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RESEARCH ARTICLE

Distinguishing rice varieties using plant image analysis by deep learning methods

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Abstract

Among the rice varieties developed for different purposes, Basmati varieties are unique for their morphological characters and quality. The origin, evolution and development of Basmati varieties has thrown challenges in terms of varietal classification and correct identification. Besides the classical method used in DUS testing for variety identification, new method consisting of whole plant images using deep learning algorithms was studied to identify basmati rice varieties. Classification of varieties by images of whole plant at different growth stages using deep learning algorithms was carried out to find the best algorithm and the best stage for effective discrimination of varieties. The ripening stage (terminal panicles ripened) was identified as the most suitable stage for effective classification of the varieties among the four stages namely, booting stage, 50% flowering, milk stage and ripening stage. The testing accuracy of all algorithms ranged between 60 to 73%. The testing accuracy at the ripening stage was found to be 73% using VGG 16, a deep learning model. Pusa Basmati 1609 and Pusa Basmati 1637 were identified with 100% accuracy. High testing accuracy was observed in identifying some other varieties namely, Pusa Basmati 1121, Pusa Basmati 1401, Pusa Basmati 1609, Pusa Sugandh 3. There was a high chance of misclassification among the genetically close varieties. Genetically close varieties that could not be differentiated using leaf and panicle characteristics, could be classified up to 90% accuracy using plant images and VGG 16. From this study it is concluded that plant image analysis by deep learning methods can be a viable alternative approach for identification of rice varieties.

Keywords: Plant image, Deep learning model, Variety identification, rice.

Introduction

Identification and differentiation of varieties based on morphological and quality parameters are essential for varietal rights and commerce. Rapid identification can help in quick introduction and further genetic improvement if needed (Korir et al. 2012). The classical method of variety identification recognized by the International Union for the Protection of New Varieties of Plants (UPOV) and Protection of Plant Varieties & Farmers' Rights Authority (PPV & FRA) of India is the DUS (Distinctiveness, Uniformity, Stability) test. It involves the recording of morphological descriptors (62 in the case of *Oryza sativa*) of different plant parts and at different growth stages. The main disadvantage of this approach is that it is a very slow method, and confusing when the varieties are very similar, and for example, varieties have similar parentage. Manual interpretation is often subjective and observer-dependent. In addition, polygenic traits are highly influenced by environmental factors. Additionally, some gene effects are pleiotropic or epistatic in nature.

New approaches to variety identification based on DNA markers have been developed. The primary advantage of this method is that it is dependent on the genetic differences of individuals and is not affected by the environment. Besides being costly, these DNA-based molecular approaches

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Table 1. Morphological characteristics of plant and grain of rice varieties as per DUS guideline based on CVRC proposal

S.No.	Variety	HT	FLA	SL	PL	PC	PAB	DGL	DGS	GC	AN
1.	Pusa Basmati 1	Medium	Semi-erect	Short	Very long	Deflexed	Erect to semi-erect	Long	Long slender	Light brown	Present
2.	Pusa Sugandh 5 (LGA)	Medium	Erect	Short	Medium	Deflexed	Semi-erect	Long	Long slender	Light brown	Absent
3.	Pusa Basmati 1121 (PB 1121)	Medium	Semi-erect	Short	Long	Deflexed	Erect to to semi-erect	Extra long	Extra long slender	Light brown	Present
4.	Pusa 1401 (Pusa Basmati 6)	Medium	Semi-erect	Very short	Medium	Deflexed	Semi-erect	Extra long	Extra long slender	Light brown	Present
5.	Improved Pusa Basmati 1 (Pusa 1460)	Medium	-	Short	Long	-	-	Extra long	Extra long slender	Light brown	Present
6.	Pusa Basmati 1509	Medium	-	Short	Long	-	-	Extra long	Extra long slender	Light brown	Absent
7.	Pusa Basmati 1609	Medium	Erect	Very Short	Long	Deflexed	Semi-erect	Extra long	Extra long slender	Light brown	Present
8.	Pusa Basmati 1637	Medium	Semi-erect	Short	Long	Deflexed	Erect to semi-erect	Extra long	Extra long slender	Light brown	Present
9.	Pusa Basmati 1728	Medium	Semi-erect	Short	Medium	Deflexed	Semi-erect	Extra long	Extra long slender	Light brown	Present
10.	Pusa Basmati 1718	Medium	Semi-erect	Short	Very long	Deflexed	Semi-erect	Extra long	Extra long slender	Light brown	Present
11.	Pusa Basmati 1692	Early	Erect	Very short	Very long	Semi-straight	Semi-erect	Extra long	Extra long slender	Light brown	Absent

are not accepted either by UPOV or PPV & FRA of India mainly because of analysis strategies of DNA fingerprinting that depend on primers and polymorphic markers, which may not be universal in identifying varieties of a crop.

Among the rice varieties developed for different purposes, Basmati varieties are unique for their morphological characters and quality. In the eyes of consumers and traders, rice is considered to be Basmati if it possesses a harmonious combination of minimum kernel dimension, the intensity of aroma, the texture of cooked rice, high volume expansion during cooking showing linear kernel elongation and minimum breadth-wise swelling, fluffiness, palatability, easy digestibility, and longer shelf life (Singh 2000). Basmati varieties have been developed using a limited germplasm base and grown in a relatively small geographical area in India. Therefore, the diversity of DUS-defined traits among the Basmati varieties is low, which makes variety identification a difficult task for plant breeders, seed technologists and producers, particularly at the field level (Table 1).

Variety identification of not only plants but also animals (Trnovszky et al. 2017) and insects (Sagar et al. 2020) was done with the help of images using machine learning models. Learning a sub-set of images in Machine Learning enables computers to solve more complex problems with the computation of multilayer neural networks. Attempts have been made to use image analysis for identification of varieties based on images of seeds (Chatnuntawech et al. 2018; Aznan et al. 2017; Kiratiratanapruk et al. 2020) and other parts of the plant like inflorescence (Raznny et al. 2022). No attempt has been made in India to comprehensively study the classification of varieties based on the whole plant, plant parts and the seeds, in particular.

Therefore, it is necessary to explore precise methods to characterize closely related varieties using plant morphology-based traits as a whole, which human eyes may not discern. With this background, we have attempted to use a convolution neural network (CNN) as a solution for the identification of rice varieties, particularly since the size of the training dataset used to train an algorithm has an influence on their efficiency. Collection of large datasets from field-grown plants of many varieties at an appropriate stage is a difficult task. Therefore, with the minimum possible dataset in some known varieties, we aimed to examine the scope and potential of using the CNN

Table 2. List of varieties and their pedigree used in the study

S. No.	Variety	Pedigree	Year of release
1.	Pusa Basmati 1	Pusa 150/Karnal Local	1989
2.	Pusa Sugandh 2 (LGA)	Pusa 1238-1/Pusa 1238-81-6	2001
3.	Pusa Sugandh 3 (LGA)	Pusa 1238-1/Pusa 1238-81-6	2001
4.	Pusa Sugandh 5 (LGA)	Pusa 3A/Haryana Basmati	2004
5.	Pusa Basmati 1121(PB 1121)	Pusa 614-1-2/Pusa 614-2-4-3	2008
6.	Pusa 1401 (Pusa Basmati 6)	Pusa Basmati1/Pusa 1121-92-2-7-1	2008
7.	Improved Pusa Basmati 1 (Pusa 1460)	Pusa Basmati-1/IRBB55//Pusa Basmati 1	2013
8.	Pusa 1612 (NB)	Pusa Sugandh 5 / C101A51 // Pusa Sugandh 5*2 /Pusa Sugandh 5 / Tetep // Pusa Sugandh5*2	2013
9.	Pusa Basmati 1509	Pusa 1301/ Pusa Basmati 1121	2013
10.	Pusa Basmati 1609	Pusa 1602 / Pusa 1603	2015
11.	Pusa Basmati 1637	Pusa Basmati 1/IRBL 9-W//Pusa Basmati 1*3	2016
12.	Pusa Basmati 1728	PB 6 / Pusa 1460 // PB 6 *3	2016
13.	Pusa Basmati 1718	PB 1121/ SPS 97// PB 1121*3	2017
14.	Pusa Samba 1850 (NB)	BPT5204/DHMASQ164-2b//BPT5204*3	2018
15.	Pusa Basmati 1692	Pusa Basmati 1509/ Pusa 1601	2020

LGA = Long grain aromatic and NB = Non-Basmati

system for identifying Indian basmati varieties under field conditions.

Materials and methods

The experimental material comprised 10 basmati, three long grain aromatic (LGA) and two non-basmati (NB) type released rice varieties in India. The following varieties (Table 2) were grown at the field of the Division of Seed Science and Technology in the monsoon season *(Kharif)*, 2021.

About 30 days old seedlings of the varieties were transplanted using a single seedling per hill with a spacing of 30 × 30 cm in 2 rows of 4.5 m length. The standard package of practices was followed to grow a healthy crop.

Characterization of varieties using DUS guidelines

All the varieties were observed at a particular growth stage and expression of the characteristics was recorded following DUS test guidelines (Annonymous 2007). The varieties were classified using the polymorphic characteristics.

Acquisition of whole plant photograph of rice varieties at different stages of growth

Twelve plants were randomly selected from each variety for capturing photographs using a NIKON D 3200 DSLR camera with an exposure time of 1/1600 seconds and a focal length of 18 mm under open field growing conditions. The photos of the plants were captured at 4 stages of growth of plants, namely booting, 50% flowering, milk stage, and ripening stage (Plate 1). The photographs were captured from 3 angles – top and two opposite sides at almost an equal distance (Plate 2). From each angle 15 photos were captured for each plant. The photos were resized to 1024 X 681 pixels. All pictures were used to train and test using available models of transfer learning of convolution of neural network (CNN). At each stage, four open-source algorithms (Inception V3, RESNET 152V2, VGG 16 and VGG 19) were used to find the best method to classify the varieties. The details regarding the algorithms used are given below.

CNN architecture

Convolutional neural networks (CNNs) are feed-forward networks in which information only moves in one way, from inputs to outputs. An input layer, an output layer, and several hidden layers are all parts of the CNN architecture. It performs a differentiable function on an input volume that converts it to an output.

Deep learning algorithms used for the classification of whole plant images

The following deep learning models (Table 3) were used

- INCEPTION V3 (Third edition, Google) : 48-layer deep model, convolution neural network
- RESNET 152V2: 152 deep layers, a specific type of neural network
- VGG 16: 16 layers deep, convolution neural network
- VGG 19: 19 deep layers, convolution neural network

Confusion matrix

The matrix is represented by the values of four classes (Markoulidakis et al. 2021).

Stage 1 (Booting stage)   Stage 2 (50% Flowering stage)

Stage 3 (Milk stage)   Stage 4 (Ripening stage)

Plate 1. Scheme of imaging the varieties in 4 stages

- True Positive (TP): The real value was positive and it was predicted positive by the model. The diagonal values represent the true positive.
- True Negative (TN): The real value was negative and it was predicted negative by the model.
- False Positive (FP): The real value was negative but was predicted positively by the model.
- False Negative (FN): The real value was positive but predicted negative by the model.

These values were used to define the following.

$$Precision_i = \frac{TP_i}{TP_i + FP_i}$$

$$Recall_i = \frac{TP_i}{TP_i + FN_i}$$

Top view

Side view   Side view 2

Plate 2. Scheme of image acquisition at a particular stage

$$F1\,Score_i = 2\frac{Precision_i . Recall_i}{Precision_i + Recall_i}$$

Results

Characterization and classification of varieties using DUS test guidelines

Fifty-two characteristics were considered to classify the varieties. Of these characteristics twenty-four were monomorphic, i.e., those showed similar expression of characteristics across the varieties studied. Twenty-eight characteristics were found polymorphic.

Identification of growth stage of plant image and model for classification

While analyzing the images, the top-view images could not provide any useful information. Hence, the image analysis was carried out with side-view images. The number of images used for training and testing the algorithms are presented in Table 4. The variety wise images used for training and testing at different stages is presented in Table

Table 3. A brief about the models used

Model	Layers	Filters and information	Activation function	Classification method	References
INCEPTION V3	Total 48 Layers	3 different sizes of filters (1*1, 3*3, 5*5). Average pooling and max pooling are used in the model architecture. 1*1 filters used in 64 and 128 filters. 2*2 filters used in 256 filters. 5*5 filters used in more than 256 filters.	ReLU and Softmax	Supervised Learning	Christian Szegedy et al, 2015
RESNET 152V2	Total 152 Layers	Residual block consists 1*1, 3*3 and 1*1 size of filters are used. 64 filters, 128 filters and 512 filters are used in the model architecture.	ReLU and Softmax	Supervised Learning	K. He, X. Zhang, S. Ren, and J. Sun. 2016
VGG 16	13 Convolution Layers and 3 fully connected layers. Total 16 layers.	Kernel Size of filter is 3*3. Two 64 filters, two 128 filters, three 256 filters, and six 512 filters are used. Five maxpool layers with 2*2 kernel size have been used in the model.	ReLU and Softmax	Supervised Learning	K. Simonyan, A. Zisserman. 2015
VGG 19	16 Convolution Layers and 3 fully connected layers. Total 19 Layers	Kernel Size of filter is 3*3. Two 64 filters, two 128 filters, four 256 filters, and eight 512 filters are used. Five maxpool layers with 2*2 kernel size have been used in the model.	ReLU and Softmax	Supervised Learning	K. Simonyan, A. Zisserman. 2015

Table 4. Number of images used for training and testing the algorithms at different stages

Stage	No. of training image (No. of Variety)	Training accuracy (%)	No. of test image	Test accuracy (%)
Stage 1	3863 (13)		854	
VGG19		84.48		73.21
VGG 16		87.01		62.31
InceptionV3		88.66		61.59
Resnet 152V2		84.93		66.04
Stage 2	3989 (15)		955	
VGG19		82.58		66.36
VGG 16		87.05		68.85
InceptionV3		90.73		62.40
Resnet 152V2		84.69		64.49
Stage 3	4567 (15)		951	
VGG19		81.60		66.36
VGG 16		85.07		61.99
InceptionV3		91.75		54.38
Resnet 152V2		84.63		65.42
Stage 4	4543 (15)		933	
VGG19		95.49		62.16
VGG 16		95.83		72.97
InceptionV3		87.71		59.25
Resnet 152V2		93.06		60.60

Table 5. Variety-wise number of images used at different stages

S. No.	Variety Name	Stage of acquiring image							
		Stage 1		Stage 2		Stage 3		Stage 4	
		Train Image	Test Image	Train Image	Test Image	Train Image	Test Image	Train Image	Test Image
1.	Pusa Basmati 1121	279	79	289	62	314	61	293	64
2.	Pusa 1401	310	62	310	66	312	59	310	62
3.	Pusa Basmati 1509	202	51	286	65	296	62	306	62
4.	Pusa Basmati 1609	309	67	300	49	303	60	284	58
5.	Pusa 1612	320	52	280	65	315	71	307	64
6.	Pusa Basmati 1637	316	66	271	68	288	76	288	45
7.	Pusa Basmati 1692	314	70	281	66	312	61	311	62
8.	Pusa Basmati 1718	300	66	281	66	315	61	304	63
9.	Pusa Basmati 1728	305	61	270	74	311	57	304	63
10.	Improved Pusa Basmati 1	317	68	222	67	308	67	307	62
11.	Pusa Basmati 1	308	78	276	67	310	62	305	62
12.	Pusa Sugandh 5	280	68	213	68	301	54	306	66
13.	Pusa Sugandh 3	-	-	193	50	283	64	305	69
14.	Pusa Sugandh 2	-	-	222	68	288	67	300	62
15.	Pusa Samba 1850	303	66	290	67	311	69	311	65
Total		3863	854	3989	955	4567	951	4543	933

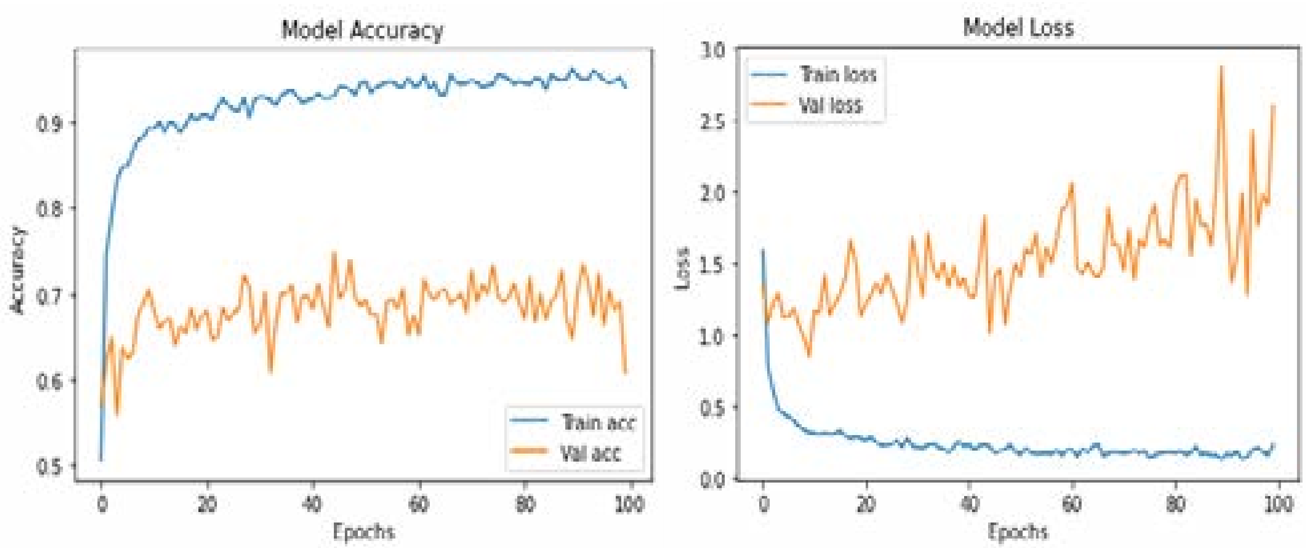

Fig. 5. Graphical representation of VGG 16 model performance on stage 4 of all varieties

5. At stage 1, training accuracy ranged from 84.48 to 88.66% while it was 61.59 to 73.21% for test accuracy. Training accuracy increased up to 90.73% and testing accuracy up to 62.40% by Inception V3 at stage 2. At Stage 3, training accuracy ranged from 81.60 to 91.75%, while it was 54.38 to 66.36% for test accuracy. Further, training accuracy increased to 87.71 to 95.83% and testing accuracy to 59.25 to 72.97% using the four models with a maximum training and test accuracy of 95.83 and 72.97%, respectively, using VGG 16. Therefore, the VGG 16 model could provide the best

Table 6. Precision, recall and F 1 score of each individual variety in the test dataset using VGG 16 at Stage 4

S. No.	Variety	Precision	Recall	F1-Score
1	Pusa Basmati- 1	0.53	0.6	0.56
2	Pusa Sugandh -2	0.5	0.52	0.51
3	Pusa Sugandh 3	0.72	0.81	0.76
4	Pusa Sugandh-5	1	0.08	0.14
5	Pusa Basmati- 1121	0.75	0.88	0.81
6	Pusa Basmati- 1401	0.5	0.92	0.64
7	Improved Pusa Basmati- 1	0.69	0.6	0.64
8	Pusa 1612	0.95	0.63	0.76
9	Pusa Basmati 1509	0.82	0.23	0.35
10	Pusa Basmati- 1609	0.31	1	0.47
11	Pusa Basmati- 1637	0.75	1	0.86
12	Pusa Basmati- 1728	0.74	0.68	0.71
13	Pusa Basmati- 1718	0.95	0.3	0.45
14	Pusa Sambha- 1850	1	0.93	0.96
15	Pusa Basmati- 1692	0.25	0.08	0.12
	Mean	0.69	0.61	0.64

result using plant images at stage 4 among the varieties studied.

The model Inception V3 showed the highest training accuracy up to stage 3 with the lowest testing accuracy, while for the model VGG 16, the training and testing accuracy reached the highest value at stage 4. The curve variation per epoch of loss and accuracy value in both training and testing steps for the VGG 16 has been shown in Fig. 5. The efficiency of the model increased since the epoch number equaled 10/20 and got stability reaching 50, as shown in Fig 5.

The precision, recall, and F1 scores are shown in Table 6. The mean precision, recall, and F1 score of the varieties were 0.69, 0.61 and 0.58, respectively. The values of F1 score for varieties ranged from 12 to 96%. The highest value of F1 is for Pusa Sambha- 1850 (96%) followed by Pusa Basmati 1637 (86%) and Pusa Basmati 1121 (81%). In the range of 60 to 80% F1 score, classification performance was moderately better for Pusa Sugandh 3 (76%), Pusa- 1612 (76%), Pusa Basmati 1728 (71%), Pusa Basmati 1401 (64%), Improved Pusa Basmati 1 (64%). The F1 score was low in the case of Pusa Basmati 1 (56%) and Pusa Sugandh 2 (51%). Further, the classification performance was poor in the case of Pusa Basmati 1692 (12%), Pusa Sugandh 5 (14%), Pusa Basmati 1509 (35%), Pusa Basmati 1718 (45%), Pusa Basmati 1609 (47%). Precision as well as recall, was very low in the case of Pusa Basmati 1692. In the case of Pusa Sugandh 5, the precision was 100%, while recall was only 8% because out of 60 images of Pusa Sugandh, five were correctly classified, whereas 55 images were misclassified to Pusa Basmati 1609.

Fig. 6. Normalized confusion matrix of 15 varieties based on results from VGG16 model at stage 4 The rows represent the true variety and the columns represent the predicted variety. The colors represent the fraction of the true variety that was classified as the corresponding predicted variety. Ideally, squares on the diagonal would be 1(bright) and all others 0 (light).

Identification of varieties based on whole plant image analysis using deep learning model, VGG16

The confusion matrix of classification results from VGG16 model at stage 4 is presented in Fig. 6. In the multiclass confusion matrix (unnormalized), the diagonal elements represent the total number of images classified correctly per variety (true positives per variety). For example, 56 out of 64 images of Pusa Basmati 1121 have been correctly classified as Pusa Basmati 1121. Each row of the confusion matrix represents the total number of actual values for each class label (variety). To get the normalized confusion matrix, each row element is divided by the sum of the entire row. The normalized confusion matrix shows the percentage, i.e., out of all true labels for a particular class, what was the % prediction of each class made for that specific true label? The diagonal value of the normalized confusion matrix is equivalent to the accuracy measure, recall (or true positive rate) for a particular variety. The diagonal values indicated the accurate classification for each variety. It ranged from 8% (in Pusa Basmati 1692 and Pusa Sugandh 5) to as high as 100% in Pusa Basmati 1609 and Pusa Basmati 1637. A low to medium accuracy rate was recorded in all the varieties indicating high chances of misclassification among the varieties. However, the varieties namely, Pusa Basmati 1121, Pusa 1401, Pusa Samba 1850, Pusa 1612, Pusa Basmati 1728 and Pusa Sugandh 3 showed 88, 92, 93, 63, 68, and 81%, respectively showing a high chance of matching with plant images. Pusa Basmati 1509 and Pusa Basmati 1718 showed

Table 7. Differences in leaf characteristics (as per DUS testing guideline) among rice varieties

Variety/ Character	PB-1	PS-2	PS-3	PS-5	PB 1121	P-1401	IPB-1	PB-1612	PB 1509	PB 1609	PB 1592	PB 1637	PB 1728	PB 1718	P 1850	PB 1692
PB-1	-	LIGC, LL,LW, CA,	LIGC, LL,LW, CA,	CA, FLAE, FLAL	FLAE	LL, FLAE, FLAL,CA	-	FIGC, LL, CA, FLAE	LL, CA, FLAL	LL, CA, FLAE	LL, CA, FLAE	FLAE	LL, CA, FLAL, FLAE	-	FLAE, FLAL, LS	LL, CA, FLAE
PS-2		-	-	LIGC, LL, LW, CA, FLAE, FLAL	LIGC, LL ,LW, FLAE	LIGC ,LW, FLAE, FLAL CA,	LIGC, LL, LW,CA,	LIGC, LW, CA, FLAE,	LIGC, ,LW, FLAL	LIGC, ,LW, FLAE	LIGC, ,LW, FLAE	LIGC,LL ,LW,CA, FLAE	LIGC, ,LW, FLAE, FLAL	LIGC,LL, ,LW, CA	LIGC,LL, ,LW,CA, FLAE,FLAL, LS	LIGC, ,LW, FLAE
PS-3			-	LIGC,LL, ,LW FLAE, FLAL,	LIGC, ,LW, CA, FLAE	LIGC, ,LW FLAE, FLAL	LIGC, ,LL, CA	LIGC, ,LW, FLAE	LIGC, ,LW, FLAL	LIGC, ,LW, FLAE	LIGC, ,LW, FLAE	LIGC, LL, ,LW, CA, FLAE	LIGC, ,LW, FLAE, FLAL	LIGC,LL, ,LW, CA	LIGC,LL, ,LW,CA, FLAE,FLAL, LS	LIGC,, ,LW, FLAE,
PS-5				-	CA	LL	CA, FLA	LIGC, ,LW, FLA	LL	LL	LL	LL, CA	LL	FLA	LS	LL
PB-1121					-	LL, CA	FLAE	LIGC, ,LL, CA	LL	LL	LL, CA	-	LL, CA	FLAE	LS	LL, CA
P- 1401						-	LL, CA, FLAE	LIGC	-	FLA L	FLAL	LL, CA, FLAL	-	CA, FLA E	LL, CA, LS	FLAL
IPB-1							-	LIGC, ,LL, CA, FLAE	,LL, CA, FLAE	LL, CA, FLAE	LL, CA, FLAE	FLAE	LL, FLAE, FLAL	-	FLAE, FLAL, LS	LL, CA, FLAE
PB-1612								-	LIGC, FLAL	LIGC	LIGC	LL	LIGC, FLAL	LIGC, LL, CA, FLAE	LIGC, LL, CA, FLAL, LS	LIGC
PB-1509									-	FLAL	FLAL	LL, CA	-	LL, CA, FLAE	LL, CA, LS	FLAL
PB-1609										-	-	LL, CA	FLAL	LL, CA, FLAE	LL, CA, FLAL, LS	-
PB-1592											-	LL, CA	FLAL	LL, CA, FLAE	LL, FLAE, LS	-
PB- 1637												-	LL, CA, FLAL	FLAE	FLAL, LS	LL
PB-1728													-	LL, CA, FLAE, FLAL	LL, CA, LS	FLAL
PB-1718														-	FLAE, FLAL, LS	FLAL
PS- 1850															-	LL, CA, FLAL, LS
PB-1692																-

LIGC = Leaf Intensity of green colour, LL = Leaf: Length of blade, LW = Leaf Width of blade, CA = Culm attitude, FLAE = Flag leaf Attitude of blade (early observation), FLAL = Flag leaf Attitude of blade (late observation) and LS = Leaf senescence

Table 8. Differences in panicle characteristics (as per DUS testing guideline, PPVFRA) among rice varieties

Variety/ Character	PB-1	PS-2	PS-3	PS-5	PB 1121	P-1401	IPB-1	PB-1612	PB 1509	PB 1609	PB 1592	PB 1637	PB 1728	PB 1718	P 1850	PB 1692
PB-1	-	PC,A, PSB	PC, A,PSB	PL,A, PA	A, PA	PL	PA	AL, AD,	PC, A, PA	PL, PC,A,	PC, AL, AD	-	PL,PC, AL,AD, PA	PC,A, AL, AD,	PL,PC,A,	A
PS-2		-	-	PL,PSB	PC, PSB, PA	PL, PC,A, PSB	PL, PC,A, PSB,	PC,A,PSB	PCB,PA	PC,PSB,	PC,A,PSB	PC,A, PSB	PLPC,A, PSB,PA	PL, PC, PSB,	PL, PC, PSB,	PC,PSB
PS-3			-		PC, PSB, PA	PL,PC, A, PSB	PL, PC,A, PSB,	PC,A,PSB	PSB,PA	PC,PSB,	PC,A,PSB	PC,A, PSB	PLPC, A,PSB,PA	PL, PC, PSB,	PL, PC, PSB,	PC,PSB
PS-5				-	PL,	PL,A,	PL,A,	PL,A	PL,PC,PA	PL,PC,	PL,PC,A,	PL,A,	PL,PC, A,PA	PL,A	PC,	PL,
PB-1121					-	PL,A, PA,	PL,A, PA,	A,	PC,PA	PL, PC,	PC,A,	A,	PL,PC, A,PA	PL	PL,PC,	-
P- 1401						-	-	PL,	PL, PC, A,	PC,A,	PL,PC,	PL,	PC,PA	-	PL,PC,A,	PL,A,
IPB-1							-	Pl,	PL, PC,A,	PC,A,	PL,PC,	PL,	PC,PA	AL, PD	PL, PC,A,	PL,A,
PB-1612								-	PC,A,PA	PL, PC,A,	PC,	PC,	PL,PC, PA	PL,	PL,PC,A,	A
PB-1509									-	PL,PA	PC,A,	PC,A,	PL,PC,A,PA	PL,PC,A	PL, PC, PA	PC,PA
PB-1609										-	PL,PC,A,	PL,PC,A,	PC,A,PA	PC,A	PL,PC,	PL,PC,
PB-1592											-	PC,AD	PL,PC,PA	PL,PC,	PL,A,	PC,A,
PB- 1637												-	PL,PC,PA	PL,AD	PL,PC,A,	-
PB-1728													-	PC,PA	PL, PC, A,PA	PL,PC,A
PB-1718														-	PL,PC,A,	PL,A,
PS- 1850															-	PL,PC,
PB-1692																-

PL = Panicle length, PC = Panicle curvature of main axis, A = Awn, AC = Awn colour, AL = Awn length, AD = Awn distribution, PSB = Panicle secondary branching and PA =:Panicle attitude

Table 9. Classification accuracy (%) between Pusa Sugandh 2 and Pusa Sugandh 3

Transfer learning model	Model accuracy	Testing accuracy
InceptionV3	0.9691	0.5000
VGG16	0.9691	0.4306
VGG19	0.9863	0.5139
ResNet152V2	0.9656	0.5556

Training data (80% - 291 images) and testing data (20% - 72 images)

Table 10. Classification accuracy (%) between of Pusa Basmati 1121 vs Pusa Basmati 1718

Transfer Learning Model	Model accuracy	Testing accuracy
InceptionV3	0.9038	0.7191
VGG16	0.9698	0.7079
VGG19	0.9533	0.6854
ResNet152V2	0.9753	0.6629

Training data (80% - 364 images) and testing data (20% - 89 images)

Table 11. Classification accuracy (%) among Pusa Basmati 1, Improved Pusa Basmati 1 and Pusa Basmati 1637

Transfer learning model	Model accuracy	Testing accuracy
InceptionV3	0.8024	0.5734
VGG16	0.8866	0.4336
VGG19	0.8385	0.4615
ResNet152V2	0.8814	0.6014

Training data (80% - 582 images) and testing data (20% - 143 images)

Table 12. Classification accuracy (%) between Pusa 1401 and Pusa Basmati 1728

Transfer learning model	Model accuracy	Testing accuracy
InceptionV3	0.9559	0.7667
VGG16	0.9752	0.9000
VGG19	0.9504	0.7778
ResNet152V2	0.9504	0.8444

Training data (80%-363 images) and testing data (20%-90 images).

correct images in only 23 and 30% samples, respectively. The confusion matrix of stage 4 image results showed a mismatch among/between the varieties that are genetically related (through their pedigree). For example, in Pusa Basmati 1 and Improved Pusa Basmati 1, 60% of plants could be identified accurately. However, 27% of plants of Pusa Basmati 1 were classified as Improved Pusa Basmati 1. Also, 8 and 5% of samples of Pusa Basmati 1 were classified as Pusa 1401 Pusa Basmati 1637, respectively. It is noteworthy that both Pusa 1401 and Pusa Basmati 1637 have Pusa Basmati 1 as one of the parents. However, PB-1637 could be identified with percent accuracy among the samples tested.

Similarly, among the 62 samples, 52% of samples could be correctly identified as Pusa Sugandh 2; and 81% as Pusa Sugandh 3 among 69 samples. 35 and 19% of plant images in Pusa Sugandh 2 and Pusa Sugandh 3, respectively, have been identified as of the other variety. It is also indicated that Pusa Sugandh 2 and Pusa Sugandh 3 are sister genotypes (derived from same cross). At the same time, 18% of plants of Pusa 1612 were identified as Pusa Sugandh 2. It could not be interpreted by similarity in their pedigree.

Pusa 1401 was identified correctly in 92% of samples among 62 samples, but 2% of the same was identified as Pusa Basmati 1728. Pusa Basmati 1728 can be identified in correctly 68% samples out of 62 samples while 2% as Pusa 1401.

Pusa Basmati 1121 has been identified accurately in 88% of samples out of 64 samples, while 2% of samples were misclassified as Pusa Basmati 1718. Pusa Basmati 1718 could be identified accurately in only 30% samples out of 63 samples, while 22% was similar to PB 1121. Pusa Basmati 1718 has been developed from Pusa Basmati 1121 and SPS-97 which could be the cause of retrieving Pusa Basmati 1121 type plants in this variety.

Distinguishing closely related varieties

Pairwise classification of varieties using leaf and panicle characteristics: Seven leaf characteristics recorded as per DUS guidelines were used to find similarity/dissimilarity between the pair of varieties. The results showed that the pair of varieties, namely PS 2 and PS3, PB 1 and IPB 1, PB 1 and PB 1718, PB 1121 and PB 1637, P 1401 and PB 1509, P 1401 and PB 1728, IPB 1 and PB 1718, PB1609 and PB 1592, PB 1609 and PB 1692, and PB 1592 and PB 1692 showed no difference between the pair of varieties in the seven leaf characteristics (Table 7). Similarly, among the eight panicle characteristics studied PS 2 and PS 3, PB 1 and PB 1637, P 1401 and PB 1718, P 1401 and IPB 1, PB 1121 and PB 1692, PB 1637 and PB 1692 did not show any difference between the pair of varieties (Table 8).

Pair –wise classification of varieties using plant images

Pairwise classification was carried out for the varieties most related by pedigree. All the models were tested to find out the model which was able to identify the varieties. For comparison between Pusa Sugandh 2 and Pusa Sugandh 3 (sister lines) 291 images as training dataset and 72 for testing were used. All the models were used for identification and it was found that ResNet 152V2 showed the best performance with a training accuracy of 96.56% and testing accuracy of 55.56% (Table 9). Similarly, a comparison between Pusa Basmati 1121 and Pusa Basmati 1718 was done using 354 images as training datasets and 89 for testing. The results showed that Inception V3 showed maximum accuracy with a training accuracy of 90.38% and a testing accuracy of 71.91%

Table 13. Classification between genetically similar varieties based on differences in leaf and panicle characteristics and image-based testing accuracy

Pair of variety	Leaf characteristics	Panicle characteristics	Testing accuracy
PS2 and PS3	No difference	No difference	0.55 (Resnet 152V2)
PB 1121 and PB 1718	Flag leaf attitude (early observation)	Panicle length	0.72 (Inception V3)
PB 1 and IPB 1	No difference	Panicle attitude	0.60 (Resnet 152 V2)
PB 1 and PB 1728	Flag leaf attitude (early observation)	No difference	0.60 (Resnet 152 V2)
IPB 1 and PB 1728	Flag leaf attitude (early observation)	Panicle length	0.60 (Resnet 152 V2)
P 1401 and PB 1728	No difference	Panicle curvature, panicle attitude	0.90 (VGG 16)

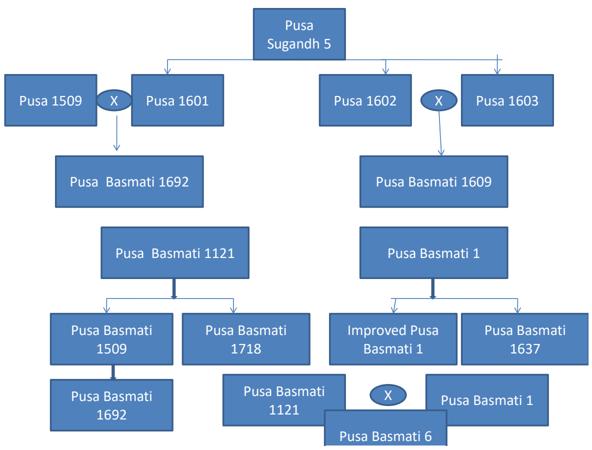

Fig. 7. Genetic relationship among the basmati varieties and their parental lines

(Table 10). A comparison between Pusa Basmati 1, Pusa Basmati 1637 and improved Pusa Basmati 1 using 582 images as training dataset and 143 for testing showed that ResNet 152V2 showed maximum accuracy with a model accuracy of 88.14% and a testing accuracy of 60.14% (Table 11). The model VGG16 was most effective with a training accuracy of 97.52% and a testing accuracy of 90% while comparing Pusa Basmati 1401 and Pusa Basmati 1728 using 363 images as training dataset and 90 for testing (Table 12).

Considering leaf, panicle and plant images, some closely related varieties showed either no or a minor difference in the leaf and panicle characteristics (Table 13). Flag leaf attitude (early observation) and panicle length and its attitude differentiated some similar varieties. On the other hand, testing accuracy based on images of plants at the ripening stage ranged between 55.56% (between PS2 and PS3) and 90% (between P1401 and PB 1728) using Resnet 152V2 and VGG 16, respectively. This clearly showed the strength of machine learning methods in a variety of classification/identification. This limited data showed that testing accuracy declined in case of no difference in panicle characteristics between the pair of varieties during the image capturing.

Discussion

Image-based classification for varietal level classification has shown very encouraging results (Liu et al. 2005; Guzman and Peralta 2008; Yang et al. 2010; Mousavi Rad et al. 2012) but relies on manually engineered features that call for in-depth topic expertise. These technologies require the characteristics to be given as input to the machine. Deep learning (DL), a branch of machine learning that derives from artificial neural networks, has arisen as an alternative to traditional classification techniques, motivated by the need to skip a present feature extraction stage. The convolutional neural network (CNN) is reported to be the best DL method to identify, detect and extract the image content. DL models have been reported in plant classification (Kamilaris, 2018; Ubbens and Starness, 2017) and also for rice variety classification (Lin et al. 2018; Patel and Joshi 2018; Qiu et al. 2018).

Paddy varieties classification and identification based on whole plant images using DL methods without targeting any particular plant part has not been investigated yet. This study was undertaken to devise a new method using digital images of the whole plant to classify genetically close varieties.

The test accuracy level depends on image accusation methods, their processing, extracting features, number of images in the dataset used. Therefore, the scope of investigations in these areas would improve the efficiency and precision of using a high throughput method in varietal identification and quality assurance. This study was undertaken to identify the best deep learning algorithm and best stage that could be used to classify the rice varieties distinctly. The algorithm VGG16 was found to be the best model in the fourth stage (ripening stage) to classify the varieties. It could identify the variety with 73 (%) accuracy. From the confusion matrix, it was concluded that the varieties Pusa Sugandh 2, Pusa Sugandh 3; and Pusa Basmati 1, Improved Pusa Basmati 1, which are morphologically most similar, have been most misclassified. Koklu et al. (2021) also concluded that while using images of seeds misclassifications were more common between varieties very similar to each other in terms of morphology.

The confusion matrices of stage 4 (ripening stage) using VGG 16 indicated both correctly and wrongly classified images. The misclassification is associated with similarity between individual images of two or more different classes. That clearly showed the closeness of some varieties to each other. The varieties like Pusa Basmati 1637 and Pusa Basmati 1609 could be most correctly identified without any misclassification. Most of the misclassification resulted in varieties like Pusa Sugandh 2 and Pusa Sugandh 3, Pusa 1401 and Pusa Basmati 1728; Pusa Basmati 1121 and Pusa Basmati 1718; Pusa Basmati 1, Improved Pusa Basmati 1 and Pusa Basmati 1637 due to high resemblance between the varieties for plant morphological traits. A genetic similarity/closeness among the basmati varieties (Fig.7) could be the obvious reason for obtaining misclassification of varieties using plant images.

Previous studies also indicated that the dataset for using these deep learning algorithms needs to be very comprehensive. The variation in the training data affects how effectively CNNs generalize in the actual world. The collection should ideally contain images that are indicative of the many contexts in which they will be used in the field (Sagar et al. 2020). A dataset created by clicking using a smartphone camera would perform better in real-life conditions. Artificial augmentation of the photographs can also be used to achieve this.

The accuracy obtained in this study is lower in comparison to those that used seed as a subject and different models (Qain et al. 2021; Hong et al. 2015; Anami et al. 2019). The reasons could be: a) narrow genetic differences among the basmati type varieties resulting in a higher level of similarity in plant morphological characteristics at its particular growing stage; b) the number of images is a critical factor in reaching a higher and comparable accuracy using the DL models. An unbalanced dataset among the varieties could be another reason for low accuracy. The higher the number of images better the test accuracy among the models. Determination of an optimum number of data for such studies could be a researchable issue to economize the testing cost.

The models showed better classification ability once the plant passed through the growth stages and differentiated to a greater extent at the ripening stage. The genetically close varieties that the leaf and panicle characteristics could not differentiate could be classified using DL methods though to a lower accuracy. While we have shown the effectiveness of a number of deep learning-based algorithms available in the public domain for the identification of rice varieties and also identified the best model for the same, creating a novel algorithm for this job falls outside the purview of the current study and should be explored in further work.

Authors' contribution

Conceptualization of research (SKC); Designing of the experiments (SKC, AR); Contribution of experimental materials (PKB); Execution of field/lab experiments and data collection (AR, AK); Analysis of data and interpretation (SM, SD, AR, SKC, SS); Preparation of the manuscript (SKC, SM, SD, MP).

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