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A DEEP LEARNING MODEL FOR IMPROVING THE RICE PLANT DISEASE DETECTION PERFORMANCE

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Abstract

Rice is one of the most utilized grains in India. It is a seasonal crop which mostly grows between June to October. This crop mostly grows in natural conditions and its production has a significant influence on different diseases in the plant. Early stage detection of diseases can help in improving the production. In this paper, an analysis and study on deep learning models for getting accurate rice plant disease detection is presented. In this context, first the recent contributions on detecting the diseases by analysing the plant leaf images are reviewed. Then, a comparison among sequential model and 2D-CNN model has been performed. The experimental analysis demonstrates that 2D-CNN outperforms as compared to the simple sequential model. The experiments are extended by including the different image feature selection models. In order to extract features, sobel based edge detection, Local Binary Pattern (LBP) based texture analysis and their combinations i.e. sobel and LBP, Sobel, LBP and color, and a combination of color and sobel are used. The experiments are performed on Kaggle based rice plant disease detection dataset and the performance in terms of precision, recall, f1-score and accuracy has been measured. The experimental evaluation highlights two major points (1) the CNN does not require additional features for better classification consequences (2) the highly trained models are able to respond faster as compared to less trained models. Based on the obtained performance, a more accurate model for plant disease detection is designed.

Keywords:

Plant Disease Detection, Machine Learning, Image Processing, Food Security, Early Disease Detection

1. INTRODUCTION

In India, farming is one of the main sources of income which also contributes in GDP [1]. But more than 60% of farmers are below poverty line and facing financial crunch. Therefore, adoption and implementation of new age technology is not feasible due to heavy cost. Due to this, a large number of farmers depend on the natural resources and classical techniques of farming. The traditional techniques of farming require a significant amount of efforts, manual monitoring, treatment and cultivation. This may increase the waste of resources and time. Additionally, it requires experience to deal with the different hidden facts of farming. Among these hidden facts, the disease in crops may greatly impact the performance of crop production. Plant diseases are the key reason for 10–16% losses in the global crops each year [2] [3].

Recently, smart farming and precision farming techniques are providing Machine Learning (ML) based advance solutions to deal with the various real farming issues. These techniques are offering various tools and techniques which offer the ability to improve the different involved processes in farming. These techniques also involve a module for detection of diseases in crops in early stages. But in Indian farming scenarios, very fewer farmers are able to utilize such kinds of dedicated services for their farms. A low cost, and accurate the diseases detection model is designed. This model will work as a centralized system to help the farmers to reduce the losses causes by the rice plant disease.

In this paper, recent techniques and methods that are utilized for recognizing the plant diseases are summarized. Next, the previously proposed architecture has been presented and then an implementation of the deep learning model has been proposed. Furthermore, based on the experiments the results are analysed. Finally, the future road map for extending the proposed working model is provided.

2. LITERATURE REVIEW

In this review, 25 recent articles based on ML and image processing are included. The summary of these contributions are given in Table.1.

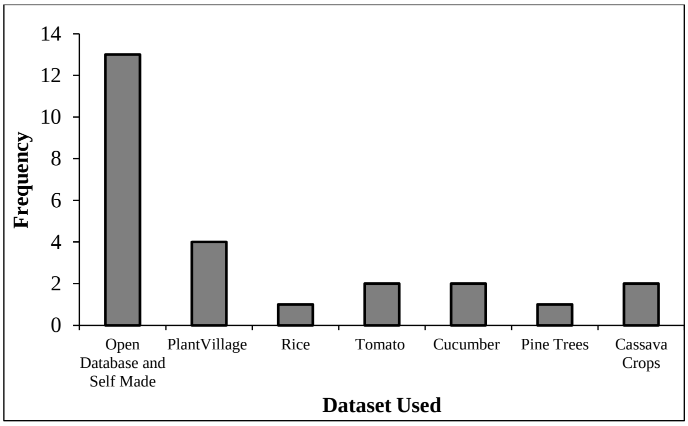


Fig.1. Plant Diseases Detected in Recent Works

Table.1. Review Summary

Reference	Key highlights
[4]	They use CNN algorithm for detection of stages of plant diseases and compare with other ML techniques
[5]	Provided a pre-processing technique to convert images into super-resolution images and improves cucumber disease diagnosis
[6]	Use cucumber leaf images for classifying them using CNN and obtained 82.3% accuracy
[7]	Used segmented images for training of the CNN for diagnosing tomato plants
[8]	Cassava plants are analysed to identify three disease and two types of pests using a Deep CNN and transfer learning concept

[9]	a database of 87,848 images were used with CNN
[10]	38 different classes based on images are recognized using a Deep CNN architecture
[11]	The PlantVillage dataset is used with a threshold-based segmentation technique to train a series of deep CNN
[12]	A SVM based model is provided to recognize the crop diseases
[13]	The Random Forest algorithm is utilized for differentiating healthy and diseased plants
[14]	Discussed the segmentation methods used for the detection of diseases in plant
[15]	Contributed an image segmentation technique using genetic algorithm for analyzing pine tree images
[16]	The plant village dataset is used for diagnosing diseases using segmentation and SVM algorithm
[17]	Presented PlantDoc: a dataset based on 13 plant species for early plant disease detection
[18]	Survey on different plants disease and advance ML techniques to detect diseases.
[19]	Employed SVM algorithm for web enabled disease detection system based on compressed sensing images
[20]	focused on the necessity of radiometric calibration to distinguish diseased trees based on aerial multi-spectral images and random forest algorithm
[21]	Presents a survey of different image processing and ML techniques based on Segmentation and classification of rice plants
[22]	Utilizing the k-medoids and ANN algorithms for describing the steps of image processing
[23]	Providing an overview of conventional methods, current trends and advances on biosensors
[24]	A discussion on diseases detection performance based on traditional classification methods from 1997 to 2016
[25]	A Strawberry disease detection network based on Faster R-CNN and multi-task learning
[26]	Generalized Matrix Relevance Learning Vector Quantization, and Principal Component Analysis are used for visible and near infrared spectral information for facilitating disease detection in cassava crops
[27]	Used SVM and ANN for early detection of diseases
[28]	Used supervised machine learning techniques like Naive Bayes, Decision Tree, KNN, SVM, and Random Forest for disease detection.

The Table.1 summarizes the key contribution of the work in article, algorithms used and the experimental dataset. Based on the studied literature, a graphical representation of summary is presented. The Fig.1 shows the different crops or datasets used for discovering diseases in plants by using machine learning and image processing techniques. In this figure, the frequency of articles is given in Y axis and X axis includes the plant/crop names. According to the observations, most of the work utilizes an open database or syntatic dataset for their experiments. In addition, PlantVillage dataset is most popular images dataset used for diagnosing of diseased using ML approaches.

The Fig.2 demonstrates the utilization of ML algorithms which are used for analysing the plant leaf image data. Initially, the studied articles are categorized into two main parts i.e. research article and reviews. It was found that in research articles, the different kinds of ML techniques can be used for segmentation and classification of image information. According to the frequency of the used ML algorithms, it was found that CNN and SVM are the most used algorithms for image classification task. Additionally, some articles are utilizing the decision trees and other similar techniques also. That is described in Fig.2 where X axis shows the algorithms used and Y axis shows the frequency of ML algorithm utilization. During this review, it was observed that there are two kinds of approaches that can be developed using the ML algorithms:

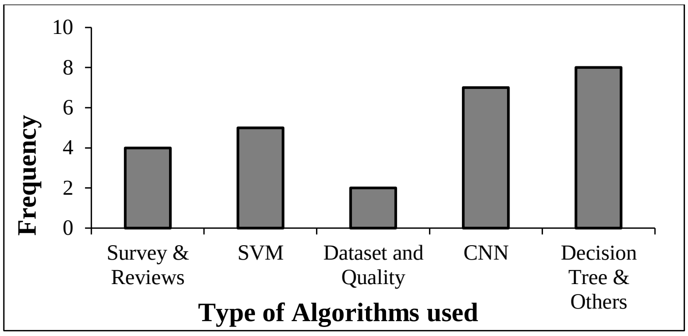


Fig.2. Type of Research and Algorithms Used

- Employ different feature extraction techniques to recover the key insights from image and make use of supervised learning technique to classify the features.
- Apply the segmentation techniques on image to recover the edge features from image and use of CNN to learn and classify the image features.

3. PROPOSED WORK

The aim of the proposed work is to develop an efficient and accurate plant disease detection technique for rice plants. It is proposed to investigate the different deep learning models and hand-crafted features for improved classification performance. The proposed work describes the following contributions:

- Comparing the deep neural network architectures to select the better performing architecture
- Experimentation with different combination of image features and obtained accurate CNN architecture

To provide the proposed experimental study, a suitable dataset for rice plant disease detection is required. Rice Leaf Diseases Dataset from the Kaggle [29] is taken into account. This dataset consists of 120 jpg images of disease infected rice leaves. The images are grouped into 3 classes based on the type of diseases. There are 40 images in each class. The classes are Leaf smut, Brown spot and Bacterial Leaf Blight. The aim to use this dataset is to demonstrate how the ML algorithms can identify the type of disease in rice plants. An overview of the plant leaves is demonstrated in Fig.3.

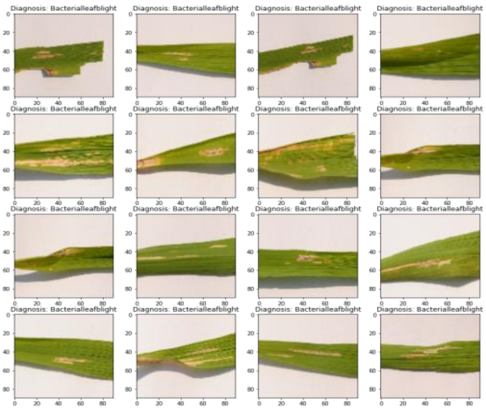


Fig.3. Dataset Sample Images

This dataset contains the leaf images specifically for the spots and the only a single leaf. It is a well processed dataset but in real world it is not expected from the end users. However, for learning and classification of leaves according to their disease class labels, we trained two different architectures of the deep neural networks. Both the deep learning architectures are described as:

3.1 SEQUENTIAL MODEL

The sequential model consists of an input layer, five dense layers and an output layer. The five intermediate dense layers consist of 360 neurons, 180 neurons, 128 neurons, 64 neurons, and 32 neurons, which are configured with the ReLu activation function. The final layer is considered as the output layer includes 3 neurons and configured with the SoftMax activation function. The train and test splits are prepared with the ratio of 70-30. Then training and testing of the model has performed.

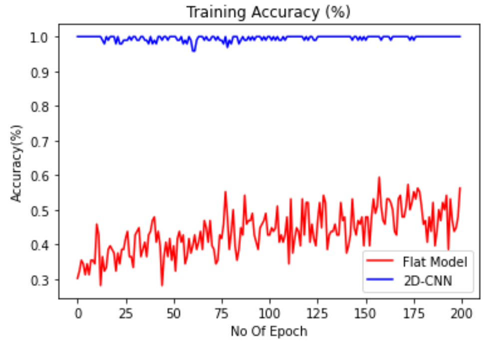
3.1 2D-CNN MODEL

The second model is 2D CNN architecture of deep neural network, which consist of an input layer, two MaxPooling layers, one Convolutional layer, one flatten layer, two dense layer and one output layer. The input layer has the input shape of 90 * 90 * 3, with a filter size 32 and configured with ReLu activation function. Next, a max-pooling layer is included and then a convolution layer is included which consists of 64 neurons and ReLu activation function. Then again a Max-Pooling layer is included. After that, the flatten layer is involved and then two dense layers are included with the 64 and 32 neurons and “ReLu” and “Sigmoid” activation functions. Finally, the output layer includes 3 neurons and SoftMax activation function.

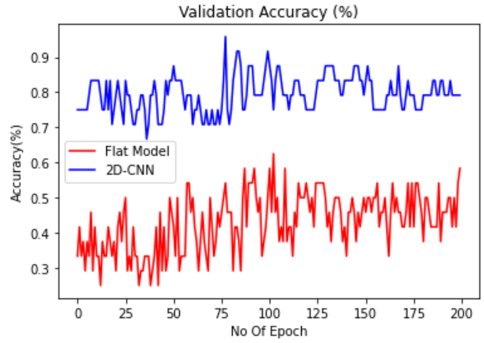
Table.2. Performance Comparison

P = Precision, R = Recall, and F1 = F1-Score						
Classes	Sequential			2D CNN		
	P	R	F1	P	R	F1
0	0.50	0.75	0.60	0.73	1.00	0.84
1	0.50	0.57	0.53	0.71	0.71	0.71
2	1.00	0.44	0.62	1.00	0.67	0.80
Accuracy	0.58			0.79		

In order to compare the performance of both the models, model is trained with the 200 epoch cycles and the measured performance is reported using Table.2 and Fig.4.



(a)



(b)

Fig.4. Performance Comparison of the 2D-CNN and Sequential CNN Model in terms of (a) Training Accuracy and (b) Validation Accuracy

According to the obtained performance of the models, it was found that the 2D-CNN model is more accurate than the sequential model. Additionally, it provides higher classification accuracy in terms of precision, recall and F1-score. Thus, for the purpose of classifying the rice plant diseases, the 2D-CNN is more appropriate than the simple sequential model. Thus, it is proposed to extend the 2D-CNN model for achieving higher accurate classification results.

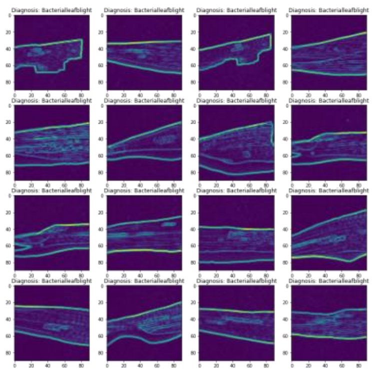


Fig.5. Sobel Based Edge Features

4. EXPERIMENTS WITH LOCAL FEATURES

The experiments are extended with the 2D-CNN model and the local image feature extraction techniques. The following two main feature extraction techniques are considered:

4.1 SOBEL OPERATOR

Sobel operator is one of the methods which are used for edge detection from the images. It 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 relevant 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 is demonstrated in Fig.6. The aim of these kernels is to identify edges vertically and horizontally.

The kernels can be applied, to produce separate computation 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.6. Sobel Kernels

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

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

Typically, it is computed using:

$$|G|=|G_x|+|G_y|$$

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

$$\theta=\arctan(Gy/Gx)$$

The Fig.5 demonstrates the processed dataset using the sobel operator.

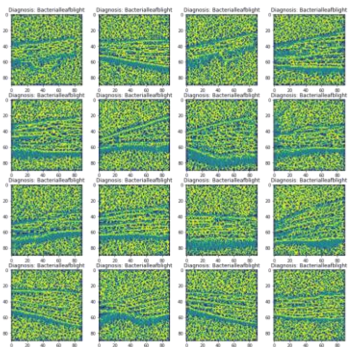
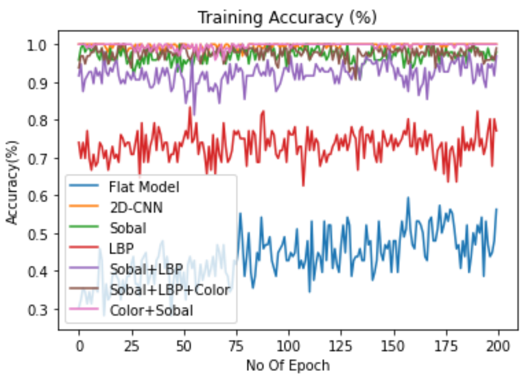
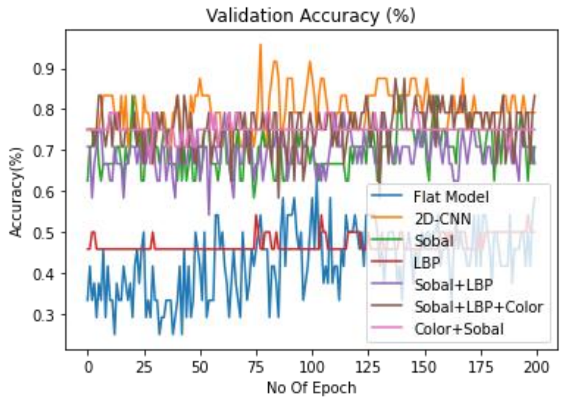


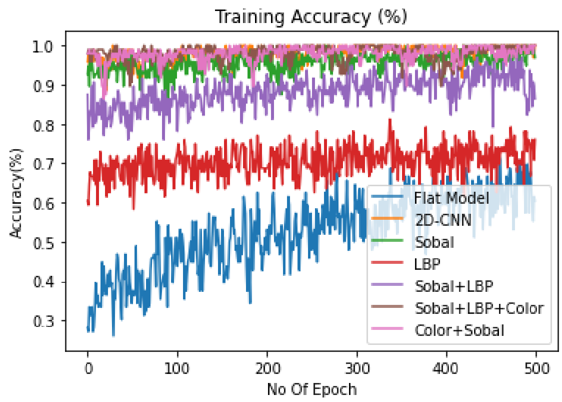
Fig.7. LBP based Processed Dataset



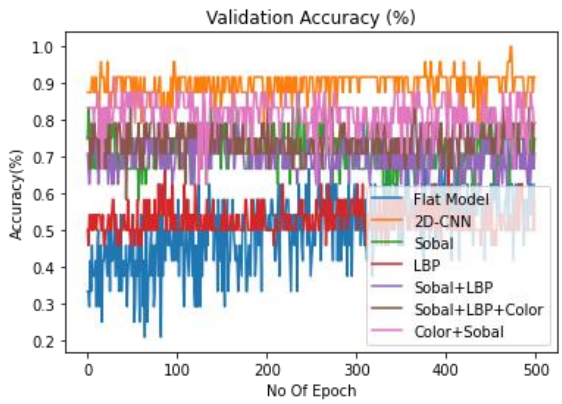
(a)



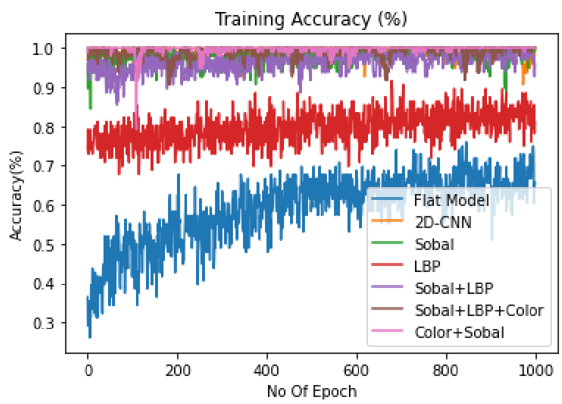
(b)



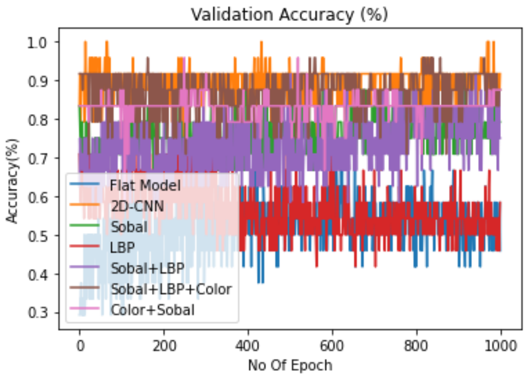
(c)



(d)



(e)



(f)

Fig.8. Performance of the proposed 2D-CNN model with increasing number of training cycles where (A) shows the Training Accuracy for 200 epoch (B) Validation Accuracy for 200 epoch (C) Training Accuracy for 500 epoch (D) Validation Accuracy for 500 epoch (E) Training Accuracy for 1000 epoch (F) Validation Accuracy for 1000 epoch

4.2 LBP TEXTURE ANALYSIS

The second feature is based on the texture analysis. The local binary pattern (LBP) is used for texture feature extraction which is also discussed in [30]. The processed dataset images using the LBP technique is demonstrated in Fig.7.

4.3 EXPERIMENTAL SETUP

For experimentation, to extract the features and enhance the performance of classification, different combinations of the features are prepared and then utilized with the prepared 2D-CNN model. The following features-based data has prepared for classification task:

- **Dataset processed with sobel operator:** The dataset is processed using sobel operator as described earlier. The same CNN model is trained with the different epoch cycles i.e. 200, 500 and 1000.
- **Dataset processed with LBP:** The dataset is processed using the LBP texture analysis technique and the performance of CNN model has been measured and reported.
- **Combining sobel and LBP features:** A combined image is prepared by processing the image data using LBP and sobel operator. This combined feature has the three dimensional vector with the size of 90* 90* 2. Where the 90*90 is the image size and there are two vectors combined which has the single channels.
- **Combining sobel, LBP and color channels:** A combined image is prepared with the help of LBP based images, sobel based image and three color channels. That consists of the size 90 * 90 * 5.
- **Combining sobel and color channels:** In this dataset samples, we first extract each color channel and then each channels are processed using the sobel operator finally a combined data vector is prepared.

5. RESULT ANALYSIS

The proposed deep learning-based architecture and the different combinations of the image features are trained and then their validation has been performed. The obtained performance is reported in the Fig.8 in terms of training and validation accuracy.

Table.3. Class Wise Performance for Different Number of Epoch Cycles

P = precision, R= recall, F = F1-score, A = accuracy															
200 Epoch															
	Sobel			**LBP**			**LBP + Sobel**			**Color + LBP + Sobel**			**Sobel + Color**		
	P	**R**	**F**	**P**	**R**	**F**	**P**	**R**	**F**	**P**	**R**	**F**	**P**	**R**	**F**
0	0.78	0.88	0.82	0.47	1.00	0.64	0.80	1.00	0.89	0.73	1.00	0.84	1.00	1.00	1.00
1	0.62	0.71	0.67	0.00	0.00	0.00	0.50	0.57	0.53	0.83	0.71	0.77	0.54	1.00	0.70
2	0.71	0.56	0.63	0.57	0.44	0.50	0.67	0.44	0.53	1.00	0.78	0.88	1.00	0.33	0.50
A	0.71			0.50			0.67			0.83			0.75		
500 Epoch															
0	0.88	0.67	0.71	0.47	0.89	0.62	0.83	0.56	0.67	0.75	1.00	0.86	1.00	0.89	0.94
1	0.78	0.75	0.71	0.50	0.12	0.20	0.75	0.75	0.75	0.75	0.75	0.75	0.70	0.88	0.78
2	0.82	0.71	0.71	0.60	0.43	0.50	0.60	0.86	0.71	1.00	0.57	0.73	0.67	0.57	0.62
A	0.75			0.50			0.71			0.79			0.79		
1000 Epoch															
0	0.78	0.78	0.78	0.62	0.89	0.73	0.86	0.67	0.75	0.89	0.89	0.89	1.00	1.00	1.00
1	0.78	0.88	0.82	0.43	0.38	0.40	0.64	0.88	0.74	0.78	0.88	0.82	0.73	1.00	0.84
2	0.83	0.71	0.77	0.75	0.43	0.55	0.83	0.71	0.77	1.00	0.86	0.92	1.00	0.57	0.73
A	0.79			0.58			0.75			0.88			0.88		

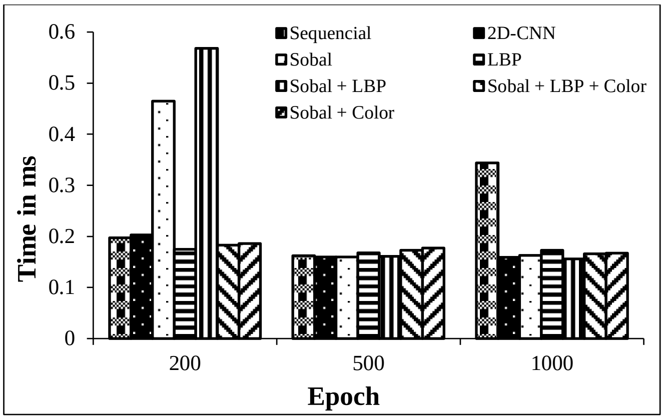


Fig.9. Performance in terms of Classification or Validation Time

In addition to that, the performance of the models in terms of precision, recall and F1-score is also measured as the class wise classification report. The performance of the required model is demonstrated in Table.3.

According to the obtained results, by comparing all the models, the visible difference can be seen in performance when the number of epoch cycles is low. The figures 8(A) and (B) demonstrate that the 2D-CNN with the self extracted features performs better. Additionally, the feature combination of sobel, LBP and color based model provides higher accuracy as compared to other models. Moreover, when the training cycles are increased to 500 and 1000 epochs, the performance of all the models increases and the same can be seen in figures 8(C), 8(D), 8(E) and 8(F).

On the other hand, when the performance of the model in terms of precision, recall and f1 score is compared, it was found that the model becomes more accurate with the increasing amount of training cycles. Therefore, it can be said that the feature combination of edge, color and texture provides higher accurate results as compared to other scenarios of the experiment. In addition, the validation time of the different models is also measured which is described in Fig.9.

According to the validation time recorded, it is observed that the model which has been trained for long training cycles responds faster as compared to the less trained models. Thus, according to the experimental analysis of the obtained results, it is found that the features color, texture, and edge combination provides higher accurate classification. Additionally, the longer training can reduce the validation time of the model.

6. CONCLUSIONS

In Indian farming scenarios where most of farming is performed using natural resources, a low cost and common decision support system will help to improve the productivity of Indian farming. In this context, a decision-making framework for detecting diseases in crops using the leaf images has been recently introduced. However, that model provides better accuracy, but it takes a significant amount of time for learning and the validation response. In this paper, a comparative performance study of different image feature selection techniques and convolution neural network is presented. The Convolutional neural network is mainly utilized to deal with the large amount of data and precise training to detect the diseases in crop. First, a sequential neural network and a 2D-CNN model are compared. Based on the initial experimentation, it was found that the 2D-CNN model provides better accuracy as compared to sequential model. So, the experiments were extended to get a better accuracy. Five different combinations of image features are prepared namely, sobel based edge feature, LBP based texture feature, combination of sobel and LBP, a combination of sobel, LBP and color channels, and finally a model is prepared which extract the sobel feature from all the color channels. The experiments have been carried out with the different number of epoch cycles and their performance has been recorded in terms of accuracy, precision, recall and f1-score. Based on the experimental evaluation it can be concluded that the 2D-CNN without additional feature can perform better and enhances its performance with increasing amount of training cycles. In addition, when the model is trained for a longer time, then the validation time of the recognition reduces significantly as compared to less the trained models. In near future, the proposed model can be extended further for getting more accurate results.

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