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Improving Rice Plant Disease Detection Performance for Roughly Captured Images Using VGG-16 and 2D-CNN

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ABSTRACT: Rice is one of the main food grains in India. It mostly grows in natural conditions and its production is influenced by different infectious diseases. However, there are various rice plant disease detection techniques available based on machine learning. These techniques require a suitable dataset to be learned. The collection, processing, and organization of datasets are complex issues and they require significant effort and time. In this paper, this problem is addressed by contributing an approach which will accurately identify the rice plant disease using roughly captured images. An investigation of statistical features like Sobal and k-means segmentation as well as deep feature selection like VGG-16 is done to classify with the deep Convolutional Neural Network. The experiments with Mendeley dataset are performed. The experimental result demonstrates that the simple sequential CNN directly with dataset provide 76% classification accuracy. Additionally, when the 2D-CNN is utilized with the dataset, it provides 96% accuracy. On the other hand, when statistical features Sobal and k-means then are utilized, 2D-CNN delivers 81% and 79% accuracy respectively. Furthermore, the combination of VGG-16 and 2D-CNN provides the highest classification accuracy of 99%. Lastly, the results also describe that the combination of VGG-16 and 2D-CNN provides this high classification accuracy with very fewer epochs.

Keywords— *plant disease detection, machine learning, deep learning, image processing, food security, early disease detection.*

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I. INTRODUCTION

Adoption and implementation of new-age technology in Indian farming are not feasible due to heavy costs of installation and maintenance. Due to this, a large number of farmers depend on the natural and conventional techniques of farming [1]. The traditional methods of farming may increase the waste of resources and time. Additionally, dealing with the different issues in farming requires experience such as disease identification [2]. The disease may significantly impact the quality and quantity of crop production [3]. This results in losses in farming business. However, recently a number of Machine Learning (ML) techniques-based disease detection solutions are contributed by different researchers. These techniques automatically identify diseases in crops and help to reduce the losses [4].

The ML techniques needed to utilize a well-defined and labelled dataset for performing the training. The appropriate training of ML models helps to improve the recognition ability. In this scenario, the dataset becomes an essential part of ML based disease detection system development. In addition, the preparation of dataset requires significant efforts and time [5]. Therefore, there is a need of a method that will work on raw images without processing them into laboratory and obtained directly captured from the farms. Feature extraction is an essential part of machine learning based disease detection system. The effective method of feature selection will help to improve the classification accuracy of ML models. In this paper, the investigation of the statistical feature selection techniques and deep feature selection technique are proposed to accurately classify the plant images which are roughly captured and organized as dataset. That study will also be helpful to those farmers who are not able to utilize expensive disease detection systems.

In this section, the overview of the proposed work is discussed; next, a review of recently contributed techniques by different authors for identifying diseases in crops is presented. Further, a study of different feature selection techniques and deep neural network is described for accurately classifying the rice plant disease. Moreover, the experiments are conducted and the comparative results are reported. Finally, based on the experiments, conclusion and future extension have been proposed.

II. RELATED STUDY

The key aim of this study is to identify a machine learning method which utilizes the raw crop images to identify the disease in rice plant. Early and accurate disease detection in rice plants will yield better productivity. Thus, to identify the better approach, a review is conducted based on 25 recent research articles. These articles are based on ML and image-processing methods that accurately detect the plant disease. Figure 1 shows the crops used for disease detection in plants using machine learning techniques.

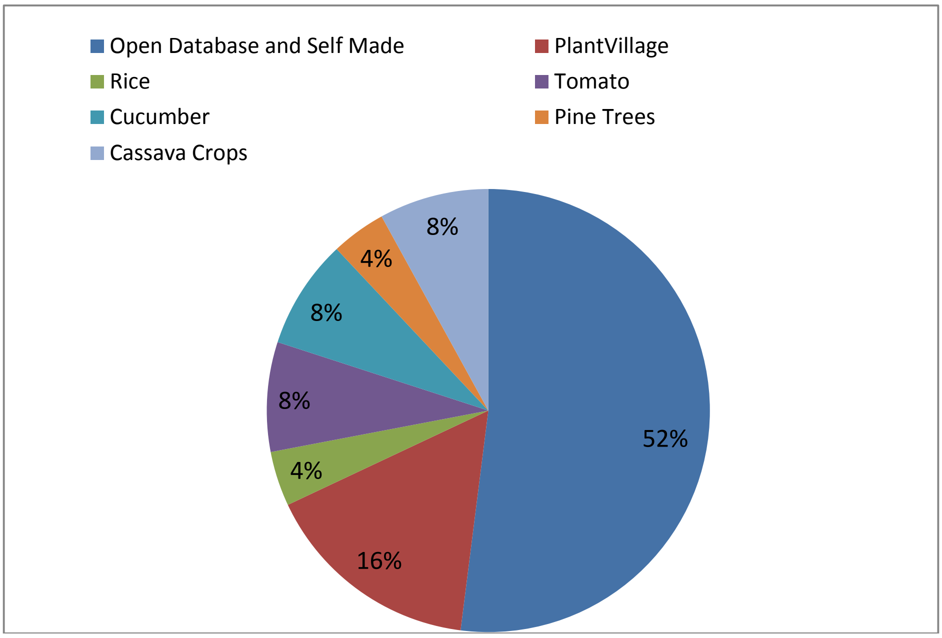

Fig. 1 Plant Diseases Datasets used [15]

This diagram shows the percentage ratio of the crops used for experiments, and the different crops are indicated using different colors. Most of the work utilizes an open database or synthetic dataset (52%) for the experiments. In the second place, the PlantVillage dataset (16%) [7], is the most popular image dataset. But it was found that there are a few works that have been done for rice plant (4%) disease detection [8]. From the review [6] the percentage of machine learning algorithms used in different crop disease detection was also calculated which is given in Figure 2.

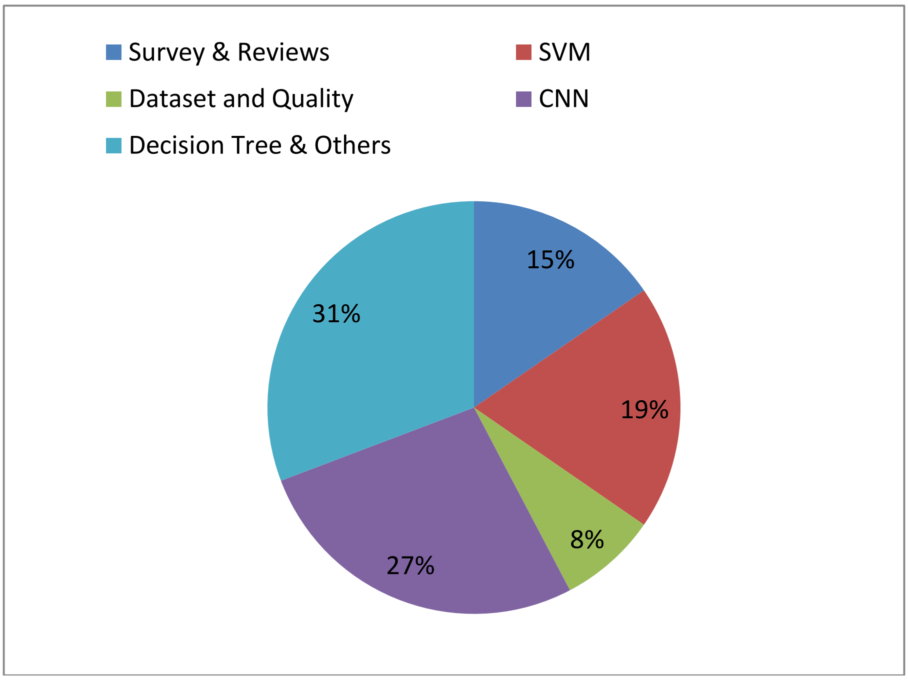

Fig. 2 Algorithms Used [15]

According to the findings, decision trees and others (31%) [9], classical approaches are the most used classification techniques. Next, CNN (25%) [10] [11] and SVM (19%) [12] are the most used algorithms for plant leaf-based disease classification.

III. PROPOSED WORK

The proposed work is intended to find an appropriate feature selection technique that will help to develop an accurate rice plant disease detection system using roughly captured images. This investigative study has three main chapters:

1. Apply sequential and 2D-Convolutional Neural Network to classify the rice plant disease without any additional feature selection approach [16].
2. Apply statistical feature selection technique i.e. sobel and k-means segmentation [17] for performing classification of rice plant disease.
3. Apply VGG-16 for extracting deep features [18] and utilize the 2D-CNN for classifying the rice plant disease.

RICE LEAF DISEASES DATASET

The aim of this experiment is to utilize the raw or roughly captured images for rice plant disease detection. In this context, initially, two publicly available rice plant disease detection datasets were obtained. The first dataset is taken from Kaggle [13] and the second is obtained from Mendeley [14]. The Kaggle dataset consists of 120 color jpg images of disease-infected rice leaves. The images are grouped into 3 classes (diseased) and each class consists of 40 images. The classes are Leaf Smut, Brown Spot, and Bacterial Leaf Blight. The dataset is made with images of a single rice plant leaf and is cropped and processed well to demonstrate the infection. The second dataset is Mendeley, which contains roughly captured rice plant images. The dataset contains four different classes i.e., Tungro, Brown Spot, Blast, and Bacterial blight. A total of 5932 images are available in this dataset. These images are naturally captured images and are easily available. It is a practical dataset and the extension of the dataset requires less effort. Therefore, in this presented work the Mendeley dataset is considered.

Before utilizing the images with machine learning algorithm pre-processing of these images is done to reduce the noisy information. The images of the dataset are available in RGB format, and the color pixels are distributed between 0-255. Normalization of the image pixels between 0-1 is done using the following equation:

$$norm = \frac{I}{255} \dots\dots\dots\dots\dots\dots (1)$$

RAW IMAGES WITH DIRECTLY ML ALGORITHMS

In order to learn with the raw images with the ML algorithms, on deep learning models can be preferred as compared to other ML algorithms. The deep learning models are the best approaches to deal with the image classification problems. Therefore, after normalization of the image data two deep learning techniques i.e. Sequential Convolutional Neural Network (SCNN) and Two Dimensional Convolutional Neural Network (2D-CNN) are used. The SCNN first utilizes a flatten layer to linearly organize the image information. Then the information is passed through further layers. In this context, the models are configured in the following manner as described in table 1:

Table 1 Sequential Network Configuration

Layer Type	Neurons	Activation
Dense	360	“ReLu”
Dense	180	“ReLu”
Dense	128	“ReLu”
Dense	64	“ReLu”
Dense	32	“ReLu”
Dense	4	“ReLu”
Optimizer		Adam
Loss		categorical_crossentropy
Metrics		Accuracy

The next model is one of the most popular deep learning models which is known as 2D-CNN. This model does not require transforming the image information from 2D to 1D. It self-extracts the features from the image color channels and then utilizes the fully connected layer for learning with the self-extracted features. Therefore, using the deep layers of the model will extract more appropriate features from the image. This model can be used directly with the raw dataset images without any prior feature extraction techniques. The implemented 2D-CNN model's configuration is highlighted in table 2.

Table 2 2D-CNN Configuration

Input layer		
Layer 1	Type	Convolutional layer
	activation function	"ReLu"
Hidden Layer		
Layer 2	Type	MaxPooling layers
Layer 3	Type	Convolutional layer
	activation function	"ReLu"
Layer 3	Type	MaxPooling
Output Layer		
Layer 4	Type	Dense
	Activation function	"ReLu"
Layer 5	Type	Dense
	activation function	"SoftMax"
Optimizer		Adam
Loss		categorical_crossentropy
metrics		Accuracy

STATISTICAL FEATURES WITH ML ALGORITHMS

The image classification models utilize the feature extraction techniques for an effective classification. In this context, two popular edge detection techniques i.e. sobel operator and k-means segmentation are used before classifying the images. The normalized datasets are utilized with the Sobel operator for feature extraction. The Sobel operator is available in two variants horizontal and vertical. The Sobel operator carries out 2-D spatial gradient computation and considers the areas of high spatial frequency to edges. In an input image, this operator finds the absolute gradient level. This operator comprises of a couple of 3×3 convolution kernels which are demonstrated in Figure 2 [19]. The aim of these kernels is to identify the edges vertically and horizontally. The kernels can be applied to produce separate computations of the gradient components.

-1	0	+1
-2	0	+2
-1	0	+1

Gx

+1	+2	+1
0	0	0
-1	-2	-1

Gy

Fig. 2 Sobel Kernels

Both the kernels can be combined to find the absolute gradient magnitude using:

$$|G| = \sqrt{Gx^2 + Gy^2} \ldots\ldots\ldots\ldots (2)$$

Typically, it is computed using:

$$|G| = |Gx| + |Gy| \ldots\ldots\ldots\ldots..(3)$$

The angle of orientation of the edge to the gradient is calculated by:

$$\theta = \arctan\left(\frac{Gy}{Gx}\right) \ldots\ldots\ldots\ldots.(4)$$

The next algorithm which is used for feature extraction is k-means segmentation. The k-means algorithm is employed on the images for recovering the edges. Here, the required number of clusters k=2. Here, C_i is denoted as centroid. The k-means uses Euclidean distance function [20] which is recognized as:

$$D(x, y) = \sqrt{(x-y)^2} \dots\dots\dots\dots (5)$$

Using distance function each image pixel p_k is compared to the centroid C_i and estimates the nearest centroid C_i such that:

$$l_k(p_k) = arg \min_i D(p_k - C_i) = arg \min_i \sqrt{(p_k - C_i)^2} \dots\dots\dots\dots..(6)$$

Where l_k is the label for pixel p_k.

The k-means tries to find the centroid which has minimum distortion. The distortion is defined by the sum of distances of pixels from its centroids [21]:

$$\Delta(p_k, c) = \sum_{i\epsilon c} \sum_{j\epsilon\ ith\ cluster} \sqrt{(p_k - c)^2} \dots\dots\dots\dots\dots.(7)$$

Thus, to minimize the Δ, k-means iterates for labelling and update centroids. After n[th] iteration with a set of centroids C_i^n where i=1, 2….k the new centroid is calculated:

$$C_i^{n+1} = \frac{\sum_{p_k \in \emptyset_i} p_k}{|\emptyset_i|} \dots\dots\dots\dots.(8)$$

And

$$l_k^{n+1}(p_k) = \min_i \sqrt{(p_k - c_i^n)^2} \dots\dots\dots\dots.(9)$$

Finally, group the pixels which belong to the same centroids

$$\emptyset_j = \{p_k : l_k(p_k) = C_j\} \dots\dots\dots\dots.(10)$$

Thus, $\emptyset_j$ is clusters of the image, among the two clusters, one is preserved as the edge feature and second is discarded.

DEEP FEATURES WITH ML ALGORITHM

VGG16 is a type of CNN architecture. It is one of the excellent visions of CNN architecture. VGG16 having a large number of hyper-parameters focused on convolution layers of 3x3 filter and always uses padding and max-pool layer of 2x2 filter. It follows this arrangement of convolution and max pool layers throughout the whole architecture [22]. In the final step, it has 2 Fully Connected layers configured with a soft-max activation function for output. It has 16 layers and therefore it is known as VGG16. This network can be used as a pre-trained network, which is trained on more than a million images from the ImageNet database. The VGG-16 network can also be used for feature extraction. Here, the combination of VGG-16 and 2D-CNN is used for extracting features and performing classification.

IV. EXPERIMENTAL SETUP

In this section, the performance obtained by the experiments is described. The models are evaluated under three described experimental conditions. The performance of the implemented models is measured in terms of precision, recall, f-score, classification accuracy and training time. The precision, recall and f-score combined are reported in table 3. Additionally, the training and validation performance and their details are discussed separately. When the raw images are applied directly to the two neural network models i.e., SCNN and 2D-CNN, the recorded training accuracy is given in figure 3(A) and validation accuracy is given in figure 3(B). Precision, Recall, and F-score of both the models are given in table 3.

Table 3 Performance Analysis

Class	Precision					Recall					F1-Score				
	SC	2D	SO	KM	VG	SC	2D	SO	KM	VG	SC	2D	SO	KM	VG
0	0.72	0.85	0.78	0.75	0.96	0.79	1.00	0.69	0.74	0.99	0.75	0.92	0.73	0.74	0.97
1	0.74	1.00	0.74	0.71	0.99	0.59	0.93	0.79	0.80	0.95	0.66	0.96	0.76	0.75	0.97
2	0.87	1.00	0.86	0.94	0.98	0.85	0.96	0.79	0.69	0.98	0.86	0.98	0.82	0.79	0.98

3	0.73	1.00	0.85	0.80	0.98	0.83	0.93	0.99	0.96	0.98	0.78	0.98	0.92	0.87	0.99
SC = Sequential; 2D = 2D-CNN; SO = Sobel; KM = K-Mean; VG = VGG-16															

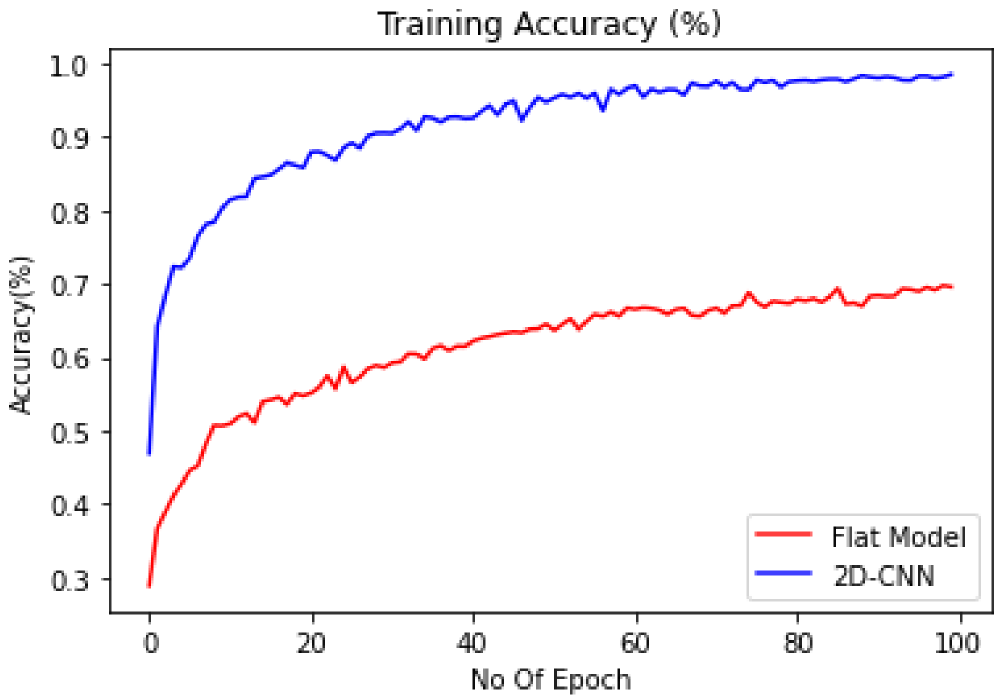

Fig. 3-A shows the classification accuracy when we directly employ classification models on raw images during training

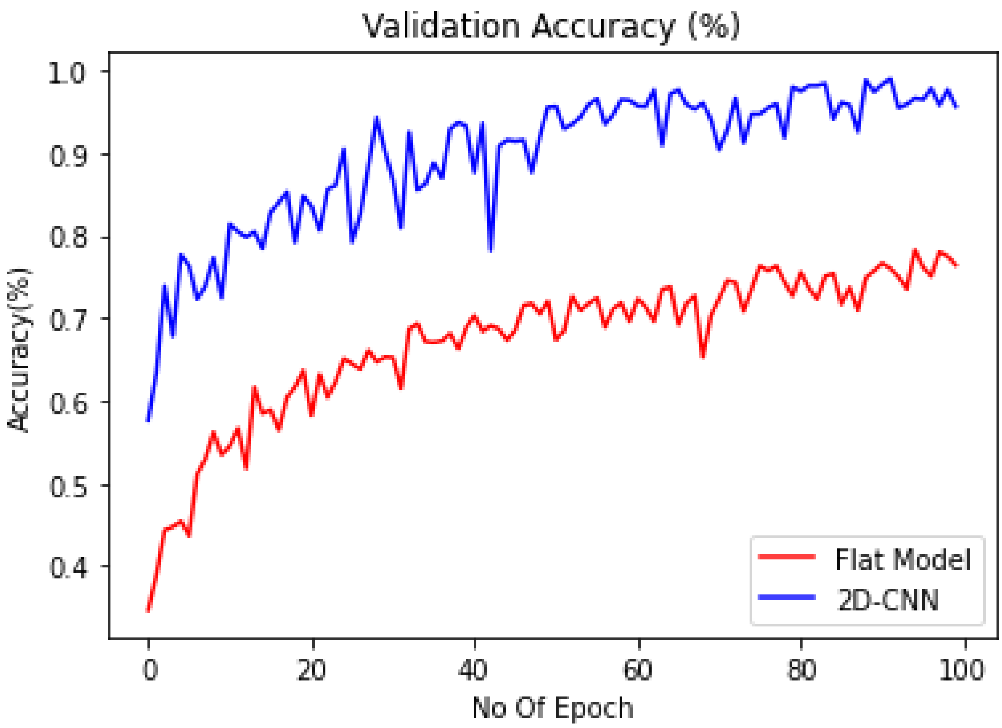

Fig. 3-B shows the classification accuracy when we directly employ classification models on raw images during validation

The training time is demonstrated in figure 4. According to the experimental results the following key facts were found:

1. The 2D-CNN model is more accurate than SCNN for both training and validation.
2. The training time of the SCNN is less as compared to 2D-CNN model.

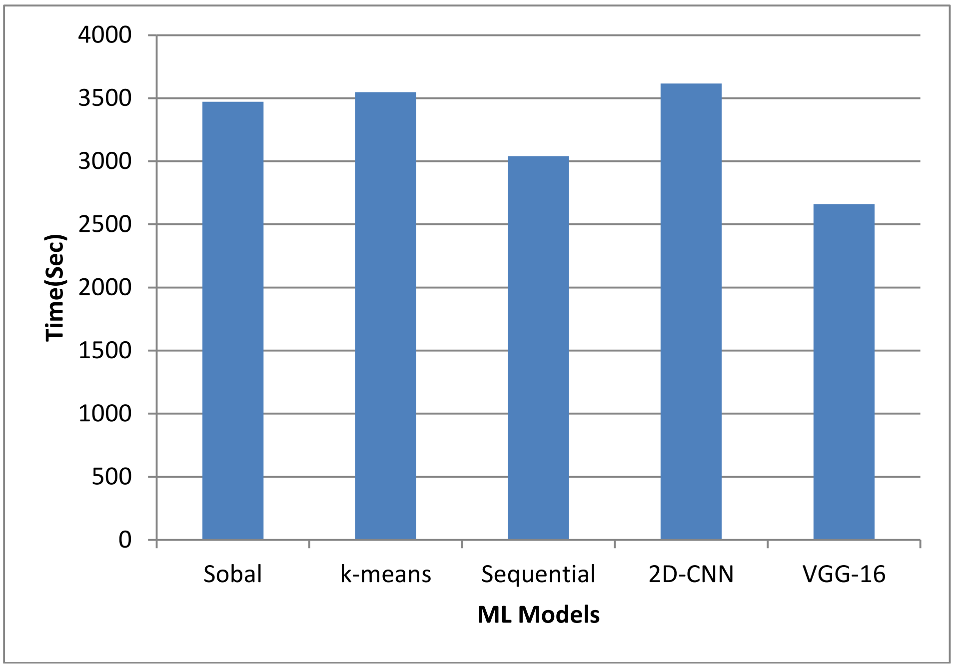

Fig. 4 shows the comparative performance of all the implemented ML based rice plant disease detection system in terms of Training time

The configured 2D-CNN model is utilized for further experiments by incorporating the statistical feature selection techniques. The experiments were with two popular feature selection techniques namely Sobal operator and k-means. The experimental results are demonstrated in figure 5(A) for training and in figure 5(B) shows the validation performance.

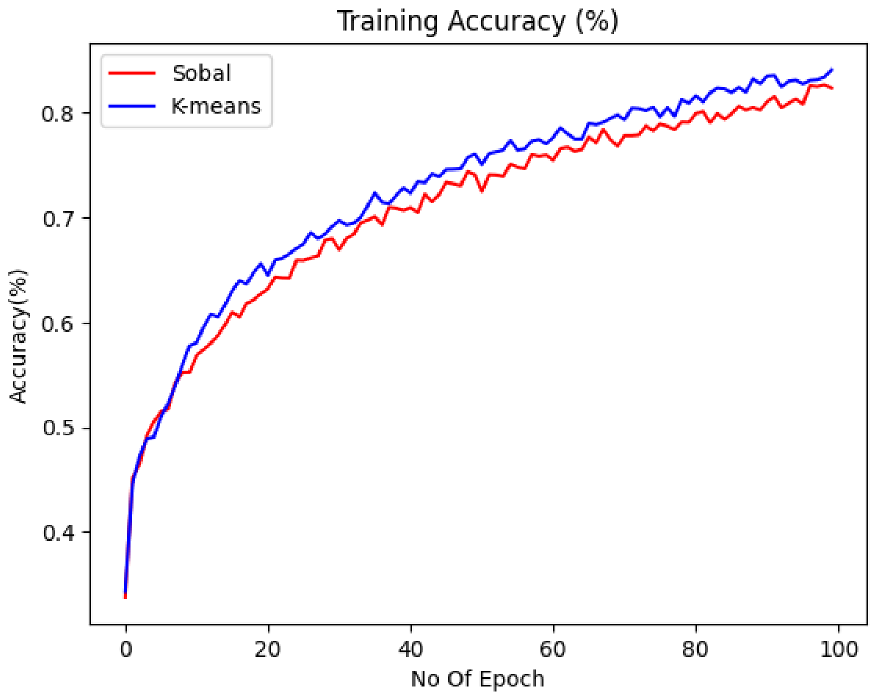

Fig. 5-A shows the classification accuracy with feature selection techniques and 2D-CNN during training

According to the obtained results it was found that the statistically extracted features can reduce the training time but due to the information loss it can negatively influence the classification accuracy. Based on the comparison of Sobal and k-means based techniques, it was found that the Sobal is time efficient than the k-means for training. But both techniques provide less classification accuracy than the self-extracted features from the 2D-CNN. Therefore, a deep feature extraction and classification technique for more accurate disease detection is introduced.

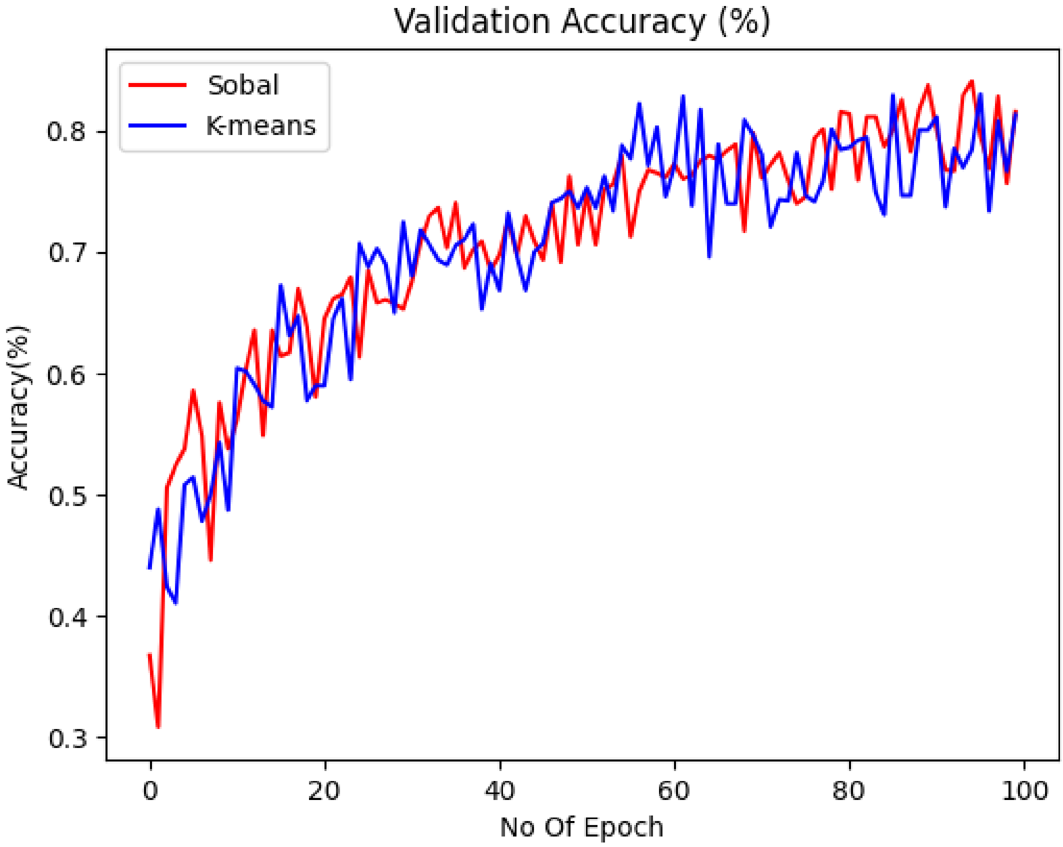

Fig. 5-B shows the classification accuracy with feature selection techniques and 2D-CNN during validation

In order to extract the deep learning features, the VGG-16 is used and the 2D-CNN model is used for the classification of extracted deep features. The figure 6(A) shows the training and validation accuracy of the VGG-16 and 2D-CNN based model. Additionally, figure 6(B) shows the training and validation loss. The obtained result shows that the combination of VGG-16 and 2D-CNN provides higher classification accuracy as compared to the other utilized model for simulation.

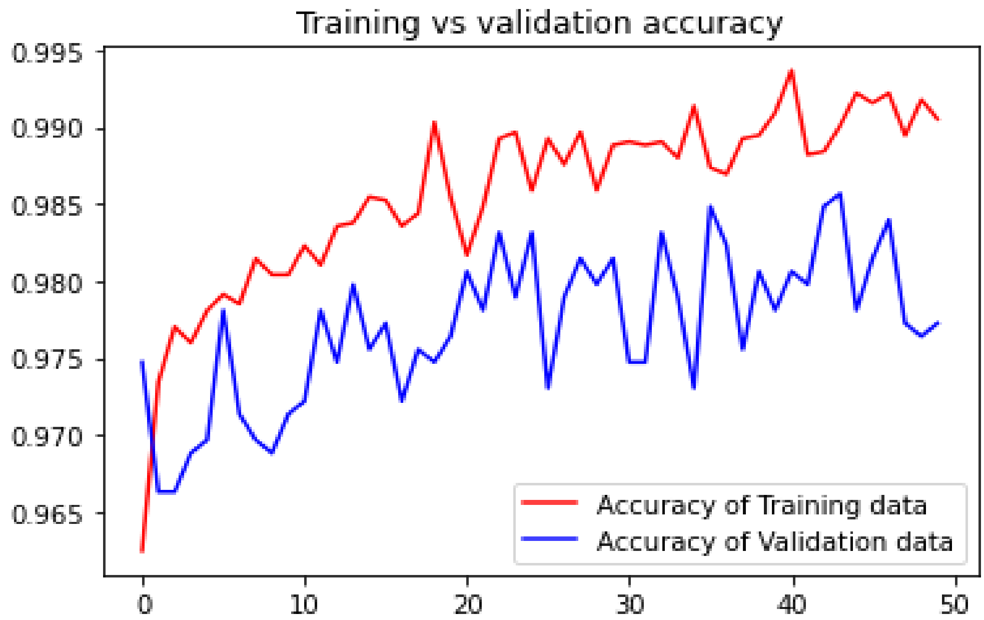

Figure 6-A shows the classification performance for the combination of VGG-16 and 2D-CNN in terms of Training and validation accuracy

According to the obtained experimental results the statistical feature extraction techniques in combination with the 2D-CNN is providing poor classification accuracy due to the information loss of the color channels. On the other hand, the complete image information with the SCNN and 2D-CNN provides the higher accuracy as compared to statistical features. Among them, the SCNN provides similar accuracy to the statistical features but the 2D-CNN model improves the accuracy. Therefore, deep features or self-extracted features by the deep learning techniques provide more effective performance then additionally calculated features. The deep features extracted by VGG-16 and 2D-CNN provide the higher performance as compared to all other techniques.

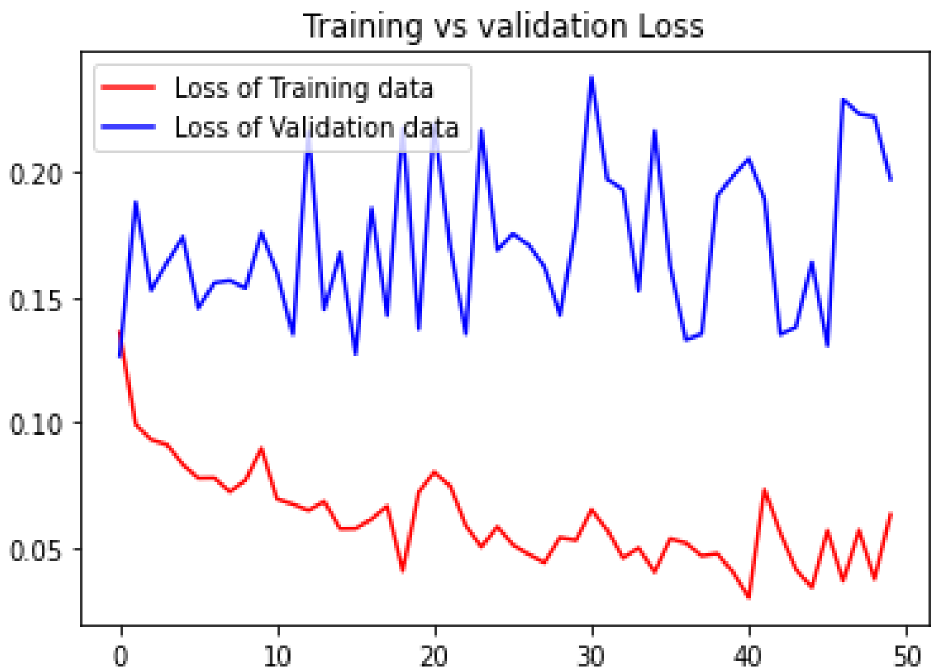

Figure 6-B shows the classification performance for the combination of VGG-16 and 2D-CNN in terms of training and validation loss

In addition, the training time of the implemented techniques was also measured in terms of seconds (Sec). According to the observed results the Sobal based, k-means based and 2D-CNN requires similar amount of time. Additionally, the SCNN requires less time as compared to 2D-CNN. On the other hand, the VGG-16 and 2D-CNN based classification model requires very fewer amount of time as compared to all other models because it requires very less amount of training epochs to take training as compared to other implemented models. Therefore, it is concluded that the deep learning-based techniques are much efficient and accurate than other kind of classical classification techniques based on hybrid learning.

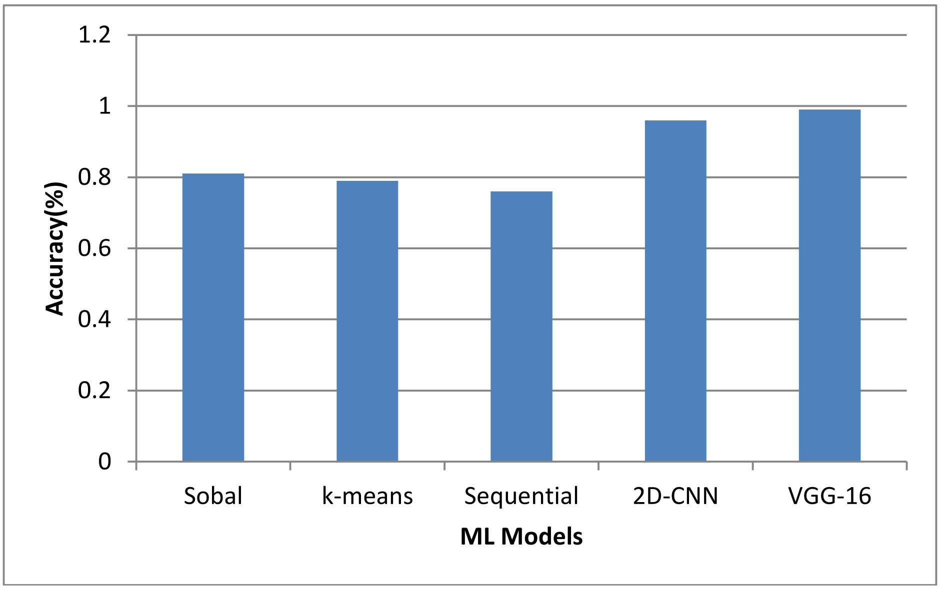

Fig. 7 shows the comparative performance of all the implemented ML based rice plant disease detection system in terms of classification accuracy

V. CONCLUSION

In the development of automated disease detection models using machine learning techniques, the development of the dataset is an essential task. The annotation and processing of the collected data in the laboratory is an expensive and time-consuming task. Therefore, a method needs to be introduced by which the machine learning algorithms will train on raw images. In this context, different models are explored to obtain an appropriate method of learning. Therefore, the experiments with the Mendeley dataset have been carried out which contains a large number of images roughly taken and organized into four classes. In order to accurately classify the crop disease, an experimental study in three scenarios is conducted. In the first scenario, the machine learning models are applied directly to the dataset's raw images. During this, it was found that the 2D-CNN model can self-extract and learn the image features. It also provides higher classification accuracy (96%) as compared to SCNN which provides only (76%) accuracy. Next, two popular image segmentation techniques are utilized for extracting edge features namely Sobal operator and k-means segmentation with the 2D-CNN. The results of these two models demonstrate that the statistical feature selection methods are providing poor performance as compared to previously trained models. In this experiment, it was observed that the Sobal-based technique provides only 79% of accuracy, and the k-means-based technique offers a 75% of accurate classification rate. Finally, it is concluded that the deep learning-based features are more effective as compared to statistical features. Thus, VGG-16 is utilized for feature extraction and 2D-CNN provides higher accuracy of 99% without any additional effort. Additionally, in fewer epochs, it can train well and provide consistent results. Therefore, in a conclusion, it can be said that the combination of VGG16 and 2D-CNN is able to work with roughly captured rice plant images and reliably analyze and provide the disease classification.

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