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Handling hypercolumn deep features in machine learning for rice leaf disease classification

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Abstract
Rice leaf disease, which is a plant disease, causes a decrease in rice production and more importantly, environmental pollution. 10–15% of the losses in rice production are due to rice plant diseases. Automatic recognition of rice leaf disease by computer-assisted expert systems is a promising solution to overcome this problem and to bear the shortage of field experts in this field. Many studies have been conducted using features extracted from deep learning architectures, so far. This study includes keypoint detection on the image, hypercolumn deep feature extraction from CNN layers, and classification stages. The hypercolumn is a vector that contains the activations of all CNN layers for a pixel. Keypoints are prominent points in the images that define what stands out in the image. The first step of the model proposed in this study includes the detection of keypoints on the image and then the extraction of hypercolumn features based on the interest points. In the second step, machine learning experiments are carried out by running classifier algorithms on the features extracted. The evaluation results show that the proposed approach in this paper can detect rice leaf diseases. Furthermore, the Random Forest classifier presented a very successful performance on hypercolumn deep features with 93.06% accuracy, 89.58% sensitivity, 94.79% specificity, and 89.58% precision. As a result, the proposed approach can be integrated into computer-aided rice leaf disease diagnosis systems and so support field experts.

Keywords Rice leaf disease · Important keypoint detection · Hypercolumn deep features · Deep learning · Machine learning

1 Introduction

Plant disease, which is variations and deterioration of the structure of the plant, affects the vital functions of the plant. Plant disease is mainly caused by bacteria, fungi, microscopic animals,

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or viruses and has a strong impact on agricultural yield and farm budget [17]. 10–15% of the losses in rice production are caused by rice plant diseases. Rice diseases not only cause a decrease in production but also environmental pollution. [23]. Usually, the detection of rice diseases is carried out by visual inspection or laboratory experiments. Visual inspection is done only by field experts and is time-consuming. Laboratory experiments need a chemically reactive and complex process [29]. Automatically detecting plant diseases by image analysis is a hopeful solution to overcome this problem and tolerate the problem of the lack of expertise in this field [26]. Developments in the field of artificial intelligence present an opportunity for the construction of computer-aided models to contribute to the solutions to agricultural field problems such as plant disease characterization [17], grape leaf disease classification [40], tomato leaf classification [31], identification of coral reef fishes [39], fish segmentation [2], viral infection detection [14], avian diversity monitoring [15], plankton classification [20], fish detection and species classification [12], detection and classification of soybean pests [34], differentiation of downy mildew and spider mite in grapevine [11], rice leaf disease [13], butterfly segmentation [33], cash crop disease identification [41], anthracnose infected trees classification [3], segmentation of apple tree canopies and trellis wires canopies [21], and temporal data classification [7].

Feature extraction techniques called handcraft features extraction are used for features to be used in classical machine learning studies. Many studies [1, 4, 9, 16, 24, 35], involving the diagnosis of rice disease based on image processing and machine learning, have been published in the literature, so far. In recent years, developments in computer technology have enabled the effective use of models based on deep learning architectures that offer high performance in many studies. While the features required in classical machine learning approaches are extracted manually in experiments, deep learning models containing layers of convolutional neural networks automatically extract features that represent images. Deep learning-based feature extraction techniques outperform handcrafted feature extraction techniques [18]. Deep learning models are widely used for the recognition and classification of plant diseases in agriculture as well as in many other fields. For example, Ghosal and Sarkar achieved 92.46% accuracy with a deep learning model based on transfer learning on the dataset they prepared [10]. Chen et al. used transfer learning based on a pre-trained MobileNet-V2 architecture on ImageNet and proposed a new model in which they incorporate the attention mechanism to identify types of rice plant diseases [8]. Yan et al. proposed a model based on the modified VGG-16 to identify apple leaf diseases. The authors used a global average pooling layer instead of the fully linked layer to reduce the parameters in their proposed model [42].

Sethyet al. used deep capabilities based on transfer learning-based deep learning architectures for the detection of four types of rice leaf disease. Then, they evaluated the performance of pre-trained deep learning and deep feature extraction methods. Accordingly, Resnet50 + SVM presented the best performance with a 98.38% value of accuracy [29]. Jiang et al. combined CNN and SVM for the detection of rice leaf disease. Also, they used the mean shift algorithm and CNN to extract the optimal feature parameters, and achieved a high success rate with an average correct recognition rate of 96.8% [13]. Bhattacharyaet al. used a Convolutional Neural Network (CNN) model with a deep learning approach to automatically classify three types of rice leaf disease, such as bacterial blight, burst, and brown spot. In their proposed study, which has two stages, they first classified healthy and unhealthy leaves with 94% accuracy, and then unhealthy leaves with 78.44% accuracy [6]. Patidar et al. classified rice leaf diseases with 95.83% accuracy using a residual neural network. In their proposed model, CNN and SVM outperformed other models [22].

Lu et al. achieved higher accuracy with the CNN-based model than the traditional machine learning model with 10-fold cross-validation on the dataset containing diseased and healthy rice leaves [19]. Bari et al. classified rice blast, brown spot, and hispa rice leaf diseases, also healthy rice leaves with high success, using a Faster R-CNN model [5]. As seen, CNN-based studies are widely used in the literature. Since there are only state-of-the-art machine learning and deep learning studies in the literature on rice leaf disease, the focus of the proposed study is to examine the extraction of hypercolumn deep features, and the performance of well-known classifiers fed with these features. Some studies on different areas in the literature where this technique is used are as follow; classification of brain magnetic resonance imaging [36], classification of Alzheimer's disease [38] and breast cancer diagnosis [37]. However, it has been observed that no studies have been carried out based on hypercolumn characteristics about agriculture problems.

This study was carried out with the motivation to design expert systems that detect rice leaf disease images quickly and accurately and provide support to field experts. With this motivation, a solution is presented with the detection of keypoints on images for the question of "How to obtain distinctive features with hypercolumn deep features extraction?". Here, the role of the keypoint detector for extracting hypercolumn deep features was focused on, in other words, in order to detect distinctive features. Accordingly, in the proposed study, firstly, keypoints were determined on the rice leaf images with Oriented FAST and Rotated BRIEF (ORB) keypoint detector. Hypercolumn deep features were extracted from the five convolutional layers of the VGG-1616 model by taking as a reference to locations of the keypoints. The hypercolumn deep features extracted from some layers were concatenated and training of the algorithm was carried out on the training set. Furthermore, the proposed study differs from approaches in the literature, especially by classifying the hypercolumn deep features for each keypoint detected for each image in the testing set and then detecting the target class by applying the majority voting technique, and therefore it has originality. In this context, the following statements summarize the major contributions of this study.

- This study is to address the detection of keypoints for each image in the testing set, the extraction of hypercolumn deep features, and the individually classification of each of these features, and the subsequent voting of the classification results.
- The proposed approach offers considerable accuracy for detecting rice leaf disease.

The rest of this study is structured as follows. Section 2 explains the dataset and gives information about the methodology used in this study. Experimental studies are presented in detail in Section 3. The results are presented and discussed in Section 4. Finally, the study is concluded with final remarks in Section 5.

2 Material and method

The main aim of this study is to propose a model that performs the classification of rice leaf disease including Bacterial leaf blight, Brown spot, and Leaf smut in a stable and efficient manner. In this context, this paper introduces a new approach based on hypercolumn deep features to detect rice leaf disease. The important keypoints on the images in the training set are detected, and then the hypercolumn deep features are extracted from these points based on the VGG-16 architecture. The performances of the Random Forest (RF), Multi-layer Perceptron

(MLP) and Support Vector Machines (SVM) classifiers trained with hypercolumn deep features are evaluated in the testing set. Thus, the performances of different models are discussed. The general blog diagram of the proposed model is shown in Fig. 1. Accordingly, the steps of the workflow are as follows:

1. Keypoints that are sharp transitions on the image are detected.
2. Hypercolumn deep features are extracted from some layers of the CNN that are fed with the RGB image.
3. The hypercolumn deep features extracted from various keypoints on the images in the training set are concatenated and matched with the images' class labels. As a result, the hypercolumn deep feature set required for classifier training is constructed.
4. The performances of various classifiers trained on these features are evaluated on the images in the testing set, and thus a comparative analysis of the classifiers is conducted.

2.1 Dataset

The rice leaf disease dataset, composed and published by Prajapati et al. [25], was used in this study. This dataset contains images of infected rice plants taken with a digital camera in a rice

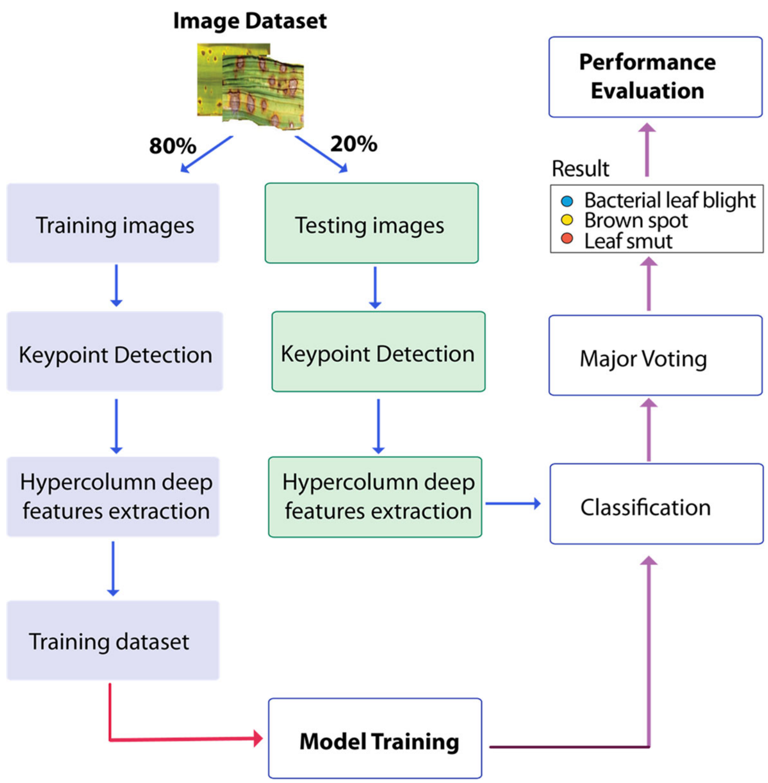


Fig. 1 Overview of the proposed model

field. The dataset contains 120 diseased rice leaf images with different resolutions, 40 of which are bacterial leaf blight, 40 brown spot, and 40 leaf smut. Figure 2 shows three types of rice leaf disease.

2.2 ORB Keypoint detector

The keypoint detector detected the keypoints, called the points where there are sharp transitions on image are used in many disciplines. Moreover, there are numerous keypoint detection algorithms available in the literature. One of the keypoint detection algorithms, ORB, is less affected by noised image and is as successful as the SIFT algorithm, and is also almost twice as fast. ORB is similar to Binary Robust Independent Elementary Features (BRIEF) detector with some modifications to improve performance [28]. The ORB first extracts keypoints from an image using a scale-invariant version of the Features from Accelerated and Segments Test (FAST) feature detector [30]. The ORB detector uses the centroid of intensity [27], which assumes that the intensity of a corner is offset from its center. Rosin employs Eq. 1 to calculate patch image moments. The centroid, C, is found using these moments, as shown in Eq. 2.

$$m_{pq} = \sum_{x,y} x^p y^q I(x,y) \tag{1}$$

$$C = \left(\frac{m_{10}}{m_{00}}, \frac{m_{01}}{m_{00}}\right) \tag{2}$$

2.3 Hypercolumn deep features

Hypercolumn is the vector of activations of all CNN units for a pixel. In other words, the hypercolumn denotes the vector of features extracted from all CNN layers. While CNN

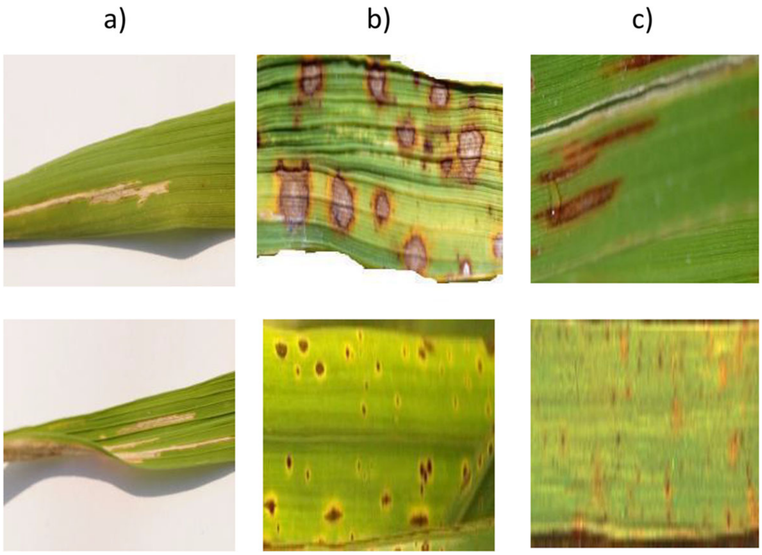


Fig. 2 Sample images for each class; From left to right; (**a**) Bacterial leaf blight, (**b**) Brown spot, (**c**) Leaf smut

typically uses the features in the last fully connected layer for classification, this technique uses the features in the previous layers, thus aiming to make the network more successful [36]. Figure 3 demonstrates the extraction of hypercolumn deep features from some layers of CNN.

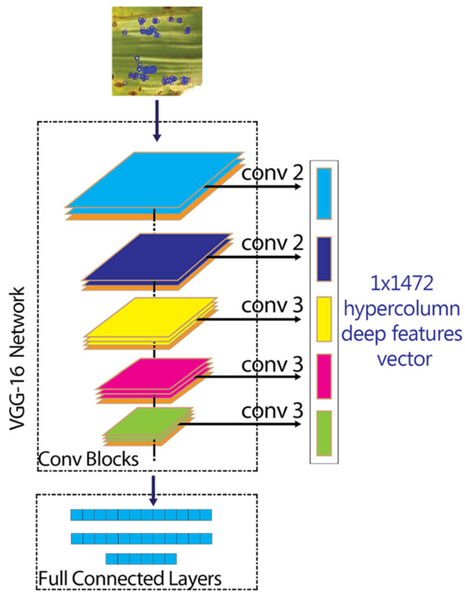
2.4 VGG-16 architecture

VGG-16 network developed by Simonyan and Zisserman is a CNN architecture trained on millions of images [32]. This network won the Large-Scale Visual Recognition Challenge held in 2014 with an accuracy score of 92.7% on the ImageNet dataset, which contains approximately 1.2 million images and 1000 class categories. The VGG-16 model consists of a total of 16 layers, including the input layer, 13 convolutions, and 3 fully connected layers. This network is a very commonly used pre-trained model for datasets containing several images.

2.5 Performance metrics

There are three types of rice leaf disease in the dataset and multi-class classifications are performed within this framework. In such classifications, the performances of the models are calculated by using true positive (TP), true negative (TN), false positive (FP), and false negative (FN) basic criteria in the confusion matrix. Here, TP and TN refer to the number of images that are correctly classified by the model, while FP and FN refer to the number of images that are incorrectly classified. The performances of the models developed are evaluated with some metrics such as Accuracy (Acc), Sensitivity (Sen), Specificity (Spe), and Precision (Pre) which are calculated, using the criteria mentioned above. Equations between 3 and 6 are used for two-class classification while Equations between 7 and 10 are used for multi-class classification. In multi-class problems, the relevant metric is calculated by taking the average of the results obtained for each class. For example, the average accuracy value depicts the mean of accuracies obtained for each class.

Fig. 3 Extracting the hypercolumn deep features from one keypoint



For a class p,

$$Acc(p) = \frac{TP + TN}{TP + FN + TN + FP} \tag{3}$$

$$Sen(p) = \frac{TP}{TP + FN} \tag{4}$$

$$Spe(p) = \frac{TN}{TN + FP} \tag{5}$$

$$Pre(p) = \frac{TP}{TP + FP} \tag{6}$$

$$Average\ Acc = \frac{1}{\#classes} \sum_{p=1}^{\#classes} Acc(p) \tag{7}$$

$$Average\ Sen = \frac{1}{\#classes} \sum_{p=1}^{\#classes} Sen(p) \tag{8}$$

$$Average\ Spe = \frac{1}{\#classes} \sum_{p=1}^{\#classes} Spe(p) \tag{9}$$

$$Average\ Pre = \frac{1}{\#classes} \sum_{p=1}^{\#classes} Pre(p) \tag{10}$$

3 Experiments

3.1 Experimental environment

All experiments were implemented using Python language including Keras and Tensorflow libraries on a 64-bit Windows 10 operating system running on Intel @ 1.850 GHz CPU and 8 GB RAM.

3.2 Keypoint detection and hypercolumn deep features extraction

Before keypoint detection, the images in the training set were set to 224 × 224 sizes, and then the keypoints on these images were detected by the ORB detector. It must be noted that ORB was used only for keypoint detection. Figure 4 shows the keypoints detected on the image with blue circles. Then, the images in the training set were sent to the VGG-16 network and hypercolumn features were extracted from some layers of this pre-trained network with

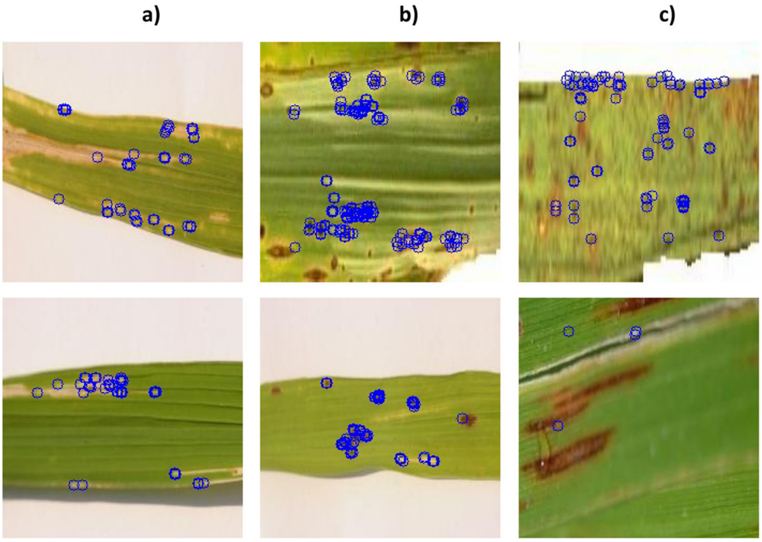


Fig. 4 Detecting of the keypoints; From left to right (**a**) Bacterial leaf blight, (**b**) Brown spot, (**c**) Leaf smut

reference to the keypoints determined in the previous step. For example, suppose that there is a keypoint on the image at coordinates x = 200, y = 300. The dimensions of the convolutional layers of the VGG-16 network were set to the size of the input image to extract hypercolumn deep features. Hypercolumn deep features were obtained by concatenating the hypercolumn deep feature vectors extracted from different layers for any keypoint. Thus, hypercolumn deep features were extracted as many as the number of keypoints detected on each RGB image. VGG-16 pre-trained model was chosen rather than a CNN to be built from scratch for extracting hypercolumn deep features, which is the core item of this study. Because, while a CNN model built from scratch on datasets including few samples has an overfitting and convergence disadvantages, the pre-trained CNN model with transfer learning and fine-tuning strategy is quite successful. VGG-16 network which has been proven successful on medical images in the literature was preferred to extract hypercolumn deep features. In the last stage, the training set was composed by labeling the hypercolumn deep features extracted from all keypoints, and target class information for each image.

3.3 Model training and testing

In this study, experiments were carried out within the framework of two scenarios. While the first scenario includes original images, the second scenario includes images obtained through a data augmentation technique. In the first scenario, the dataset is split into randomly 60:40 ratios for the training and testing sets. The numbers of training and testing sets in the public dataset at Scenario 1 are 72 and 48, respectively. There are 24 samples for each class in the training dataset. Table 1 summarizes the training and testing sets for the original dataset.

In the second scenario, the workflow is the same as the first scenario, and also data augmentation techniques which are rotation, flipping, and scaling were applied to the images in the training set to improve the model performance. Therefore, the number of images in the training set has reached four times. Thus, the training dataset contains a total of 288 images, 96 images for each class. Table 2 summarizes the training and testing sets used in scenario 2.

Table 1 Split of the images into train and test sets in the original dataset

Original dataset		Train (60%)	Test (40%)	Total
Classes	bacterial leaf blight	24	16	40
	brown stain	24	16	40
	leaf soot	24	16	40
Total		72	48	120

Important keypoints were detected by the ORB detector on the images in both training sets. Then, the hypercolumn deep feature vectors extracted from the 2,5,9,13 and 17th layers of the VGG-16 architecture were concatenated and the hypercolumn deep features set required for model training was composed. The hypercolumn deep feature vector extracted from each keypoint is labeled with the target class to which the image belongs. For example, all hypercolumn features extracted from the B image that is in the category of 'A' disease were labeled to class 'A'. All layers of the pre-trained VGG-16 architecture were set to be retrained to extract meaningful features. Then, three traditional classifier algorithms such as MLP, RF, and SVM were trained on the hypercolumn deep features extracted from the images in the training set. The number of trees is set to 100 in the RF which is an ensemble of decision trees. The 'Adam' optimization method, the Rectified Linear Unit activation function, and 100 hidden layers were used for MLP, which is inspired by the work of the human brain. The 'Radial Basis Function' kernel function was used for SVM which uses the optimal hyperplane to better classify the data, and also the polynomial degree was set to 3. After the training of the classifier algorithms on the original and augmented images, the keypoint detections were automatically performed on the testing images in the phase of the validation of models. Extracting hypercolumn features from the keypoints, the classification of each feature vector separately, and the target class prediction with the majority voting for an image was carried out in the final stage.

The fact that the CNN network is fed with the matrix form in two-dimensional as shown in Fig. 5 is known by everyone. The proposed approach that is based on automatic detection of keypoints and the subsequent extraction of hypercolumn deep features space is a handicap for CNN models. Automatically detecting the keypoints in a different number from each image is an obstacle to obtaining the required matrix structure for CNN. For example, 18 keypoints and 18×1472 features may be extracted for one image, while 146 keypoints and 146×1472 may be features for another image. The numbers 18 and 146 values are symbolic here. For a matrix that has nx1472 dimensions, the manipulations below are inevitable to overcome these problems on the features set.

Table 2 Split of the images in the augmented dataset into train and test sets

Augmentated dataset		Train (60% + Augmentated images)	Test (40%)	Total
Classes	bacterial leaf blight	96	16	112
	brown stain	96	16	112
	leaf soot	96	16	112
Total		288	48	336

$$A_{mxn} = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ a_{31} & a_{32} & \cdots & a_{3n} \\ \vdots & & \ddots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{bmatrix}$$

Fig. 5 A matrix form

(1) Some keypoints are removed randomly on the image that includes many keypoints detected.
(2) When fewer keypoints are detected on the image, the missing parts in the feature set are filled with zero.

In this study, a model that prevents the loss of keypoints on the image and does not include the above disadvantages was proposed. The problems mentioned above are not encountered in the proposed study since hypercolumn deep features are automatically extracted and labeled with the target class.

4 Results and discussion

Figure 6 shows the performance of the RF, SVM, and MLP classifiers on the testing set with confusion matrix form. Here, "before augmentation" and "after augmentation" refer to the performances of the classifiers trained on the training sets in Scenarios 1 and 2, respectively, on the testing set. In addition, Table 3 summarizes the average accuracy, sensitivity, specificity, and precision. This table presents the achievements of the classifiers on the testing set according to Scenarios 1 and 2. As can be seen in this table, Scenario 2 has improved the performances of RF and MLP classifiers except for SVM. Moreover, the RF model presented the best performance compared to MLP and SVM classifiers regarding accuracy, sensitivity, specificity and precision metrics. While the RF presents the highest accuracy with 93.06%, MLP presents the lowest accuracy with 90.28%. Additionally, RF offered the highest sensitivity with 89.58%, while MLP offered the lowest sensitivity with 85.42%. The RF gives the highest specificity with 94.79%, while MLP gives the lowest specificity with 92.71%. The RF offers the highest specificity with 89.58%, while MLP offers the lowest specificity with 85.42%. In terms of sensitivity and precision metrics, there was a 6.25% improvement for RF and 2.09% for MLP in Scenario 2 compared to Scenario 1, while the performance of SVM remained unchanged. In addition, there are a 3.12% improvement for RF and 1.04% for MLP in terms of specificity, while there is no change for SVM.

Transfer learning-based deep features were also sent to the classifiers in order to demonstrate the effectiveness of hypercolumn deep features in this study. In this context, the performances of RF, MLP, and SVM classifiers on the deep features obtained by the transfer learning approach from the VGG-16 network were given in Table 4. Accordingly, Scenario 2 has no positive effect on the performance of the classifiers trained on

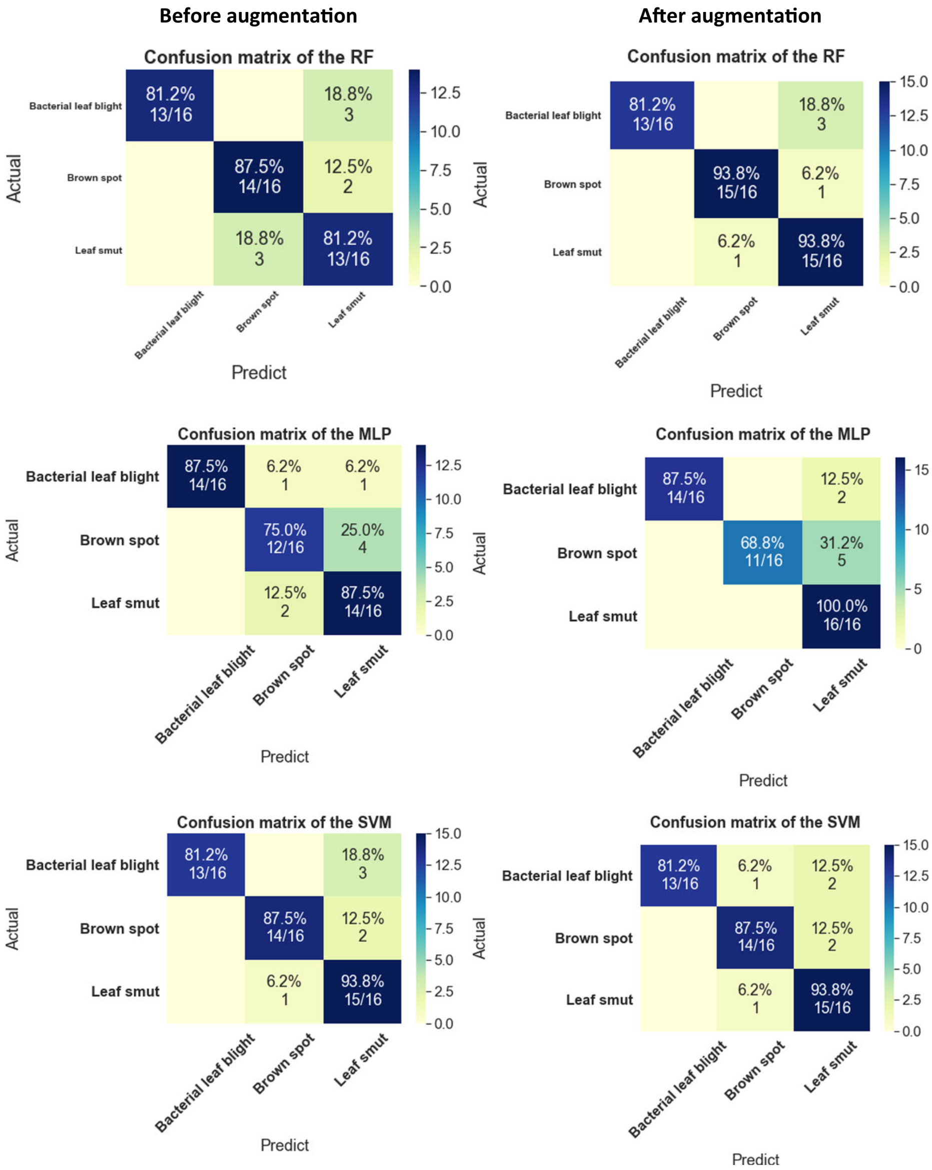


Fig. 6 Confusion matrices obtained on the test dataset

the deep features obtained by transfer learning compared to Scenario 1. Moreover, as can be seen by comparing Tables 3 and 4, the performances of the classifiers on hypercolumn deep features used in this study are better than their performances on deep features based on the transfer learning approach. Therefore, it can be said that hypercolumn deep features are more meaningful in machine learning than deep features obtained by transfer learning.

In addition, the receiver operating characteristic curves of the models built on the hypercolumn deep features are shown in Fig. 7. The values of Area Under Curve (AUC) are

Table 3 Average results obtained by the models on the testing set

	Sen (%)	Spe (%)	Pre (%)	Acc (%)
Scenario 1 (Data Augmentation: No)				
RF	83.33	91.67	83.33	88.89
MLP	83.33	91.67	83.33	88.89
SVM	87.5	93.75	87.5	91.67
Scenario 2 (Data Augmentation: Yes)				
RF	**89.58**	**94.79**	**89.58**	**93.06**
MLP	85.42	92.71	85.42	90.28
SVM	87.5	93.75	87.5	91.67

#Bold values indicate the best results.

improved for the brown spot and leaf smut classes excluded the bacterial leaf light class after the augmentation technique. Accordingly, the MLP has better classification performance than others with 0.938 and 0.953 values of AUC for the bacterial leaf blight and brown spot classes, respectively. Lastly, the RF and SVM have better classification performance than MLP with a 0.906 value of AUC for the leaf smut class.

The general classification performances of the classifiers for this problem are also shown in Fig. 8. Accordingly, while the general classification performances of the RF and MLP classifiers improve by 4.17% and 1.39%, respectively, with Scenario 2, SVM shows no improvement.

Table 5 summarizes the best results obtained with the model proposed in this study for classifying rice leaf disease types, and the results of machine learning and deep learning-based studies in the literature. Here, it is aimed to make a discussion by comparing the performances of different architectures, topologies, and approaches. VGG-16 network, which is one of the various pre-trained models used by Tom et al., presented 99.17% accuracy based on transfer learning on tomato plant leaf images containing one healthy and eight disease classes in the PlantVillage Database [31]. Ghosal and Sarkar reported that the transfer learning approach presented an accuracy of 92.46% on the rice leaf disease classification [10]. Chen et al. [8] achieved very high performance with the pre-trained MobileNet-V2 model and light attention networks on the dataset used in their study. Bhattacharya et al. reported that their proposed CNN framework was more successful in two-class classification than the multi-class classification [6]. The deep residual learning model proposed by Patidar et al. gave a good performance with a %95.83 value of accuracy [22]. Lu et al. reached a 95.48% value of accuracy using the CNN-based model with the 10-fold cross-validation [19]. Bari et al.

Table 4 Average results obtained by the models on the deep features based on transfer learning

	Sen (%)	Spe (%)	Pre (%)	Acc (%)
Data Augmentation: No				
RF	77.08	88.54	77.08	84.72
MLP	77.08	88.54	77.08	84.72
SVM	66.67	83.33	66.67	77.78
Data Augmentation: Yes				
RF	77.08	88.54	77.08	84.72
MLP	77.08	88.54	77.08	84.72
SVM	66.67	83.33	66.67	77.78

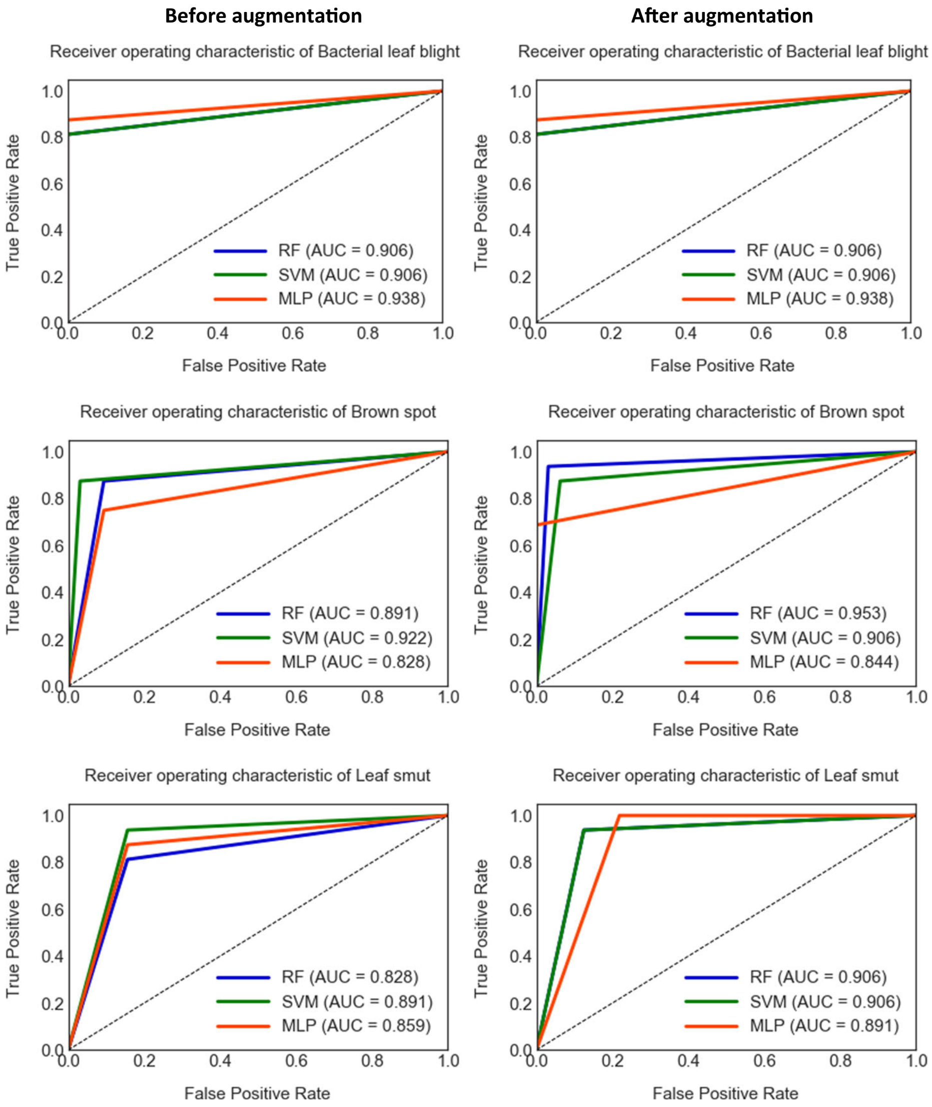


Fig. 7 ROC graphs of the models for each class on the original dataset: from top to bottom; (**a**) Bacterial leaf blight, (**b**) Brown spot, (**c**) Leaf smut

classified rice blast, brown spot, and hispa rice leaf diseases, as well as, healthy rice leaves with high success with the Faster R-CNN model [5]. Prajapati et al. carried out multi-class classification with the hand-crafted features and SVM in their study and achieved 93.33% accuracy in the training dataset and 73.33% on the test dataset. In addition, they achieved 83.80% and 88.57% accuracies with 5-fold and 10-fold cross-validation techniques, respectively [25]. As seen in this table, the deep learning-based studies offered higher performance than the study of Prajapati et al. [25]. Compared to deep learning studies, the proposed approach in this study reached an acceptable level of accuracy with 93.06% on the dataset published by Prajapati et al. [25].

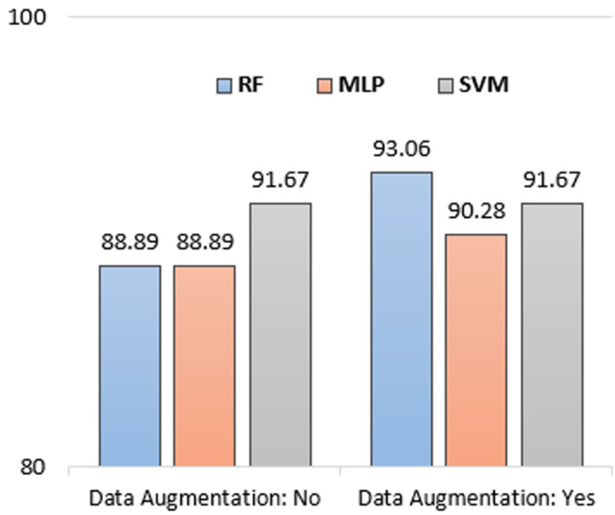


Fig. 8 Classification results of the models

5 Conclusion

In this study, a keypoint detection and hypercolumn deep feature extraction-based model was proposed to classify different rice leaf diseases including bacterial leaf blight, brown spot, and beaf smut. The model uses hypercolumn deep features extracted from some layers of the VGG-16 deep learning architecture as input data for the classifiers. The classifier reaches a decision for each hypercolumn deep features vector extracted from the important keypoints automatically detected in the testing set, and then the final classification is made by applying the majority voting technique. In experiments, the proposed model having a 93.06% value of accuracy outperformed the transfer learning approach having an 84.72% value of accuracy. Moreover, the RF classifier offered the best performance with 89.58% Sen value, 94.79% Spe value, and 89.58% Pre in the proposed model. Although the operations regarding an image in this study increase in direct proportion to the number of keypoints, the main subject in decision support systems based on artificial intelligence is an achievement of the classifier. From this point of view, it is thought that the approach proposed in this study will contribute to the literature, especially in problems where pre-trained or built from scratch CNN-based models cannot provide successful performance. Also, the proposed study with a low-cost based on deep learning architecture could play an important role in the development of expert systems to be designed for field experts. Thus, the mistakes arising from the subjective opinions of experts will be minimized.

The limitation of this study is the small number of samples in the dataset. This problem was tried to be solved with the data augmentation techniques applied to the images in the training set. In addition, the VGG-16 pre-trained network was used to overcome the overfitting and convergence problems. In future studies, it is planned to obtain a model that can be generalized to more than one dataset by conducting experimental studies on different datasets related to rice leaf disease. Finally, the use of other deep learning architectures that can achieve better performance in computer vision is among the targets in future studies.

Table 5 Comparison of the proposed model and the studies in literature

Study	Method	Dataset / Number of classes	Acc (%)
Ghosal and Sarkar [10]	Deep learning model based on transfer learning	Different	92.46
Chen et al. [8]	MobileNet-V2 and lightweight attention networks	Different	99.67%
Bhattacharya [6]	CNN framework	Different	2-class, 94.0 Multi-class, 78.44
Patidar et al. [22]	Deep Residual Learning	Different	95.83
Lu et al. [19]	CNN with 10-fold	Different / 10-classes	95.48
Bari et al. [5]	Faster-RCNN	Different / 4-classes	Rice blast: 98.09 Brown spot:98.85 Hispa: 99.17 Healthy rice leaf: 99.25
Prajapati et al. [25]	Image processing operations + SVM	Same dataset / 3-classes	73.33
	SVM with 5-fold		83.80
	SVM with 10-fold		88.57
This study	Hyper-column deep features and RF classifier	Same dataset / 3-classes	**93.06**

Bold value indicates the result obtained in this study

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Declaration of competing interest The author declares that he has no conflicts of interest.

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