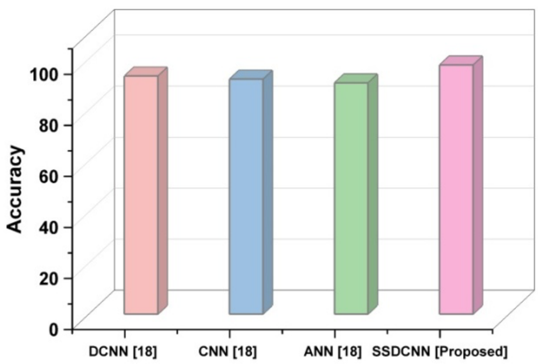


**Figure 7: Comparison of Accuracy**

It demonstrates that the proposed SSDCNN exhibit higher accuracy of 97.70% compared to DCNN (93.38%), CNN (92.15%) and ANN (90.72%).When compared to other methods currently implemented method achieves the most effective outcomes.

### 4.1 Training and validation

After building the final model, the hybrid method was trained employing the training set's images. 10 epochs were employed to train the model. Next, the test set's images were used to evaluate the trained model.Figure 8 shows the epoch-wise accuracy graph.

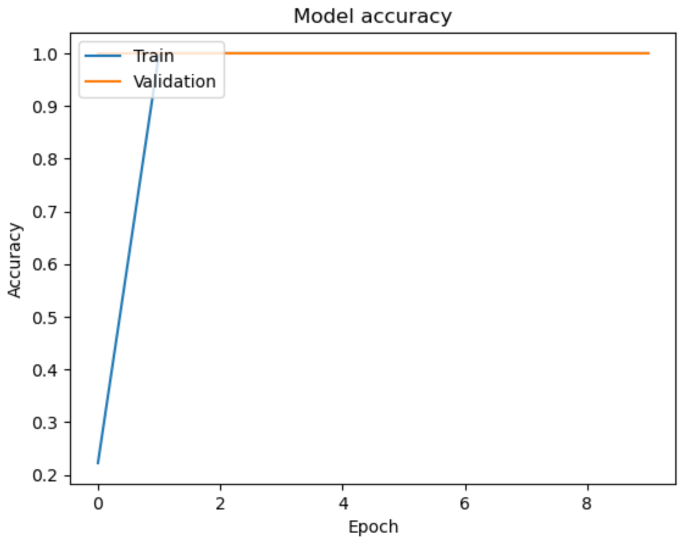


**Figure 8: Model accuracy**

The suggested model’s epoch-wise loss function value is displayed in Figure 9. They demonstrate how the model's accuracy rises along with its training over epochs, while the loss function decreases.

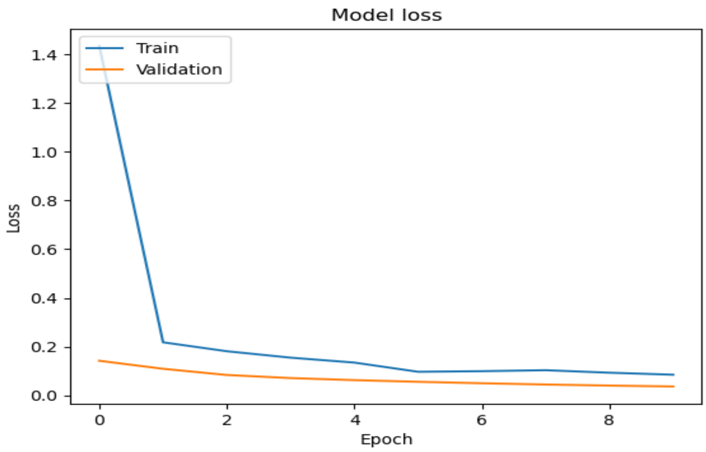


**Figure 9: Model loss**

### 5. Conclusion

The recommended method assesses disease rice blast severity conditions, sheath rot, including blast, bacterial blight, and brown spot, using images of paddy leaves that are directly collected from the farm.Masking is carried out using the hue component of the RGB photos following their conversion to HSV images during pre-processing to remove the background. The sick portion and normal portion are separated using a clustering technique.This model reduces dimensionality and enhances data quality while maintaining key features through the use of a three-phase pre-processing strategy and feature extraction techniques such as Accelerated-KAZE (AKAZE) and Histogram of Oriented Gradients (HOG). The suggested method shows higher accuracy compared to other methods and can be used to categorise plant disease rice blast severity if one is aware of the proper degree ofrice blast severity for each condition.The measured higher accuracy in severity categorization demonstrates the model's capacity for immediate benefit in agricultural settings. By accurately recognizing and organizing severity stages, the model provides a framework for better plant health surveillance methods. However, recognizing the various levels inrice blast severity of every disease is critical to maximize the performance of model.These measurements show that the model can correctly detect and categorise disease rice blast severity of paddy leaves, proving that it is prepared for application in agriculture at present. The research not only advances precision agriculture but also emphasises how important technical innovation is to addressing today's agricultural problems, particularly, rice blast severity. Future study might examine scalability, real-time implementation, and interaction with agricultural systems to improve crop health management. Firstly, exploring methods to optimize the model scalability and computational efficiency, particularly when handling large datasets or in resource-constrained environments, will be beneficial. Techniques such as parallel computing, distributed processing, or model compression could help streamline the implementation of the model across diverse agricultural contexts.Allowing farmers and agricultural practitioners to provide input, validate predictions, and refine model outputs based on their hands-on observations and experiences can contribute to the continuous improvement of the model and its effectiveness in promoting sustainable agricultural practices and safeguarding food security.This research lays the groundwork for more efficient, accurate, and useful agricultural forecasting tools, aligning with technology advances with focus on rice blast severity.

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