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# Deep feature based rice leaf disease identification using support vector machine

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ABSTRACT

Features are the vital factor for image classification in the field of machine learning. The advancement of deep convolutional neural network (CNN) shows the way for identification of rice diseases using deep features with the expectation of high returns. This paper introduced 5932 on-field images of four types of rice leaf diseases, namely bacterial blight, blast, brown spot and tungro. In addition, the performance evaluation of 11 CNN models in transfer learning approach and deep feature plus support vector machine (SVM) was carried out. The simulation results show the deep feature plus SVM perform better classification compared to transfer learning counterpart. Also, the performance of small CNN models such as mobilenetv2 and shufflenet was examined. The performance evaluation was carried out in terms of accuracy, sensitivity, specificity, false positive rate (FPR), F1 Score and training time. Again, the statistical analysis was performed to choose the better classification model. The deep feature of ResNet50 plus SVM performs better with F1 score of 0.9838. The fc6 layer of vgg16, vgg19 and AlexNet have better contribution towards classification compared to fc7 and fc8. Further, the F1 score of CNN classification models was compared with other traditional image classification models such as bag-of-feature, local binary patterns (LBP) plus SVM, histogram of oriented gradients (HOG) plus SVM and Gray Level Co-occurrence Matrix (GLCM) plus SVM.

## 1. Introduction

Rice is the primary food in India and had more land under rice cultivation than china. Odisha holds 4th rank among the states of India for rice production. The western tract of Odisha, especially Sambalpur and Bargarh districts (known as the rice bowl of Odisha), is well known for the production of rice. In this region varieties of rice cultivars are cultivated in two farming seasons a year. The Kharif season (July to October) depends on monsoon and Rabi season (October to March) depend on the water supply of Hirakud dam. It has been reported every year; the paddy fields are damaged due to various diseases and pest attack. Again, the young farmers who have less expertise in agriculture are unable to identify the type of diseases. Without knowing the disease types, pesticide application is worthless. This situation motivates us to carry forward the research for identification of rice diseases which appear in the western region of Odisha.

In the western tract of Odisha, mostly four types of rice diseases have appeared, i.e. bacterial blight, blast, brown spot and tungro. Generally, the identification of rice diseases is supervised either by visual inspection or laboratory experimentation. The visual inspection is carried out only by an expert person and is time-consuming. Laboratory experimentation needs chemical reagent and a complicated process (Turkoglu et al., 2018; Güzel,2012; Asma, 2008). With the development of internet and mobile technology, various applications are developed for assistance to farmers. The “Rice Doctor” and “Rice Xpert” are such type of mobile-apps. The “Rice Doctor” is a questionnaire application to assist farmer. In the same manner, “Rice Xpert” describes the unusual condition of rice. The judgement towards the identification of rice diseases by use of these mobile applications not only chances of wrong but also low efficiency.

In the literature, many research papers have been published for automated rice disease diagnosis based on image processing and machine learning (Al-Hiary et al., 2011; Bashir et al., 2012; Kulkarni et al., 2012; Arivazhagan et al. 2013; Khirade and Patil, 2015; Athanikar and Badar, 2016; Barbedo et al., 2016), such as using pattern recognition techniques (Phadikar et al., 2008), support vector machine (Jian and

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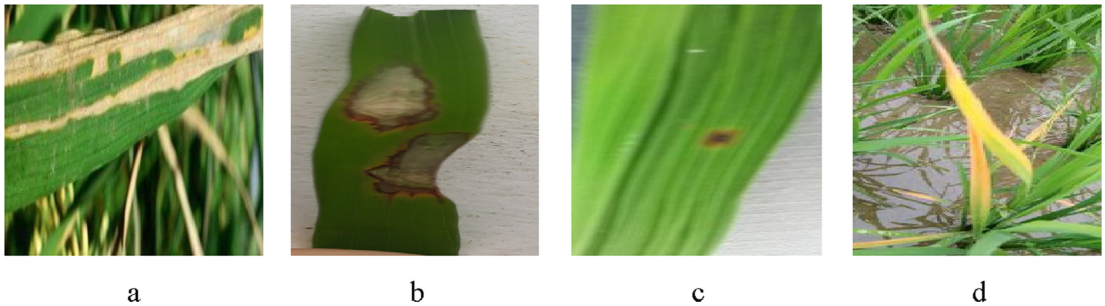


**Fig. 1.** Image samples of rice leaf diseases. (a) Bacterial blight (b) Blast (c) Brown spot (d) Tungro.

Wei, 2010), digital image processing techniques (Barbedo, 2013) and computer vision (Asfarian et al., 2014). The research is not only for rice disease classification but also for other crops such as wheat (Khairnar and Dagade, 2014; Lopes and Valiati (2017), Lu et al., 2017a,b; Shi et al., 2017), maize (Zhang and Yang, 2014), cotton (Shicha et al., 2007), cucumber (Bai et al., 2017; Ma et al., 2018), citrus (Sharif et al.,2018) and tomato (Chai and Wang, 2013) etc. Although, the machine learning techniques have made the great accomplishment on image identification, still it has some limitations: restricted data handing capability, the requirement of segmentation & feature extraction (Chen et al., 2018). The diseased region segmentation is not always an easy task for all agricultural images (Lopes and Valiati (2017), Lu et al., 2017a,b). Therefore, the traditional machine learning techniques face difficulties for classification of agricultural diseased images with adequate results. With the advancement of machine learning techniques, the deep learning methods are capable enough to solve and model the big data problems. The deep learning methods can be applied in agricultural diseased image classification without the need for pre-required processes such as segmentation and feature extraction.

In past few years, the CNN is applied in various fields such as object detection (Ren et al., 2015; Girshick et al., 2014, 2015; Zitnick et al., 2014; Uijlings et al., 2013), image classification (Deng et al., 2009; Krizhevsky et al., 2012; Simonyan and Zisserman, 2014; Donahue et al., 2014) and video classification (Karpathy et al., 2014). In the last couple of year, many researches have been conducted for the diagnosis of plant diseases based on CNN (Kawasaki et al., 2015; Zhang et al., 2016; Zhao and Peng, 2012; Lopes and Valiati (2017), Lu et al., 2017a,b; Kamilaris and Prenafeta-Boldú, 2018; Chen et al., 2020; Kounalakis et al., 2019; Lee et al., 2020; Thenmozhi and Srinivasulu Reddy, 2019). In addition to plant diseases diagnosis, the CNN is applied in identification fish species (Rauf et al., 2019), crop detection (Huang et al., 2020) and weed discrimination (Dos Santos Ferreira et al., 2019).

In this paper, a system based on deep CNNs was developed for the identification of four types of rice leaf diseases as a classification task. In this study, we use a dataset consisting of 5932 contaminated rice leaf images collected from the agricultural site of Sambalpur and Bargarh district, Odisha, India. First, we use this dataset for deep feature extraction based on deep learning architectures such as AlexNet, VGG16, VGG19, GoogleNet, ResNet18, ResNet50, ResNet101, InceptionV3, InceptionResNetV2, DenseNet201 and XceptionNet. The deep features obtained from these deep models are classified by SVM. Again, the transfer learning approach was applied for the identification of rice diseases in the aforementioned deep CNN models. Finally, we evaluated the performance results by using transfer learning and deep feature extraction methods. In addition, the performance analysis of small CNN models: mobileNetv2 and Shufflenet was carried out in both transfer learning and deep feature plus SVM approach.

The main contribution of this article is as follows.

- The deep features of most used 11 deep CNN models (AlexNet, VGG16, VGG19, GoogleNet, ResNet18, ResNet50, ResNet101, InceptionV3, InceptionResNetV2, DenseNet201 and XceptionNet) were extracted and used by SVM classifier for identification of rice diseases.
- Again, the 11 deep CNN models mentioned above are examined in transfer learning approach.
- The performance analysis of small CNN models such as mobileNetv2 and shufflenet in both transfer learning and deep feature plus SVM was carried out.
- The proposed method was tested using on-field images instead of off-line images as in traditional methods.
- The statistical analysis was performed to choose the best classification model in transfer learning and deep feature plus SVM approach individually.
- Finally, a comparative analysis of deep feature plus SVM, transfer learning, bag-of-features and traditional image classification method (LBP + SVM, HOG + SVM and GLCM + SVM) was carried out.

The remainder of this paper is structured as follows. Section 2 discussed the materials and methodology. The experimental results are detailed in section 3. At last, section 4 concludes with future scope.

## 2. Materials and methodology

In this section, the details of the dataset and suggested methods are discussed in appropriate subheadings.

### 2.1. Dataset

The dataset contains 5932 diseased rice leaf images which includes bacterial blight, blast, brown spot and tungro varieties. Initially, different rice field of western Odisha is captured using Nikon DSLR-D5600 with 18–55 mm lens with high resolution. The patches of diseased portion were extracted from the original large images. Some images of rice diseases are collected from agricultural pest and insect pests picture database (http://bcch.ahnw.gov.cn/Right.aspx). The all the patches were treated as data samples and resized to 300 × 300 pixels. Fig. 1 shows the four varieties of rice leaf diseases. From original dataset 800 images, i.e. 200 images of each category were separated and kept for testing. The remaining 5132 images were used for augmentation to enhance the dataset. For augmentation process simple image rotations and flipping operation were applied to all images such as rotate right 90 degree, rotate left 90 degree, flip vertical, flip horizontal and rotate 180 degree. So, the number of images increased to six times including images on which augmentation applied. Because of more augmented images, the chance for the network to learn the appropriate features has been increased. Table 1 list the name & number of images used for experimentation. The data samples are split randomly into 80:20 proportion for training and validation respectively. The choose of training and validation samples are in random manner for each and every execution.

**Table 1**
Details of rice leaf disease dataset.

| Leaf diseases | Number of samples | | | |
|---|---|---|---|---|
| | Number of original images | Number of images used of augmentation | Number of images used for Training and validation | Number of images used for Testing |
| Bacterial Blight | 1584 | 1384 | 8304 | 200 |
| Blast | 1440 | 1240 | 7440 | 200 |
| Brown Spot | 1600 | 1400 | 8400 | 200 |
| Tungro | 1308 | 1108 | 6648 | 200 |
| Total | 5932 | 5132 | 30,792 | 800 |

### *2.2. Rice leaf disease identification by SVM based on deep feature*

Deep feature extraction is based on the extraction of features acquired from a pre-trained CNN (Lopes et al., 2017). The deep features were extracted from fully connected layer and feed to the classifier for training purpose. The deep features obtained from each CNN networks are used by SVM classifier. After that, the classification is performed, and the performance of all classification models are measured. The rice leaf disease identification model based on deep features by SVM classifier is shown in Fig. 2. The process of automatic feature extraction based on CNN is explained in Section 2.2.1.

The deep features of CNN models were extracted from a particular layer and feature vector was obtained. The features were fed to the SVM classifier for rice leaf disease identification. The CNN is a multilayer structure network, and each layer produces a response. The layers extract the basic image feature and pass to the next layer. The feature layer and feature vector used by CNN models are detailed in Table 2. The activation is in GPU with a minibatch size of 64 and GPU memory have space enough to fit image dataset. The activation output is in the form of the column to fit in linear SVM training. To train the SVM, the function 'fit class error-correcting output codes (fitcecoc)' was used. This function returns full trained multiclass error-correcting output of the model. The function 'fitcecoc' uses K(K-1)/2, binary SVM model, using One-Vs-All coding design. Here, K is a unique class label. Because of error correcting output codes and one-Vs-all coding design of SVM, the performance of classification models was enhanced. The performance of the classification model concerning different feature layers such as fc6, fc7 and fc8 of AlexNet, Vgg16 and vgg19 were examined.

#### *2.2.1. Process of feature extraction using CNN*

The CNN consists of wide varieties of filters, non-linearities and pooling operator. The filters are learning in a supervised or, unsupervised (Huang and Lecun, 2006; Jarrett et al., 2009; Ranzato et al., 2006) fashion. The non-linearities used are hyperbolic tangents (Huang and Lecun, 2006; Jarrett et al., 2009; Ranzato et al., 2007), rectified linear units (Glorot et al., 2011; Nair and Hinton, 2010) and logistics sigmoid (Mohamed et al., 2011; Glorot and Bengio, 2010). Convolution and the application of non-linearities is followed by a pooling operator such as sub-sampling (Pinto et al., 2008), average pooling (Huang and Lecun, 2006; Jarrett et al., 2009) or, max pooling (Jarrett et al., 2009; Ranzato et al., 2007, Serre et al., 2005; Mutch and Lowe, 2006). The filters, non-linearities and pooling are allowed to be different in different network layer (Lecun et al., 2015; Goodfellow et al., 2016). (Wiatowski and Bolcskei, 2018) explained the mathematics behind the process of feature extraction based on CNN.

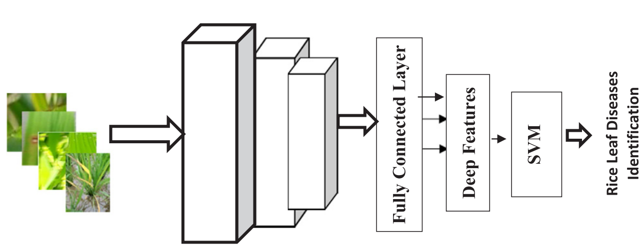


**Fig. 2.** Rice leaf disease identification by SVM based on deep feature.

**Table 2**
Details of feature layer and feature vector of CNN models.

| CNN models | Feature Layer | Feature Vector | CNN models | Feature Layer | Feature Vector |
|---|---|---|---|---|---|
| AlexNet | fc6 | 4096 | Xception | predictions | 1000 |
| | fc7 | 4096 | Resnet18 | Fc1000 | 1000 |
| | fc8 | 1000 | Resnet50 | Fc1000 | 1000 |
| Vgg16 | fc6 | 4096 | Resnet101 | Fc1000 | 1000 |
| | fc7 | 4096 | Inceptionv3 | predictions | 1000 |
| | fc8 | 1000 | Inceptionresnetv2 | predictions | 1000 |
| Vgg19 | fc6 | 4096 | GoogleNet | loss3-classifier | 1000 |
| | fc7 | 4096 | Densenet201 | Fc1000 | 1000 |
| | fc8 | 1000 | Mobilenetv2 | Logits | 1000 |
| | | | shufflenet | node_202 | 1000 |

In convolution layer, formats of enrolled channels are utilised. Each one channel is limited spatially (traverse along with height and weight), but enlarges with complete deepness of input volume. The images that has, Height H, Depth D and Width W shading channels (i.e., H × D, W), the enrolled channels isolate an image width as $W1 = \frac{(W-F+2p)}{S+1}$, here F speaks to the spatially expands neuron estimate; p is the main part of zero padding, and S is the size of way. Thus, the height is partitioned by $H1 = \frac{(H-F+2p)}{S+1}$, depth D1 is the extent of number of channels K. For instance, an image having 28 × 28 × 3 (3 is for the shading channels), if the open field (or channel) has a size of 5 × 5 × 3 (altogether 75neurons + 1bias), a 5x5 window with profundity three moves along the width and height and produces a 2-D activation map.

The Pooling Layer works individually above all the deepness portion for the input and rescales it extensional applying the MAX operation. It obtained the size of volume of HDW, and separates the image into $W1 = \frac{W-F}{S+1}$as Width and $H1 = \frac{H-F}{S+1}$ as Stature and profundity D1 is same as the info D. After the calculation against each shading channels the MAX task is finished. In this way, the feature matrix is then diminished in POOLING layer.

### *2.3. Rice leaf disease identification based on transfer learning approach*

Transfer learning is a machine learning approach that is restated as an outset to solve a different problem using the knowledge collected from an established model (Pan and Yang, 2009). The current study fine-tuned this by using pre-trained CNN models based on transfer learning. Fig. 3 illustrated the rice leaf disease identification model

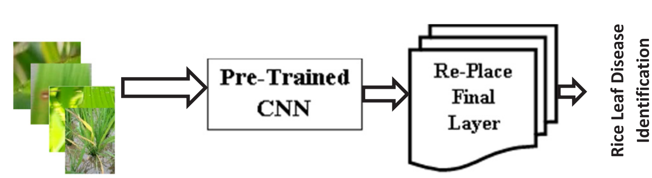


**Fig. 3.** Rice leaf disease identification based on transfer learning approach.

**Table 3**
Performance measures (%) and training time (in seconds) of SVM classifier using deep features of AlexNet, VGG16 and VGG19. (bold font shows the best results).

| Measures | AlexNet | | | Vgg16 | | | Vgg19 | | |
|---|---|---|---|---|---|---|---|---|---|
| | fc6 | fc7 | fc8 | fc6 | fc7 | fc8 | fc6 | fc7 | fc8 |
| Accuracy | **97.62 ± 0.37** | 97.23 ± 0.55 | 95.66 ± 0.76 | **97.31 ± 0.40** | 96.16 ± 0.64 | 94.40 ± 0.58 | **97.60 ± 0.31** | 96.48 ± 0.54 | 94.47 ± 0.88 |
| Sensitivity | **97.62 ± 0.37** | 97.23 ± 0.55 | 95.66 ± 0.76 | **97.31 ± 0.40** | 96.16 ± 0.64 | 94.40 ± 0.58 | **97.60 ± 0.31** | 96.48 ± 0.54 | 94.47 ± 0.88 |
| Specificity | **99.20 ± 0.12** | 99.07 ± 0.18 | 98.55 ± 0.25 | **99.10 ± 0.13** | 98.72 ± 0.21 | 98.13 ± 0.19 | **99.20 ± 0.10** | 98.82 ± 0.18 | 98.15 ± 0.29 |
| FPR | **0.79 ± 0.12** | 0.92 ± 0.18 | 1.44 ± 0.25 | **0.89 ± 0.13** | 1.27 ± 0.21 | 1.86 ± 0.19 | **0.79 ± 0.10** | 1.17 ± 0.18 | 1.84 ± 0.29 |
| F1 Score | **97.62 ± 0.37** | 97.22 ± 0.55 | 95.66 ± 0.75 | **97.30 ± 0.40** | 96.16 ± 0.64 | 94.39 ± 0.58 | **97.60 ± 0.31** | 96.48 ± 0.54 | 94.45 ± 0.914 |
| Training Time (Second) | **21.608 ± 0.108** | 23.058 ± 3.261 | 21.665 ± 0.537 | 107.684 ± 12.768 | 104.377 ± 0.281 | **103.913 ± 0.326** | **120.658 ± 0.202** | 121.294 ± 0.975 | 120.932 ± 0.286 |

based on transfer learning approach.

### 2.4. Summary steps of transfer learning and deep feature approach

The following steps summarize the proposed deep feature extraction:

Step-1: Collection of diseased leaf Images.

Step-2: Pre-processed the image, i.e. resize to 227 × 227 × 3 dimension. Again, augmentation was used to fit the image size with the input size of the network.

Step-3: Features were extracted from fully connected layers of the pre-trained network.

Step-4: Classification was performed using the deep features with the SVM classifier and measures the performance.

The similar approach was repeated for classification by SVM classifier using deep features of all CNN models.

The following steps summarize the transfer learning:

Step-1: Collection of diseased leaf Images.

Step-2: Pre-processed the image, i.e. resize to 227 × 227 × 3 dimension. Again, augmentation was used to fit the image size with the input size of the network.

Step-3: Load a pre-trained network. Replace the classification layers for the new task and train the network on the data for the new task.

Step-4: Classification was performed using the newly created deep model and measures the performance of the new network.

The similar approach was repeated for all CNN model.

## 3. Experimental results

In this study, we examined the performance of classification models for rice leaf disease identification based on thirteen number (11 most used + 2 small architecture) of CNN models. The experimental studies were implemented using the MATLAB 2019a deep learning toolbox. All applications were run on a laptop, i.e. Acer Predator Helios 300 Core i5 8th Gen - (8 GB/1 TB HDD/128 GB SSD/Windows 10 Home/4 GB Graphics) and equipped with NVIDIA GeForce GTX 1050Ti. The performance of each classifier was measured in terms of accuracy, sensitivity, specificity, false positive rate (FPR), F1 Score and training time. The performance comparison of each classifier was discussed in the following subsections. In addition, this experimentation used One-Vs-all approach and linear kernel function as the SVM classifier parameter. The confusion matrix measures are expressed in Eqs. (1) to (5).

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \quad (1)$$

$$Sensitivity = \frac{TP}{TP + FN} \quad (2)$$

$$Specificity = \frac{TP}{TP + FP} \quad (3)$$

$$FPR = \frac{FP}{FP + TN} \quad (4)$$

$$F1\,Score = 2 \times \frac{sensitivity \times precision}{sensitivity + precision} \quad (5)$$

where, TP = true positive, TN = true negative, FP = false positive, FN = false negative.

### 3.1. Performance analysis based on deep features of AlexNet, vgg16 and vgg19

In this subsection, the performance evaluation of three fully connected layers, i.e. fc6, fc7 and fc8 of pre-trained CNN models such as AlexNet, VGG16 and VGG19 was examined. The SVM uses the deep features extracted from fc6, fc7 and fc8 for classification. For the experiments, we have made 30 independent runs, and its mean & standard

**Table 4**
Statistical analysis of different classification models based on SVM using deep features of various CNN models.

| Classification Models | Accuracy | Sensitivity | Specificity | FPR | F1 Score | Training Time (in Second) |
|---|---|---|---|---|---|---|
| AlexNet | $.976256904158789^{b}$ | $.976256904158789^{b}$ | $.992085634719597^{b}$ | $.007914365280404^{b}$ | $.976246392441146^{b}$ | $21.608721067^{a}$ |
| Vgg16 | $.973124569346424^{b}$ | $.973124569346424^{b}$ | $.991041523115475^{b}$ | $.008958476884526^{b}$ | $.973078046059129^{b}$ | $107.684364717^{b}$ |
| Vgg19 | $.976068535640492^{b}$ | $.976068535640492^{b}$ | $.992022845213497^{b}$ | $.007977154786503^{b}$ | $.976056448059828^{b}$ | $120.658032433^{c}$ |
| Denset201 | $.985187557326507^{c}$ | $.985187557326507^{c}$ | $.995062519108836^{c}$ | $.004937480891164^{c}$ | $.985173068165590^{c}$ | $222.821716810^{d}$ |
| GoogleNet | $.953326795321071^{a}$ | $.953326795321071^{a}$ | $.984442265107024^{a}$ | $.015557734892976^{a}$ | $.953097192850007^{a}$ | $29.591566023^{e}$ |
| Inceptionresnetv2 | $.972495384484055^{b}$ | $.972495384484055^{b}$ | $.990831794828018^{b}$ | $.009168205171982^{b}$ | $.972491913482123^{b}$ | $257.141117750^{f}$ |
| Inceptionv3 | $.973384745312856^{b}$ | $.973384745312856^{b}$ | $.991128248437619^{b}$ | $.008871751562381^{b}$ | $.973352717361923^{b}$ | $126.716757857^{g}$ |
| ResNet18 | $.974533941382211^{b}$ | $.974533941382211^{b}$ | $.991511313794071^{b}$ | $.008488686205930^{b}$ | $.974518739167152^{b}$ | $33.344050377^{h}$ |
| **ResNet50** | $\mathbf{.983836598550945^{c}}$ | $\mathbf{.983836598550945^{c}}$ | $\mathbf{.994612199516982^{c}}$ | $\mathbf{.005387800483018^{c}}$ | $\mathbf{.983833126021209^{c}}$ | $\mathbf{69.043070567^{i}}$ |
| ResNet101 | $.983879367780354^{c}$ | $.983879367780354^{c}$ | $994626455926785^{c}$ | $.005373544073215^{c}$ | $.983864463299189^{c}$ | $107.684364717^{j}$ |
| XceptionNet | $.973741901259565^{b}$ | $.973741901259565^{b}$ | $.991247300419855^{b}$ | $.008752699580145^{b}$ | $.973759159864221^{b}$ | $195.279090083^{k}$ |

Mean values in same column denoted by same letter do not differ statistically.
($p < 0.05$, Tukey's honest significance test). (SPSS version 26).

deviation of results was recorded in Table 3.

From Table 3 it was observed that the fc6 layer have a better performance towards classification using SVM compared to fc7 and fc8 in each classification model. Also, the fc6 of AlexNet had the better performance with less training time among all fully connected layer of AlexNet, vgg16 and vgg19 model.

### 3.2. Result based on deep feature and SVM

From subsection 3.2, it was observed that the fc6 layer of AlexNet, vgg16 and vgg19 perform better for classification. So, in this subsection, only the fc6 features of AlexNet, vgg16 and vgg19 was considered. This subsection, contain the statistical analysis of 11 most used CNN models for contributing deep features to SVM for identification of four varieties of rice leaf diseases. The 11 most used CNN models are AlexNet, vgg16, vgg19, densenet201, GoogleNet, inceptionv3, inceptionresnetv2, resnet18, resnet50, resnet101 and XceptionNet. Tukey's honest significance test was performed for better comparison among the classification models, based on the results obtained from 30 independent runs.

It was observed from Table 4 the performance measures except training time were divided into three subgroups (superscripted by letter a, b, c). The three CNN models, i.e. resnet50, resnet101 and densenet201 were in the same subgroup (superscript by letter c) and perform better than others. While the GoogleNet (superscript by letter a) perform worst and the remaining eight perform average (superscript by letter b). Again, among the three best performed CNN models, resnet50 have a lesser training time. Hence, resnet50 plus SVM result better classification for identification of rice leaf disease with accuracy, sensitivity, specificity, FPR, F1 score and training time of 98.38%, 98.38%, 99.46%, 0.53%, 98.38% and 69 s respectively. The confusion matrix of this classification model was given in Table 5.

The performance score for each class of ResNet50 model plus SVM was illustrated in Table 6.

### 3.3. Result based on transfer learning

In this section, we performed fine-tuning based on transfer learning using pre-trained CNN models. The hyper parameters used in all of the experiments in transfer learning approaches are: solver type: stochastic gradient descent, initial learning rate is 0.001, learning rate policy: Step (decreases by a factor of 10 every 50/5 epochs), momentum: 0.9, drop out is 0.2, Number of Epochs is 50 and minibatch size:64. The adaptive learning rate is good compared to fixed learning rate. As an adaptive algorithm usually converge much faster than simple back-propagation with a poorly chosen fixed learning rate (Goodfellow et al., 2016). So, we used adaptive learning with decreasing the learning rate by 10 i.e. '50/5'. Here, 50 is the number of epoch and '1/5' is the magnitude of decay factor (Cubuk et al., 2019). The performance measures are given in Table 7. Note that, all the performance parameters are the average of 30 independent runs.

**Table 5**
Confusion matrix based on ResNet50 model and SVM classifier.

| Rice diseases | Bacterial Blight | Blast | Brown Spot | Tungro |
|---|---|---|---|---|
| Bacterial Blight | 1831 | 30 | 0 | 0 |
| Blast | 57 | 1627 | 4 | 0 |
| Brown Spot | 25 | 36 | 1819 | 0 |
| Tungro | 0 | 0 | 0 | 1530 |

**Table 6**
The performance score for each class of ResNet50 model plus SVM.

| Class | Bacterial Blight | Blast | Brown Spot | Tungro |
|---|---|---|---|---|
| Accuracy | 0.9838 | 0.9643 | 0.9670 | 1.0000 |
| Sensitivity | 0.9838 | 0.9643 | 0.9670 | 1.000 |
| Specificity | 0.9843 | 0.9880 | 0.9993 | 1.000 |
| FPR | 0.0157 | 0.0120 | 0.0007 | 0.000 |
| F1Score | 0.9838 | 0.9643 | 0.9670 | 1.0000 |

It was observed from Table 7, that all classification methods based on transfer learning in terms of accuracy, sensitivity, specificity, FPR and F1 score are statistically insignificant to each other as these belong to the same subset (since superscript letters are identical column-wise, i.e. 'a'). The level of statistical significance is often expressed as a p-value between 0 and 1. The smaller the p-value, the stronger the evidence that you should reject the null hypothesis. A p-value < 0.05 (typically ≤ 0.05) is statistically significant. To choose the best classification model, statistical analysis was carried out. In statistical analysis the p-value for accuracy, sensitivity, specificity, FPR and F1 score are 0.803,0.748.0.791,0.791 and 0.779 respectively. And all these values are greater than the typical value i.e. 0.005. Hence the classification models are statistically insignificant. The AlexNet is better among all CNN models with consideration of performance score value and training time.

In transfer learning, a domain D consists of two components: a feature space X and marginal probability distribution P(X), where $X = \{x_i, \ldots\ldots\ldots x_n\} \in X$. In this case, the task is rice leaf disease classification, which is based on the abstract features i.e. edges, shapes, corners and intensity. Now, X is the space of all low-level feature vector, $x_i$ is the $i^{th}$ feature vector corresponding to images and X is the particular learning sample. A specific domain, $D = \{X,P(X)\}$, a task consists of two components: a label space Y and an objective predictive function f(.), which is not observed but can be learned from the training data, which consists of pairs $\{x_i, y_i\}$, where $x_i \in X$ and $y_i \in Y$. The function f(.) was used to predict the corresponding level, f(x) of a new instance x (Pan and Yang, 2009). In case of rice leaf disease classification, by use of f(.) the all transfer learning models show almost the same general

**Table 7**
Statistical analysis of different classification models based on Transfer Learning approach of various CNN models. (bold font indicates better results).

| Classification Models | Accuracy | Sensitivity | Specificity | FPR | F1 Score | Training Time (in Second) |
|---|---|---|---|---|---|---|
| **AlexNet** | **.795856159572974**[a] | **.792944570984285**[a] | **.931835995161609**[a] | **.068164004838391**[a] | **.793354535869997**[a] | **381.799865173**[a] |
| Vgg16 | .793102963899424[a] | .789254248453318[a] | .930822208832270[a] | .069177791167730[a] | .790066088655312[a] | 385.728259577[a] |
| Vgg19 | .788860795055485[a] | .784495299440413[a] | .929437175509868[a] | .070562824490132[a] | .785333907381556[a] | 388.040710733[a] |
| Denset201 | .799157184997893[a] | .795492379400607[a] | .932917360976995[a] | .067082639023005[a] | .795984677890438[a] | 406.156112303[b,c] |
| GoogleNet | .797696305660907[a] | .794388092494563[a] | .932442724551911[a] | .067557275448089[a] | .794471255269240[a] | 384.710007107[a] |
| Inceptionresnetv2 | .792892260148897[a] | .789087126680245[a] | .930789189093435[a] | .069210810906565[a] | .789383105846650[a] | 410.014218540[c] |
| Inceptionv3 | .793102963899424[a] | .791676036459796[a] | .931642557483218[a] | .068357442516782[a] | .792161949583037[a] | 385.660891293[a] |
| ResNet18 | .793102963899424[a] | .789254248453318[a] | .930822208832270[a] | .069177791167730[a] | .790066088655312[a] | 390.025602110[a] |
| ResNet50 | .788860795055485[a] | .784495299440413[a] | .929437175509868[a] | .070562824490132[a] | .785333907381556[a] | 385.395347467[a] |
| ResNet101 | .795856159572974[a] | .792944570984285[a] | .931835995161609[a] | .068164004838391[a] | .793354535869997[a] | 391.797446297[a] |
| XceptionNet | .797808680994522[a] | .794590161133680[a] | .932429617351206[a] | .067570382648794[a] | .794997153381381[a] | 392.726223630[b] |

Mean values in same column denoted by same letter do not differ statistically. ($p < 0.05$, Tukey's honest significance test). (SPSS version 26).

behaviour at the end of 30 independent runs. This is the reason for statistical insignificant among the transfer learning models.

### 3.4. Performance evaluation of small CNN models

In this subsection, the accuracy, sensitivity, specificity, FPR, F1score and training time of small CNN models such as mobilenetv2 and shufflenet were examined. The 30 number of independent runs are recorded in Table 8 in the same procedure as Subsection 3.2 and Subsection 3.3 for deep feature plus SVM and transfer learning approach respectively.

It was observed from Table 8, the moblienetv2 plus SVM classification model perform better compared to other small architecture models in terms of accuracy, sensitivity, specificity, FPR and F1score. Noted that, in deep feature plus SVM approach, the accuracy of mobilenetv2 plus SVM is comparative enough with resnet50 plus SVM. Again, the training time in the first one is very less than later one. In addition, mobilenetv2 have small architecture and easy to integrate into a small end device like a smartphone.

### 3.5. Comparison of F1 score with other image classification methods

In image processing and machine learning approach, mostly bag-of-feature, HOG plus SVM, GLCM plus SVM and LBP plus SVM are applied for image classification. The F1 score of those approaches was recorded in Table 9.

### 3.6. Discussion and comparison of simulation results

The proposed study used pretrained CNN models to obtain the best performance for identification of paddy leaf diseases. We evaluated the performance results of transfer learning and deep feature extraction based on the AlexNet, VGG16, VGG19, GoogleNet, DenseNet201, InceptionResNetV2, InceptionV3, ResNet18, ResNet50, ReseNet101, XceptionNet, MobileNetV2 and ShuffleNet deep models. In addition, traditional methods of Bag-of-Feature, LBP plus SVM, HOG plus SVM, and GLCM plus SVM which are widely used in object recognition, were applied and their F1 scores were evaluated.

**Table 8**
Performance evaluation of small CNN architectures. (bold font indicates better results).

| Performance measures | Transfer Learning | | SVM + Deep features | |
|---|---|---|---|---|
| | Moblienetv2 | Shufflenet | Mobilenetv2 | Shufflenet |
| Accuracy | 0.7888 | 0.7931 | **0.9796** | 0.9794 |
| Sensitivity | 0.7844 | 0.7892 | **0.9796** | 0.9794 |
| Specificity | 0.9244 | 0.9308 | **0.9932** | 0.9931 |
| FPR | 0.07056 | 0.06917 | **0.00679** | 0.00686 |
| F1 Score | 0.78533 | 0.79006 | **0.97960** | 0.9794 |
| Training Time | 376.59 | 376.84 | 48.65 | 32.57 |

**Table 9**
F1 Score of traditional image classification methods.

| Methods | Bag-of-Feature | GLCM + SVM | HOG + SVM | LBP + SVM |
|---|---|---|---|---|
| F1 Score | 0.867 | 0.386 | 0.445 | 0.735 |

First, we extracted features based on deep feature extraction by using the AlexNet, VGG16, and VGG19 models. For each of these models we separately extracted features from the three fully connected layers of fc6, fc7, and fc8. The obtained deep features were calculated for their performance using SVM classifier. According to the results, the best performance for these three models was obtained using deep features extracted from the fc6 layer. For the AlexNet plus SVM model, the highest classification accuracy obtained was 97.62% using the features obtained from fc6 and the lowest classification accuracy was 95.66% using the features obtained from fc8. For the VGG16 plus SVM model, the highest classification accuracy obtained was 97.31% using features obtained from fc6 and lowest classification accuracy 94.40% using feature obtained from fc8. For the VGG19 plus SVM model, the highest classification accuracy obtained was 97.60% using the features from fc6 and lowest classification accuracy was 94.47 using features obtained from fc8. As a result, the features extracted from fc6 of the AlexNet, VGG16, and VGG19 models produced better accuracy than the features extracted from either fc7 or fc8. The performance of AlexNet, VGG16 and VGG19 was better with the feature of fc6 layer not only in terms of accuracy but also in terms of sensitivity, specificity and F1 score.

Next, we extracted features from a specific layer using the AlexNet, VGG16, VGG19, GoogleNet, DenseNet201, InceptionResNetV2, InceptionV3, ResNet18, ResNet50, ReseNet101 and XceptionNet deep learning models. The obtained deep features were calculated for their performance using SVM classifier. According to the results, the ResNet50 plus SVM model, achieved the highest F1 score, i.e. 0.9838 and the GoogleNet plus SVM resulted the lowest F1 score 0.9533.

Later, we performed fine-tuning based on transfer learning using pretrained CNN networks. According to these performance results, the AlexNet achieved the highest F1 score i.e. 0.7933. Again, as per statistical analysis there was no statistical significance among the classification model in transfer learning approach. Again, the small CNN model i.e. MobileNetV2 and ShuffleNet were evaluated for identification of rice leaf diseases in both transfer learning and deep feature extraction methods. The MobileNetV2 plus SVM achieved the highest F1 score, i.e. 0.9796 among small CNN models.

Finally, traditional methods of Bag-of-Feature, LBP plus SVM, HOG plus SVM and GLCM plus SVM were evaluated for rice leaf diseases identification. According to the results, among these four methods, the highest F1 score was 0.8670 by Bag-of-feature model and the lowest F1 score was 0.3860 using the LBP plus SVM classification model.

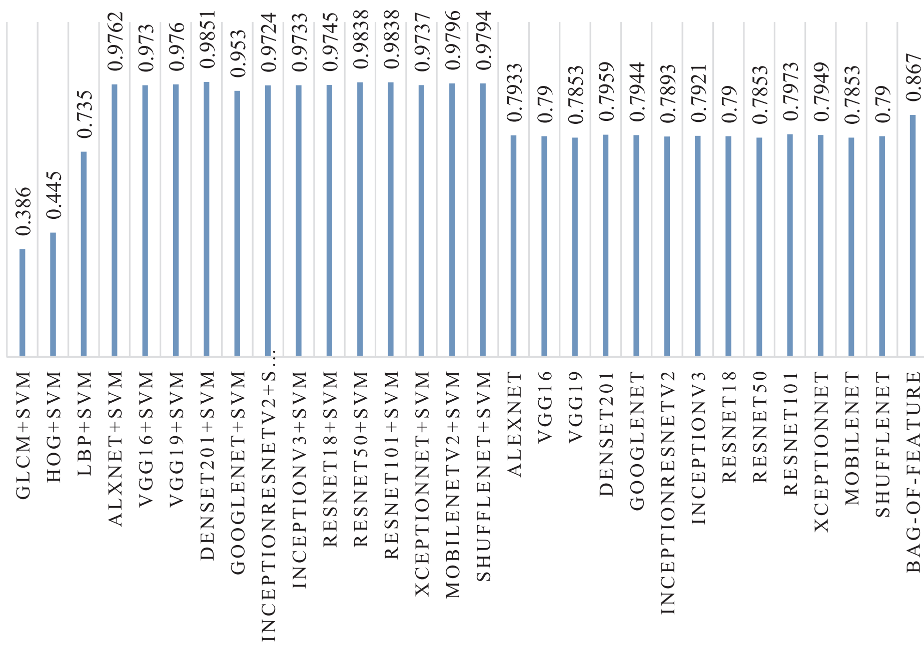


**Fig. 4.** F1 score of all executed methods and models.

The F1 Score of all executed methods and models are shown in Fig. 4.

The performance of traditional methods, transfer learning and deep feature based are noted below.

- The deep features plus SVM have better performance in terms of accuracy, sensitivity, specificity, FPR, F1 score and training time compared to its transfer learning counterparts.
- The Resnet50 feature plus SVM is statically superior among deep feature approach. It results F1 score of 0.9838 with 69 s training time.
- No statically difference among the CNN models in the transfer learning approach. If training time is taken into account, AlexNet was the better one. It results F1 score of 0.7958 and training time 6 min 35 s.
- Among the small architecture CNN models, mobilenetv2 plus SVM have the accuracy, sensitivity, specificity, FPR, F1score and training time are 97.96%,97.96%, 99.32%, 0.67%,97.96% and 48.65 s respectively. Its performance is comparable with the resnet50 plus SVM.
- The bag-of-feature had F1 score of 0.867 but, the training time required is very high, i.e. 25–30 min.
- Among the traditional image classification methods, LBP plus SVM had the highest F1 score, i.e. 0.735. The other two methods resulted very less F1 score, i.e. below 0.5.

The above investigation of different classification models (as in Table 3 to 9) was based on validation set. It was observed that the ResNet50 plus SVM is the best classification model to identify the types of rice leaf diseases. The next step is to cross examined with a new dataset i.e. test dataset. The test dataset contains 800 images with 200 images of each type of rice leaf diseases. The confusion matrix of ResNet50 plus SVM classification model for test dataset was recorded in Table 10.

It was observed from Table 10 the confusion matrix of test dataset that, out 200 images of bacterial blight 3 images were misclassified as blast. Similarly, out of 200 images of blast 7 images were classified as bacterial blight. Again, out of 200 images of brown spot 4 images were misclassified as blast. The misclassification is because of the similarity of color. The lesion color of brown spot, bacterial blight and blast are brown, milky white and ashy respectively. Hence, the misclassification is due to closeness of color proximity of these three diseased leaf images.

**Table 10**
Confusion matrix of ResNet50 plus SVM for test dataset.

| Rice diseases | Bacterial Blight | Blast | Brown Spot | Tungro |
|---|---|---|---|---|
| Bacterial Blight | 197 | 3 | 0 | 0 |
| Blast | 7 | 193 | 0 | 0 |
| Brown Spot | 0 | 4 | 196 | 0 |
| Tungro | 0 | 0 | 0 | 200 |

## 4. Conclusion

In this study, we evaluated the performance of 13 number CNN models in transfer learning and deep feature plus SVM approach. Initially, the deep feature of three fully connected layers, i.e. fc6, fc7 and fc8 of AlexNet, vgg16 and vgg19 were extracted. These features were used by SVM for classification purpose. The feature of fc6 had significant contribution towards classification compared to features of fc7 and fc8. Hence, only the feature of the fc6 layer of AlexNet, vgg16 and vgg19 was considered for choosing the best classification model. The best classification model was chosen by statistical analysis, i.e. Tukey's honest significance test. The resnet50 plus SVM was the superior classification model with F1 score of 0.9838 and 69 s training time among deep feature approach. There was no statistical difference among the CNN models in the transfer learning approach. Among small CNN models, the deep feature of mobilenetv2 plus SVM had F1 score of 0.9796 and training time 48 s. This one is a comparable model with resnet50 plus SVM. In bag-of-features approach, the F1 score was not satisfactory, i.e. 0.867. Also, the F1 score of traditional methods was very less. This research is carried forward with more varieties of rice diseases and more fine-tuned CNN model with the expectation of better performance. Additionally, the subsequent research develops an integrated application to fit in low-end devices.

## 5. Authors statement

PKS is the corresponding author, and was involved in data collection, data analysis, mathematical model design and simulation setup. SKB was responsible for analysing the related work and determining the simulation components needed to setup the simulation experiments. NKB and AKR were the mentor and guiding us for overall writing of the manuscript and putting together all needed formats for journal submission. All authors have contributed to the content of this paper and have agreed to submission policy of this journal. All authors read and approved the final manuscript.

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## Data availability

The four varieties of diseased rice leaf images used in this study makes available in "https://data.mendeley.com/datasets/fwcj7stb8r/draft?a = d8923d70-cfc6-4c6c-adc0-640f10152fdf" and can be shared on request.

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The Authors have no significant competing financial, professional or personal interests that might have influenced the performance or presentation of work described in this manuscript.

## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.compag.2020.105527.

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