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# Rice Diseases Identification And Classification Using Digital Image Processing And CNN Based Transfer Learning

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**Abstract**

Indeed, the growth of most important field crops such as rice and wheat are affected by the attack of various pests and different types of diseases that can drastically reduce the crop production. In Asian countries such as India, paddy is one of the major staple foods, and the agricultural sector is one of the largest employers in India's economy. Hence, it is necessary to have an effective mechanism that should be adopted for food security and its production. The classification and identification of various crop diseases correctly is a difficult task for the farmers due to the similar appearance in the earlier stage of crop growth and lack of sufficient knowledge about each disease. To tackle this issue, a digital image processing technique and Convolutional neural network-based transfer learning (DIP_CNN_TL) is being applied since it performs automatic feature extraction and learns complex high-level features in image classification applications. This method proposed an efficient CNN_TL model to classify disease classes such as bacterial leaf blight (BLB), brown spot (BS) and healthy on three publicly available leaf disease datasets. For the image acquisition the images of rice plant leaves are directly taken from the Kaggle and UCI machine learning website for healthy, bacterial blight and brown spot diseases. In pre-processing, for the background removal the K-Means clustering method is used and then resultant RGB images are converted into LAB images and based on the A channel and B channel masking is applied then at the end again resulted image is converted into LAB and from that B channel is taken to extract the diseased and non-diseased part. The extracted images are fed to CNN_TL for classification for this VGG-16 transfer learning model is used. The experimental results are evaluated and compared with existing state of art techniques. DIP_CNN_TL achieved high accuracy as 99.99% for the healthy, 96% for the bacterial blight and 96% for the brown spot leaf image.

**Keywords:** Machine learning, Transfer learning, Convolutional neural network, Paddy leaf, K-means clustering, Colour space

## 1 Introduction

Agriculture has always played a vital role in the economy of the most of the developing countries, mainly in South Asian countries such as India and China. Farming is not only meant to feed the increasing population, but at the same time, it helps to handle global warming problems to a great extent. Agricultural production is greatly affected by the crop diseases caused either by pest or leaf disease. The amount of crops that are damaged by adverse climatic condition and by invasion of pathogens can never be neglected. due to inadequate soil fertilizer, mineral deficiency, environmental agents and other various factors leads to many plant diseases which will hamper the farm production. So, it is very important to monitor plants/crops from early stage in order to detect and prevent the diseases. It includes so many tasks like soil fertilizer preparation, seeding, using organic manure, irrigation, using required quantity of pesticides, timely harvesting and storage. In addition to it crop quality can also be achieved by utilizing the proper automation techniques such [1]. Hence identifying diseases from various images of plant leaves is consider to be one of the most important research areas in precision agriculture [2]. Moreover, advances in artificial intelligence (AI), image processing and graphical processing units (GPUs) can expand and improve the practice of precise plant protection and growth in agriculture sector. Most of the plant diseases generate various types of symptoms in the visible spectrum, and thus learning models should possess good observation skills so that one can identify the characteristic symptoms of any diseases [3]. Several machine learning (ML) approaches are been currently used for identifying and classifying the plant diseases. The most common approaches are the K-means clustering decision tree, support vector machine (SVM) [4] and deep convolutional neural network (Deep CNN). These techniques are combined with several image pre-processing methods in order to enhance the feature extraction process. DIP_CNN_TL intends to use a Deep CNN based transfer learning model to solve the plant leaf disease identification problems. The Deep CNN is nothing but a class of deep learning algorithm. The deep learning is sub division of traditional machine learning by adding more complexity and hierarchical data representations into the model. The Deep CNNs can be used in wide area of applications such as in image classification, speech recognition, object detection, recommender systems and natural language processing (NLP) [5]. Transfer learning (TL) is a research problem in machine learning that focuses on storing knowledge gained while solving one problem and applying it to a different but related problem that ultimately reduces the size of the training data, the time and the computational costs when building deep learning models [6]. Transfer learning has been used in various applications, such as software defect prediction, plant classification, activity recognition and sentiment analysis. Performance of the DIP_CNN_TL model has been compared with some popular artificial neural network (ANN) and deep neural network (DNN).The DIP_CNN_TL uses state-of-art digital image processing technique in association with VGG-16 transfer learning model. Our evaluations show that the proposed DIP_CNN_TL model can achieve excellent results with the dataset,

**just using ten epochs** compared with the other state-of-art algorithms. The rest of the paper is organized as follows. Section 2 presents the related works. Section 3 discusses the problem definition. Section 4 proposed methodology. The results and related discussions are given in Section 5. Finally, Section 6 presents the conclusions and future research direction.

## 2. Related work

Some of the recent researches that are related to the identification and classification of rice plant diseases are given below.

On the basis of the deep convolutional neural network, a novel rice plant disease detection method was developed by Yang Lu et al. [7] They have used a dataset which contains 500 images which includes diseased and non-diseased paddy stems and leaves. Classification was carried out with ten most common rice diseases. They have showed that their approach achieves higher accuracy than the conventional machine learning method. The experimental outcomes associate and represents the effectiveness and feasibility of their proposed model.

By using image processing techniques, D. Nidhis et al. [8] developed a novel method for identifying the disease type that affects the paddy leaves. By assessing the percentage of diseased affected area, and the severity of the disease infection was calculated. Based on the graveness of diseases the pesticides were utilized for the brown spot, bacterial blight and rice blast which are the major diseases affect the rice crop and their productivity.

For the evaluation of ROI, a segmentation method based on neutrosophic logic extended from its fuzzy set was brought in by Gittaly Dhingra et al. [9]. They basically used three membership functions for the segmentation process. To detect the plant leaves are infected by disease or not, feature subsets were considered based on segmented regions. Various classifiers were evaluated for the demonstration and the random forest (RF) method overcome the other approaches. They have used the dataset with 400 leaf images which consists of 200 diseased leaf image and 200 non diseased leaf images.

For the detection and the classification of rice plant diseases a new approach was presented by Taohidul Islam et al. [10]. In their work, based on percentage of RGB value of the diseased part, they detected and identified the diseases by employing the digital image processing techniques. They incorporate Naïve Bayes classifier which is a simple classifier for classification of the disease into various classes. Their proposed method successfully recognized and classified three major types of rice plant diseases by using only one feature. Hence, it was a faster method which takes less time for computation

In their proposed study Aydin Kaya et al. [11] investigated the results of the effect of four different types of transfer learning models for deep neural network-based plant classification on four publicly available datasets. Their experimental study demonstrated that transfer learning can furnish an important benefit for automated plant identification and can improve low-performance plant classification models.

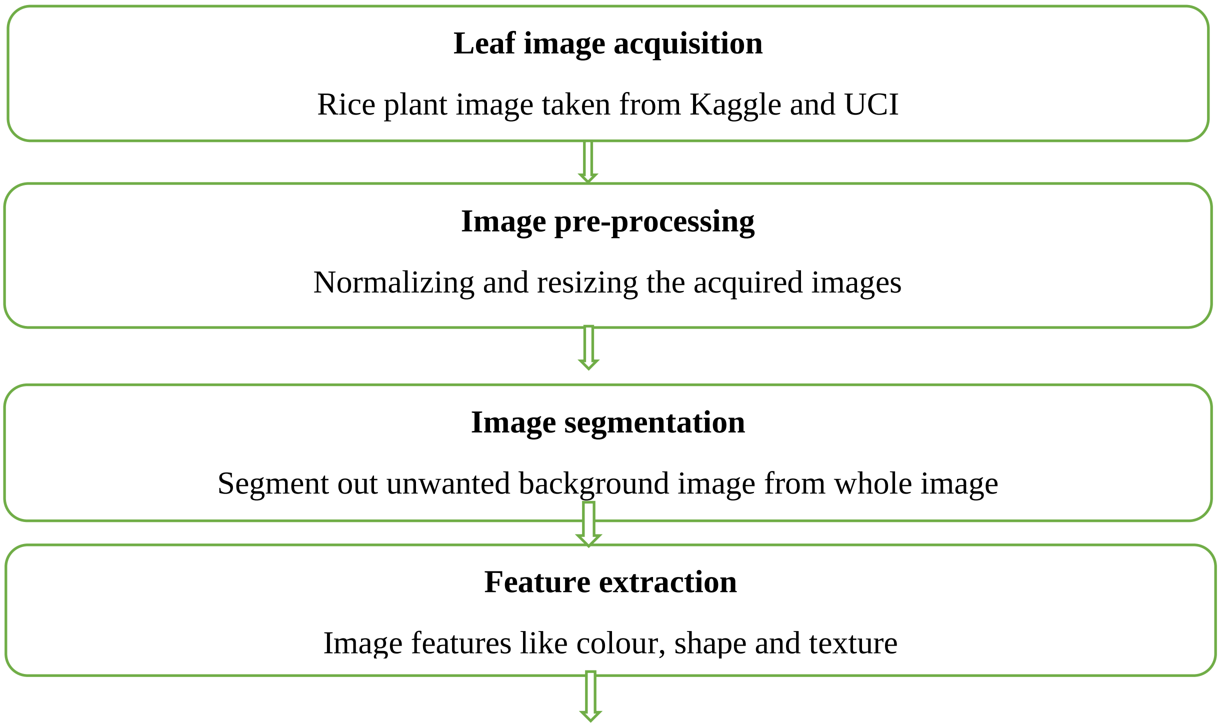
Alessandro dos Santos Ferreira et al. [12] used the deep Convolutional Neural Networks (CNN) to perform weed detection in soybean leaf images and classified the weeds among grass and broadleaf. An image database of leaves was created containing over fifteen thousand images of the soil, soybean, broadleaf and grass weeds. The deep Convolutional Neural Networks used in this work represented a Deep Learning architecture that has achieved remarkable success in image identification and classification.

## 3. Problem definition

For detecting rice leaf diseases, the old conventional approaches are human vision-based method. In these cases, pursuing the expert advice is very expensive and time consuming. Moreover, the human vision-based approaches suffer from many drawbacks. The accuracy and precision of human vision-based approach is entirely dependent on the eyesight of the person or expert engaged. So, it is good to have machine learning based method that enables to identify the types of diseases correctly and make the right decision and to select proper treatment. One of the major advantages of using machine learning based method is that it performs tasks more accurately and consistently as compared to human experts. Therefore, to overcome the drawbacks of conventional human vision methods there is a need for the state-of-art machine learning and digital image processing-based classification approach. It is seen that very few recent developments were recorded in the field of plant leaf disease identification using ML approach and that too for the rice leaf disease identification and classification is the very rare.

## 4. Proposed DIP_CNN_TL

DIP_CNN_TL system incorporates basic five phases which include leaf image acquisition, pre-processing, image segmentation, feature extraction and at last classification. The rice leaf images are directly taken from publicly available dataset repository Kaggle and UCI machine learning. The dimensions of the leaf images are reduced and normalized in the pre-processing step. The next step is leaf image segmentation in which k-means clustering method is applied to segment the unwanted background portion from whole image. Then the classification of diseases is performed by convolutional neural network-based transfer learning (CNN_TL) method. The above process flow steps are shown in Figure 1.



**Classification**

Images are classified by CNN_TL

**Fig 1** Basic architecture for rice disease identification

### 4.1 Acquisition leaf images

Acquisition of leaf images means the process of collecting the images directly from dataset repository or from farming land which are used in DIP_CNN_TL. Then for the identification and classification of diseases all the images are moved to the computer in separate folder for each class of disease then the implementation process will be carried out. This dataset consists of images having the leaves with various degree of disease spread. The images that are taken from Kaggle and UCI machine learning contain totally 1007 images in which include 397 healthy images, 223 brown spot images and 387 bacterial blight images. From total images 857 images are used to train the model, 75 images are used for validation and 75 images are used for testing purpose. Some of the sample images are shown in **figure 2.**

### 4.2 Pre-processing

In pre-processing techniques, minimization of leaf images and normalization are required. Under the minimization leaf images are cropped and resize into the dimension of 300 x 300 and under normalization each pixel of leaf image is divided by 255 in order to make each pixel between 0 and 1. By performing such steps memory and computation power of central processing unit (CPU) and graphical processing unit (GPU) will be minimized.

### 4.3 K-means clustering based segmentation

For segmentation of leaf image K-means clustering method is incorporated in this proposed work. Clustering is the process of group the image into clusters. Using this clustering background portion from whole image is eliminated in order to simplify the classification process. This technique is applied on the A channel of the LAB colour space and background is removed from image as shown in **figure 3**.

**Bacterial leaf blight** **Brown spot** **Healthy**

**Fig 2** Sample images of healthy and diseased leaves

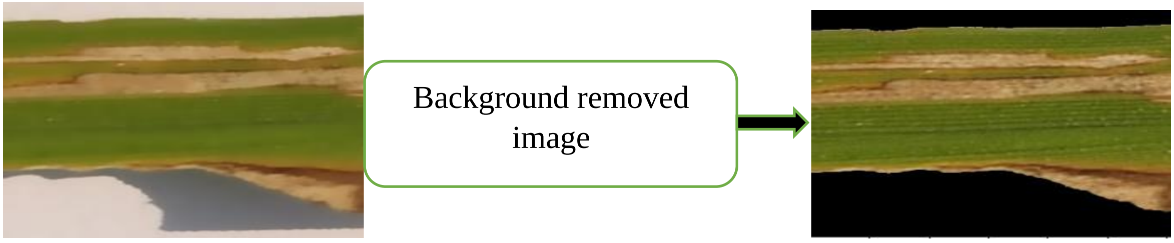



**Fig 3** Background removed image

### 4.4 Feature extraction

In this proposed work shape feature is extracted. The whole feature extraction workflow is shown in **figure 4.**

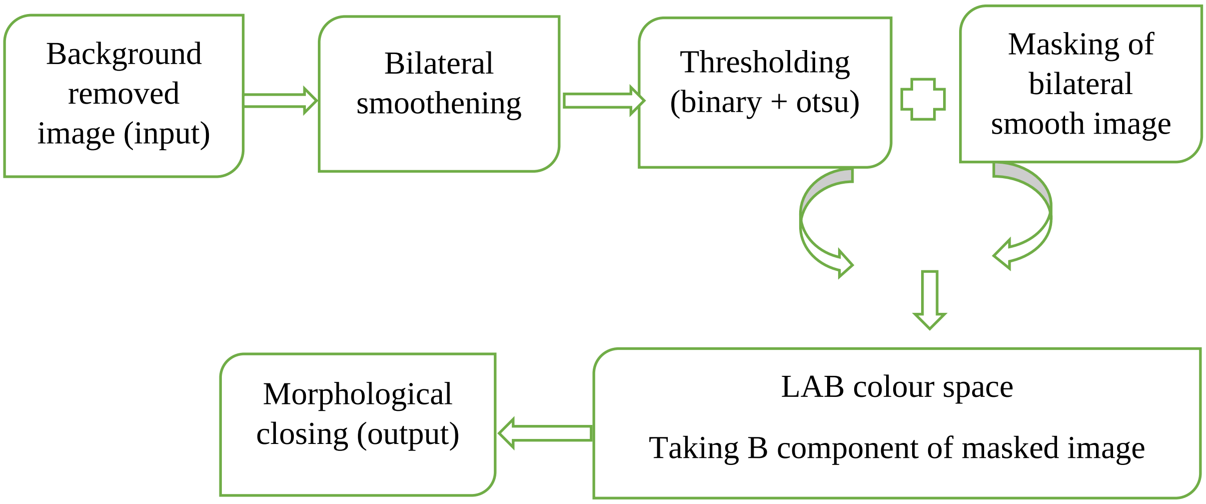



**Fig 4** Feature extraction process

#### 4.4.1 Bilateral filter

Bilateral filtering smooths the images by preserving edges, through a nonlinear combination of nearby image values called pixels. The method is simple, noniterative and local. It basically combines the gray levels or colours on the basis of both their geometric closeness and their photometric similarity, and favors near values to far values in both domain and range. In contrast with some other filters that are operate on the three bands of a color image separately, the bilateral filter can enforce the perceptual metric underlying the CIE-LAB colour space, smooth colors and preserve edges in a way that impersonate to human perception [13]. Bilateral filtered image is shown in figure 5 (b).

#### 4.4.2 Binary thresholding and otsu thresholding

Image thresholding plays significant role in medical image analysis. Thresholding segmentation has attracted much attention of many scholars due to its simplicity and convenience in implementation and very efficient in finding the closed boundary within an object. Thresholding is one of the important steps in digital image processing field, whose result can directly affect the accuracy of the following feature extraction process and object detection. It is a vital technology in digital image processing to select an adequate threshold for extracting objects from their background. Otsu segmentation method works on the variance between clusters as the criterion to select the optimal threshold [14]. Otsu plus binary threshold image is shown in figure 5 (c).

#### 4.4.3 Masking

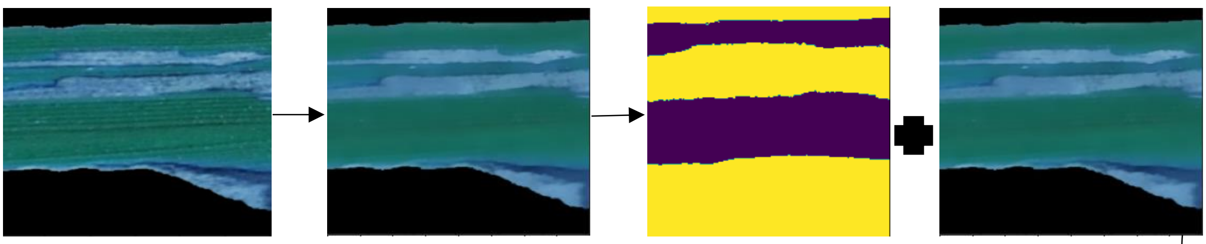
Colour masking is an useful approach to remove dim/extraneous features from images as a result it improves the identification and classification to distinguish celiac with villous atrophy from the control image. This can be helpful to identify and mapped regions of pathology, to screen for celiac disease, and to determine the effectiveness of a gluten free diet [15]. Masked image is shown in figure 5 (e)

#### 4.4.4 LAB colour space

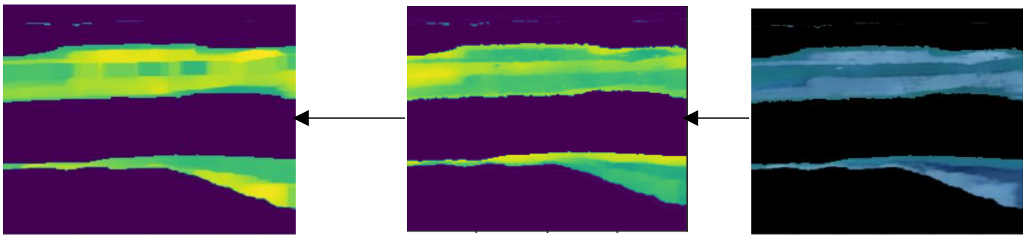
Colour plays a vital role in information processing and visualization. To utilize the colours as visual representations of the object effectively, utilizing colour space that is consider to be perceptual differences between colours is necessary. This CIELAB or LAB color space is having a property that the Euclidean distances between any of the two colours in the space can approximate the perceptual differences between them [16]. The perceptually uniform color space CIELAB (Commission Internationale de l' Eclairage) is advantageous for image analysis, especially in applications that involving colour acceptability decision making. Extracting out B-component of masked images is shown in figure 5 (f).

#### 4.4.5 Morphological closing

closing and Opening processes are the process that alter the dilation and erosion processes to improve the randomness of image. Both processes dependent on the characteristics of the structuring element to process the image so as to obtain a better image. During digital image processing, image segmentation often generates holes unexpectedly. So, to suppress, such holes can be filled up by using closing operation in morphology [17]. Figure 5 (g) shows morphological closing operation.



(a) (b) (c) (d)



(g) (f) (e)

**Fig 5** (a) Background removed image, (b) Bilateral smooth image, (c) Images after Binary + Otsu thresholding, (d) Image for masking, (e) Masked image, (f) B-component of masked image, (g) Morphological closed image

## 4.5 Deep CNN based on transfer learning

The basic architecture of neural network essentially contains three primary components which include input layer, hidden layer and output layer. The first layer is called the input layer, where the features are used as the initial input. The middle layers or hidden layer which can be one or more, are called hidden layers as in case of deep learning model hidden layer are two or more than that. Finally, the last layer, which is the output layer, which has as many nodes as the wanted number of outputs from the model. As deep learning has made considerable progress in recent years. This has enabled us to tackle more complex problems and indeed obtain amazing results. However, the training time and the amount of data required for such deep learning systems are much more than that of traditional ML systems. There are various deep learning networks with state-of-the-art performance (sometimes as good or even better than human performance) that have been developed and tested across domains such as computer vision and natural language processing (NLP). Transfer learning is the idea of vanquishing the isolated learning paradigm and utilizing the knowledge acquired from one task to solve other related tasks. In most cases, teams/people share the details of these networks for others to use. These pre-trained networks/models form the basis of transfer learning in the context of deep learning, or deep transfer learning which ultimately be useful to tackle the tasks having less data available [18]. The VGG-16 transfer learning model is a 16-layer (convolution and fully connected) as name suggest, network model built on the ImageNet database, which is built for the purpose of image recognition and classification. This model was built by Karen Simonyan and Andrew Zisserman and is mentioned in their paper [19]. It can be clearly seen in figure 6 that it has a total of 13 convolution layers using 3×3 convolution filters along with max pooling layers for down sampling and a total of two fully connected hidden layers of 4096 units in each layer followed by a dense layer of 1000 units, where each unit represents one of the image categories in the ImageNet database. Last three layers are not needed since it will be using our own fully connected dense layers to predict our own number of classes. Figure 6 shows original VGG-16 model and table no.1 shows modified VGG-16 model for proposed work.

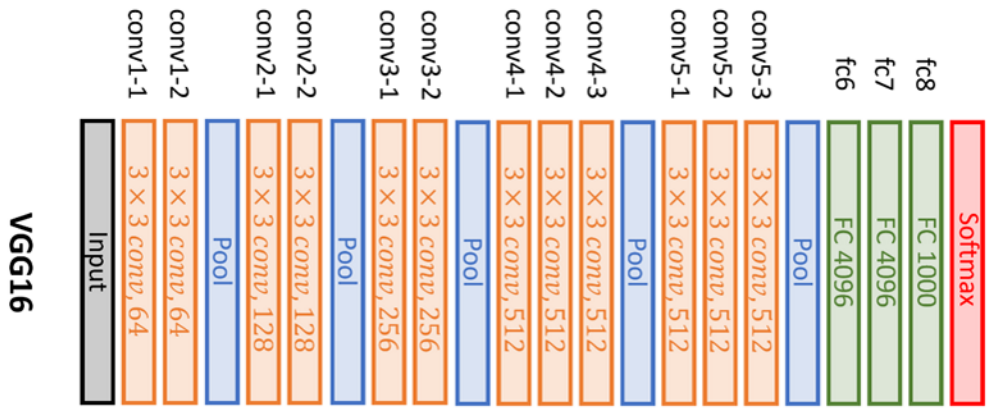



**Fig 6** VGG-16 architecture

**Table 1-** Modified VGG-16 model for DIP_CNN_TL.

| | Layer | Feature map | Size | Kernel Size | Stride | Activation |
|---|---|---|---|---|---|---|
| Input | Image | 1 | 300x300x3 | None | None | None |
| 1 | 2xConvolution | 64 | 300x300x64 | 3x3 | 1 | Relu |
| | Max pooling | 64 | 150x150x64 | 3x3 | 2 | Relu |
| 3 | 2xConvolution | 128 | 150x150x128 | 3x3 | 1 | Relu |
| | Max pooling | 128 | 75x75x128 | 3x3 | 2 | Relu |
| 5 | 2xConvolution | 256 | 75x75x256 | 3x3 | 1 | Relu |
| | Max pooling | 256 | 38x38x256 | 3x3 | 2 | Relu |
| 7 | 3xConvolution | 512 | 38x38x512 | 3x3 | 1 | Relu |
| | Max pooling | 512 | 19x19x512 | 3x3 | 2 | Relu |
| 10 | 3xConvolution | 512 | 19x19x512 | 3x3 | 1 | Relu |
| | Max pooling | 512 | 10x10x512 | 3x3 | 2 | Relu |
| 13 | Fully connected | None | 25088 | None | None | Relu |
| 14 | Fully connected | None | 4096 | None | None | Relu |
| 15 | Fully connected | None | 4096 | None | None | Relu |
| Output | Fully connected | None | 3 | None | None | Softmax |

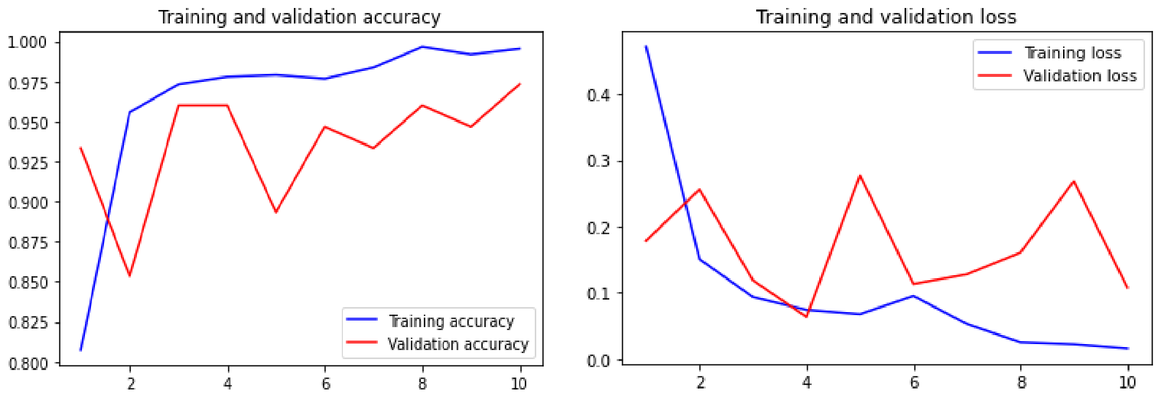
## 5 Results and Conclusion

DIP_CNN_TL is implemented using CNN_TL on Python platform version 3.6. The performance of DIP_CNN_TL is evaluated and compared with the performance of some existing state-of-art classifiers such as DAE, AAN and DNN. The results are compared on the basis of disease classes which includes healthy, bacterial blight and brown spot. From the dataset nearly 80% of images are used to train the model, 10% are used for testing purpose and the remaining 10% are used to validate the model.

Figure 7 (a) shows a plot of accuracy on the training and validation dataset. From the plot it can be seen that the model does not overfit, as it is showing comparable skill on both datasets (training and validation). Similarly, in figure 7 (b) shows a plot between training loss and validation loss against the number of epochs, from the loss plot it is observed that training loss rate of DIP_CNN_TL is approximately 0.04 and it shows that model is trained well. Moreover, it is also seen that validation loss is going up and down but at the end it goes close proximity to training loss.

Figure 8 (a) shows the classification accuracy of all the three classes of rice leaf disease in the form of confusion matrix of 3x3 size and figure 8 (b) shows the confusion matrix plot for True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN) values are predicted. The values of TP, TN, FP and FN from the below confusion matrix are 25, 50, 0 and 0 respectively for the healthy image; the values of TP, TN, FP and FN are 24, 49, 1 and 1 respectively for the brown spot; the values of TP, TN, FP and FN are 24, 49, 1 and 1 respectively for the bacterial leaf blight affected image.

Table 2 shows the classification performance of the DIP_CNN_TL method. Using the DIP_CNN_TL classifier the highest accuracy is achieved for each of the healthy leaf image nearly 100%, for brown spot it is 96% and 96% for bacterial leaf blight. Moreover, using the DIP_CNN_TL classifier, the highest average testing accuracy is achieved for all the three healthy, bacterial leaf blight and brown spot leaf images is 97.33%.




(a) (b)

**Fig 7 (**a) Training and validation accuracy, (b) Training and validation loss

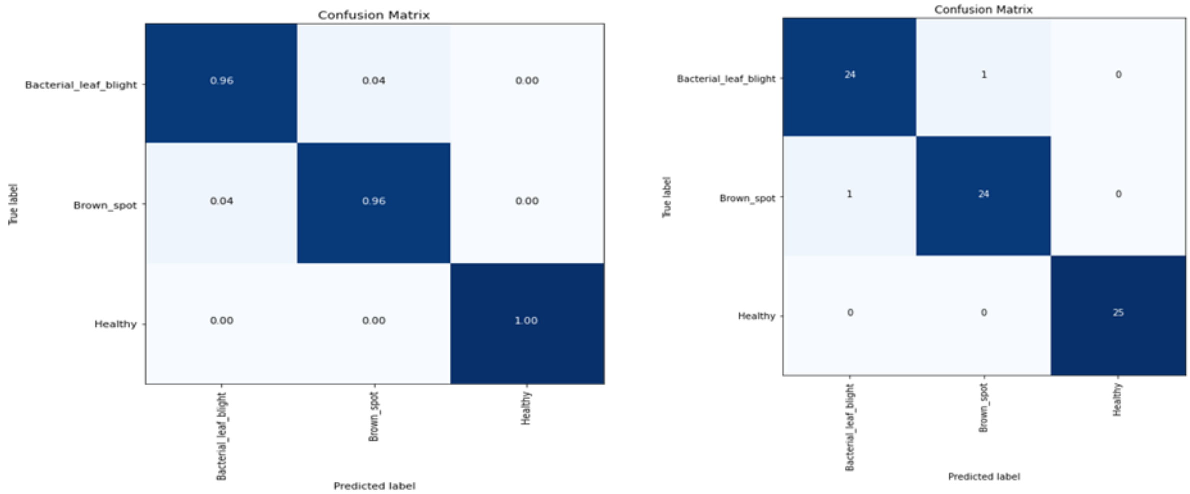



**Fig 8** (a) Confusion matrix plot for CNN_TL accuracy, (b) Confusion matrix plot for TP, TN, FP and FN

**Table 2 –** Classification performance of healthy and diseased leaf images.

| **Leaf type** | **Healthy** | **Bacterial blight** | **Brown spot** |
|---|---|---|---|
| Accuracy | 99.9 | 96 | 96 |
| F1-score | 1.00 | 0.96 | 0.96 |
| Precision | 1.00 | 0.96 | 0.96 |
| True positive rate (or sensitivity): TPR | 1.00 | 0.96 | 0.96 |
| False positive rate: FPR | 0.00 | 0.02 | 0.02 |
| True negative rate (or specificity): TNR | 1.00 | 0.98 | 0.98 |

The graphs are shown for the performance metrics such as accuracy, F1-score, False Positive Rate (FPR), False Negative Rate (FNR), False Discovery Rate (FDR), Negative Predictive Value (NPV), precision, True Positive Rate (TPR), True Negative Rate (TNR) and loss function.

Figure 9 represents the comparison graph of accuracy for the three classes with respect to the five classifiers which includes the proposed and existing classifiers. When using our

DIP_CNN_TL the accuracy of healthy image is 100%, bacterial blight is 96% and brown spot is 96%. When using ANN classifier, the accuracy of healthy image is 77.24%, bacterial blight is 78% and brown spot is 81.5%. When using DAE classifier the accuracy of healthy image is 81.4%, bacterial blight is 86.2% and brown spot is 87.7%. When using DNN classifier the accuracy of healthy image is 83%, bacterial blight is 91.7% and brown spot is 90.6%. When using DNN_JOA classifier the accuracy of healthy image is 90.75%, bacterial blight is 95.78% and brown spot is 94% [20].

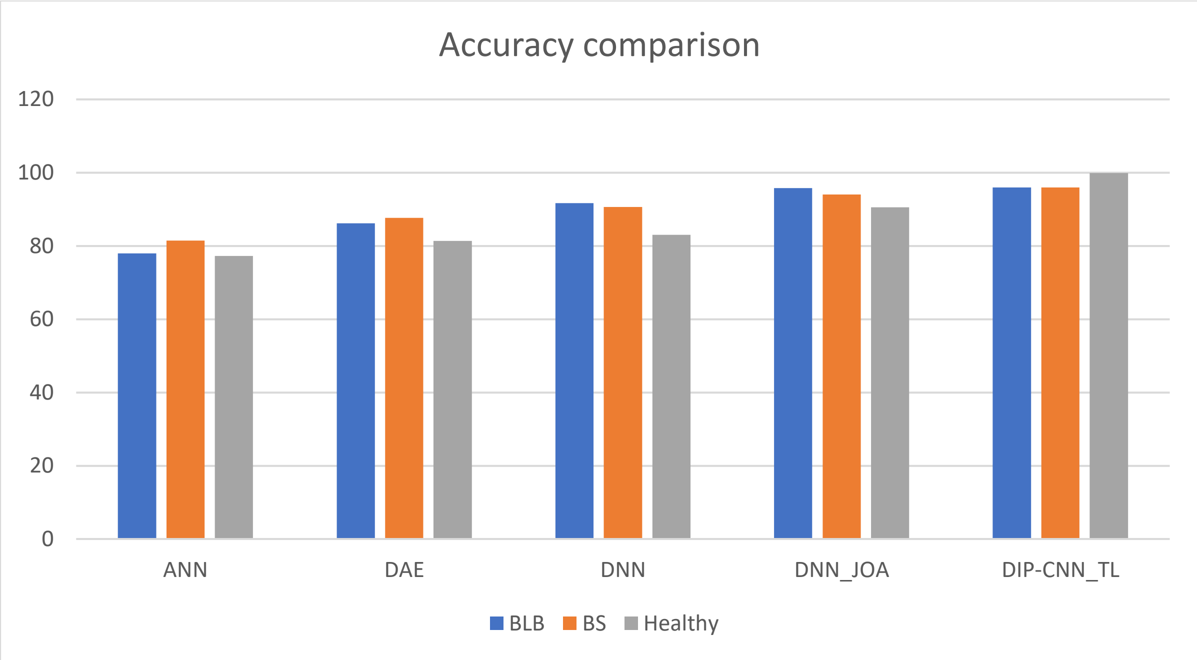



**Fig 9** Accuracy comparison

**Figure 10** represents the comparison graph of F1-score for the three classes with respect to the five classifiers which includes the proposed and existing classifiers. When using DIP_CNN_TL the F1-score of healthy images is 1.00, bacterial blight is 0.96, and brown spot is 0.96. When using ANN classifier, the F1-score of healthy images is 0.61, bacterial blight is 0.68% and brown spot is 0.65. When using DAE classifier the F1-score of healthy images is 0.69, bacterial blight is 0.75 and brown spot is 0.77. When using DNN classifier the F1-score of healthy images is 0.73, bacterial blight is 0.81 and brown spot is 0.81. When using DNN_JOA classifier the F1-score of healthy images is 0.81, bacterial blight is 0.89 and brown spot is 0.85 [20].

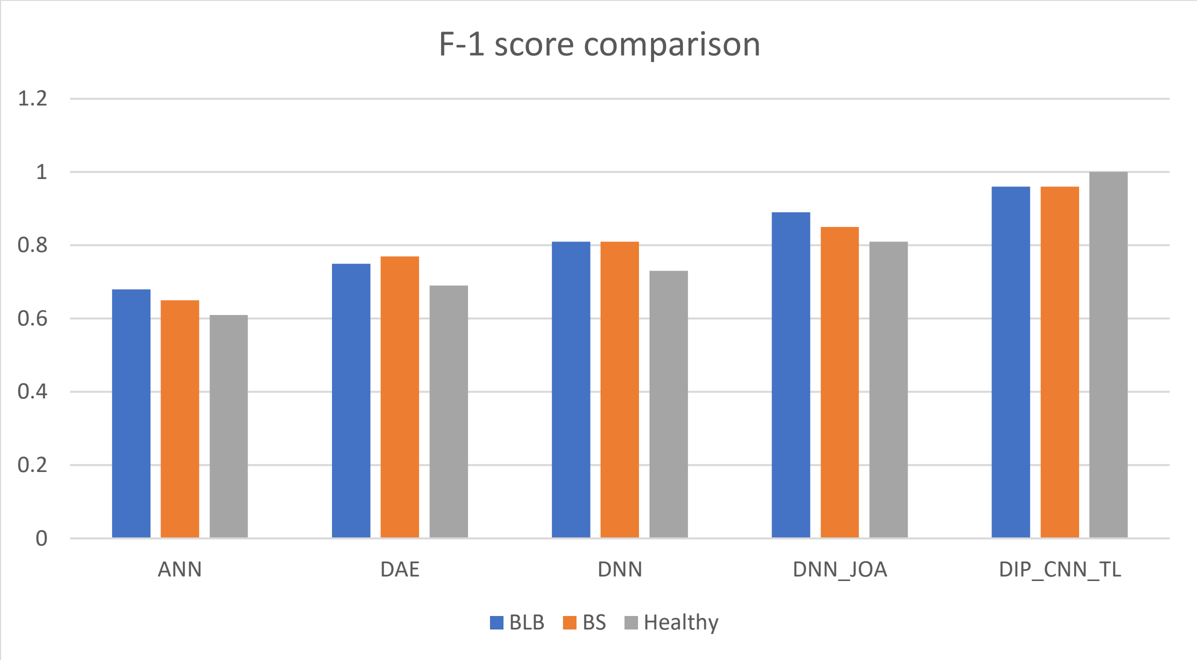



**Fig 10-** score comparison

**Figure 11** represents the comparison graph of TNR for the three classes with respect to the five classifiers which includes the proposed and existing classifiers. When using DIP_CNN_TL the TNR value of healthy image is 100, bacterial blight is 98 and brown spot is 98. When using DNN_JOA the TNR value of healthy image is 90.7, bacterial blight is 91 and brown spot is 94.5. When using ANN classifier, the TNR value of healthy image is 73.6, bacterial blight is 87.5 and brown spot is 83.6. When using DAE classifier the TNR value of healthy image is 85.5, bacterial blight is 88.2 and brown spot is 85. When using DNN classifier the TNR value of healthy image is 85.6, bacterial blight is 89.6 and brown spot is 88.4 [20].

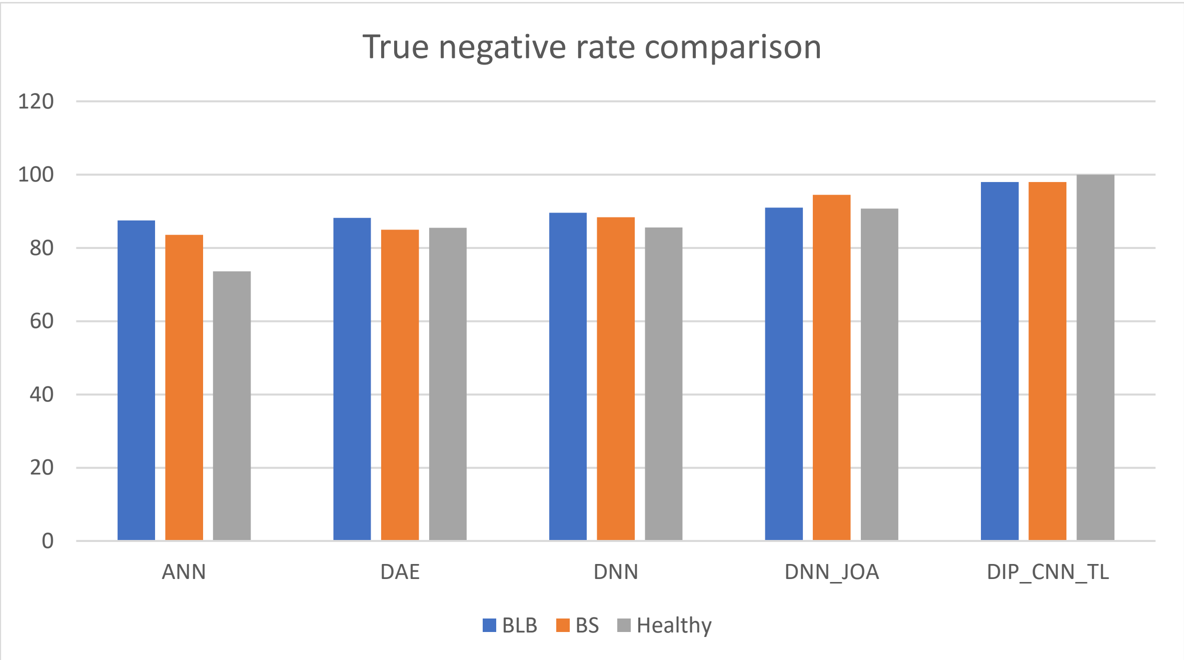



**Fig 11** True negative rate comparison

Figure 12 represents the comparison graph of precision for the three classes with respect to the five classifiers which includes the proposed and existing classifiers. When using DIP_CNN_TL the precision value of healthy image is 100, bacterial blight is 96 and brown spot 96. When using DNN_JOA the precision value of healthy image is 73, bacterial blight is 80.4 and brown spot is 85. When using ANN classifier, the precision value of healthy image is 54, bacterial blight is 65 and brown spot is 58.4. When using DAE classifier the precision value of healthy image is 65.32, bacterial blight is 70.4 and brown spot is 65. When using DNN classifier the precision value of healthy image is 68.9, bacterial blight is 77.56 and brown spot is 73 [20].

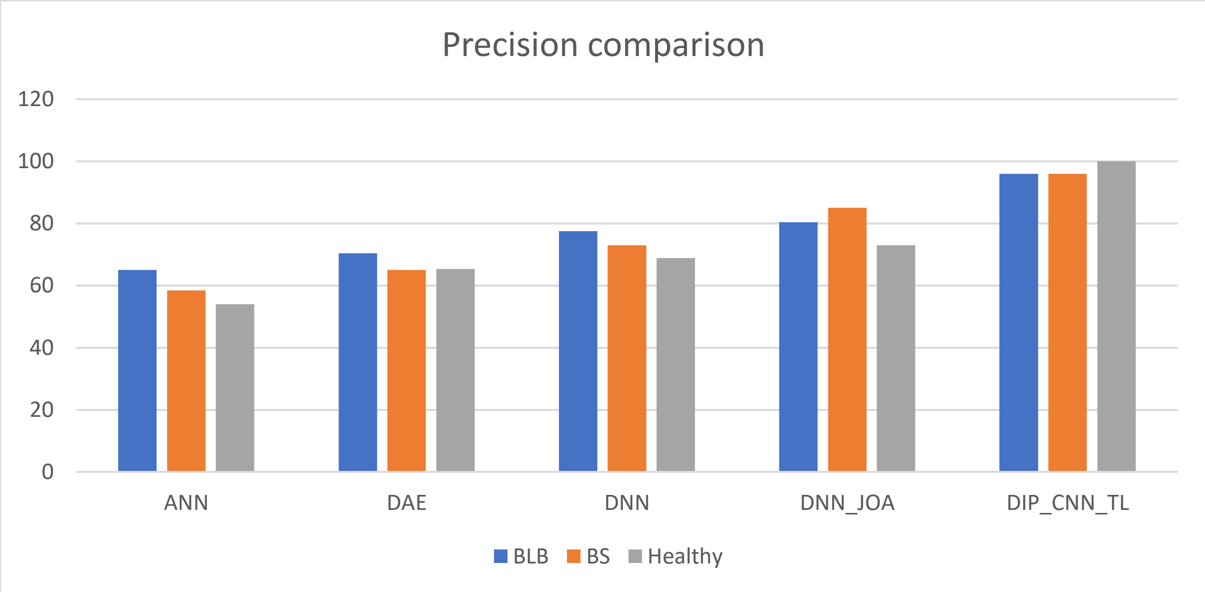



**Fig 12** Precision comparison

## 6 Conclusion

The images of rice leaves are directly taken from publicly available websites Kaggle and UCI machine learning for healthy and the diseases like bacterial blight, brown spot. In pre-processing images are cropped and resized to 300x300, to remove the background, K-Mean clustering method is applied then in feature extraction step resultant images are smoothened and thresholding plus masking is performed then the resultant RGB images are converted into LAB images. At last B component of LAB colour space is taken in order to segmentation of diseased portion and normal portion. By using DIP_CNN_TL method, classification of diseases is carried out using transfer learning. The experimental results are evaluated and compared with ANN, DAE, DNN and DNN_JOA by evaluating accuracy, precision, F1-score, TPR and FPR. When compared with other classifiers DIP_CNN_TL method achieved high accuracy of 99.9% for the healthy leaves, 96% for the bacterial blight and 96 %brown spot leaves image. On comparing the training and testing accuracy, the testing accuracy attained the highest of 97.3% by using the DIP_CNN_TL classifier, 83% by using the ANN classifier, 90% by using the DAE classifier, 93.5% by using the DNN classifier and 97% by using DNN_JOA.

In the future, to improve the recognition and the classification of plant diseases, any improved method can be used to achieve the best performance by reducing the false classification.

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