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Vision based Rice Genotype Identification using Machine Learning Techniques

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ABSTRACT: Images of ten rice genotypes consisting of Chithrakar, Kuliyadichan, TRY 4, ADT 53, ACK 14090, ACK 15004, ADT 45, ASD 19, IR 64, Bhavani were selected and subjected to various image processing machine learning tools for vision based classification. Using Grain analyzer, morphological features of rice seed such as length, breadth, thickness, geometric mean diameter, sphericity, surface area, weight and area were estimated. The mean data were subjected to PCA analysis in STAR software to reduce the dimensionality. The trait such as length, surface area, geometric mean diameter, area and weight contributed significant variation as they possessed positive values in both PC1 and PC2. The predicted variables of PCA and visual, textural, spectral characteristics of rice seed image obtained from Image Analyser (LEICA) were subjected to various image processing process. The processed images were fed into the machine tools *viz*., Partial Least Square Regression (PLS) and Support Vector Machine (SVM) for vision based classification. Totally 2000 images were taken and 80 percent images were used for training the model, 20 percent images were kept for testing the model. By comparing accuracy, precision, recall and F_1 score of both the methods, PLS gives better performance than the SVM classifier. By using these classifiers, genotypes could be identified based on morphological features, visual characteristics and textural characteristics, as the accuracy and prediction are reliable.

Keywords: Rice seeds, Principal Component Analysis, Machine learning tools, Partial Least Square Regression, Support Vector Machine classifier.

INTRODUCTION

More than half of the world's population consumes rice as their main staple meal, especially in Asia, Sub-Saharan Africa, and South America. Over half of the world's population uses it as their main source of energy since it has complex carbohydrate, besides protein, iron, manganese, fibre, and vitamin B. Production and supply of quality seed is important in fighting against malnutrition and meeting out the demand in rice farming.

Seed quality is decided by their physical and genetic purity. If a seed appears typical in terms of size, shape, and general outside appearance, it is said to be physically pure. The genetic purity of the seed is assessed by grow out test, which is a kind of destructive type of seed purity assessment procedure and also it takes entire cropping season to assess the purity of the seed lot. To minimize the time consuming period of assessment, use of visual based machine learning tools are most efficient for purity test and varietal identification.

Thus, it is evident from recent research that by employing machine vision systems and image processing techniques, the products can be assessed for a variety of physical characteristics, including color, texture, quality, and size. Machine learning tool is an advanced and emerging approach for varietal identification, with the assistance of an algorithm, lots of classifier models are evolved. Based on the features of the dataset, the appropriate classifiers are chosen. At a broad level, machine learning can be classified into three types - Supervised learning, Unsupervised learning, Reinforcement learning. In supervised learning, sample labelled data is given to the machine learning system as training material, and then it uses that information to predict the outcome. The system builds a model using labelled data to comprehend the datasets and learn about each one. After training and processing, the model is tested by utilising sample data to see if it accurately predicts the desired outcome. The objective of supervised learning is to correlate input and output data. In this study, supervised learning tools were used to classify the rice genotypes, by training and testing the model by sample images

Many computer-aided machine vision systems that autonomously check and quantitatively measure grains have been created for the purpose of evaluating the quality of rice grains (Sun, 2016). The shapes of four different varieties of brown and polished rice were determined by the use of two-dimensional image processing method (Sakai *et al.*, 1996). A comparative study of the handcrafted features extracted from well-known local image descriptors and the deep learning approach for rice seed classification revealed that deep learning approaches clearly displayed a higher accuracy (Hoang *et al.*, 2020). By using a variety of image processing algorithms to the generated images of two different rice species, product features have been retrieved using shape and colour in addition to morphological features. They observed that the success rates were greater than 90%, particularly when colour, shape, and morphological characteristics were assessed simultaneously (Cinar *et al.*, 2019).

A machine vision method for classifying rice seed varieties of Vietnam was performed by using advanced machine learning models, including KNN, SVM, and RF. They identified that machine learning can be used to accurately identify the appropriate rice genotypes (Hong *et al.*, 2015). In order to categorise different varieties of rice using colour and form features (Liu *et al.*, 2005), an identification approach was created based on neural networks. Grain features were collected from each sample image and used multilayer artificial neural network models to automatically identify the sizes, shapes, and variety of samples of 52 rice grains in the Philippines (Guzman *et al.*, 2008).

Genotype-based selection is generally based on univariate analysis, but the scope in plant breeding is too small for univariate approaches, because it ignores the interdependence of the factors and selection based on one or a few features frequently results in failure (Fidalski *et al.*, 2007). On the other hand, multivariate analysis enables researchers to extract more information from a data collection by taking into account both the relationship between each variable and the variable individually (Grobe, 2005). Multivariate approaches are a crucial tool in plant breeding programmes because they improve selection efficiency (Beebe, 1998).

Principal components analysis (PCA),one of multivariate analysis techniques, aims to reduce the set of traits and thereby simplify the structural makeup of the data set so that differences between treatments, which are theoretically influenced by a larger set of traits, can be assessed in two- or three-dimensional spaces with simple geometric interpretation (Piedade *et al.*, 2019). The Partial Least Squares (PLS) and Support Vector Machines (SVM) regression techniques are used in the study for varietal identification. The former is frequently employed for regression models due to its ease of use, speed, generally acceptable performance, and accessibility, whereas, the latter may have a significant benefit due to its capacity to model nonlinear relations (Thissen *et al.*, 2004).

Rice image classification is done in two steps. (i) Principal Component Analysis (PCA) for optimizing the feature set of rice images and morphological extracts and (ii) Partial Least Square Regression analysis and Support Vector Machine classifiers to classify the genotypes. The objective of this study is to demonstrate classification of rice varieties by using image based machine learning tool based on visual characteristics of rice grains in order to minimize the time period for accessing the genetic purity and to find out the major trait contributing maximum variation among the genotypes.

MATERIALS AND METHODS

Images of rice samples were obtained from Grain Analyzer and Image Analyzer (LEICA – MC 170 HD). The samples consist of landraces, advanced cultures and some released varieties of Tamilnadu, which are given in table 1**.** The obtained images are subjected to various image processing techniques and then fed into classifiers for classification. Morphological features such as length, breadth, thickness, geometric mean diameter, sphericity, surface area, L/B ratio, weight and area were estimated.

Table 1: List of rice genotypes.

Landraces	Chithrakar, Kuliyadichan
Advanced Cultures	ACK 14090, ACK 15004.
Released varieties	TRY 4, ADT 53, ADT 45, ASD 19, IR 64, Bhavani

PLS method was used for classification of rice seed samples and a comparative study using SVM classifier was performed with the same dataset. The schematic diagram of workflow is depicted in Fig. 1.

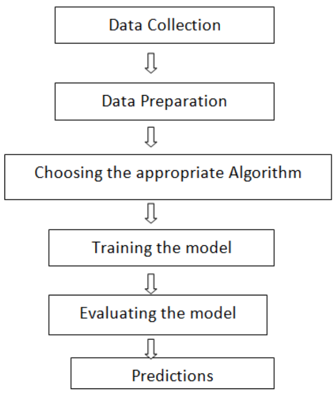

Fig. 1. Schematic representation of work flow.

Morphological Characteristics of Rice grain. Samples of 50 rice seeds per variety were randomly selected and placed in the scanner to obtain scanned image; the captured image was transferred to the system and fed in the software for feature extraction. Morphological features like length, breadth, L/B ratio and area were extracted using grain analyzer. Geometric mean diameter, sphericity and surface area were calculated using a following formula. Totally nine characteristics are obtained for analysis.

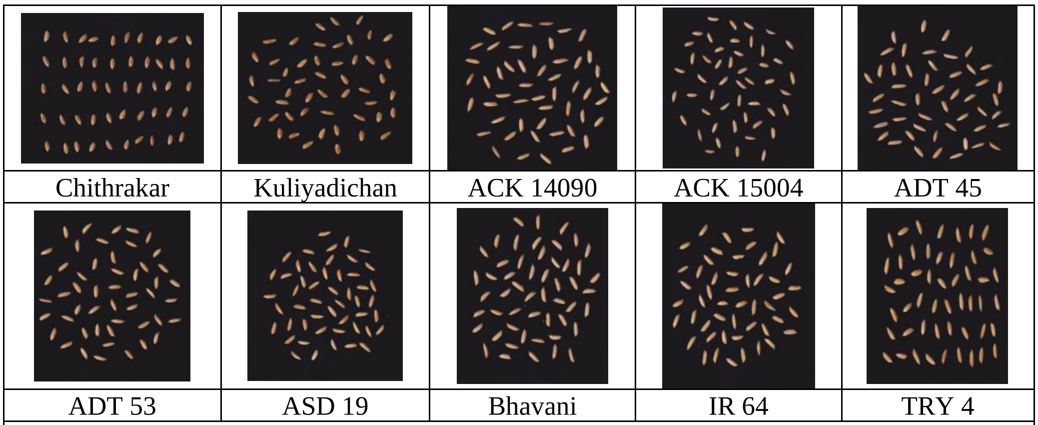

Fig. 2. Sample images obtained from Grain analyzer.

(a) Length : Measured from tip of the pedicel point to awn point of the grain and expressed in mm.
(b) Breadth : Measured across the widest point of the grain and expressed in mm.
(c) Thickness : Measured using a vernier caliper and expressed in mm.
Geometric mean diameter : The GMD of the sample was calculated by using a following formula (Kumar *et al.*, 2017).
(d) GMD = $(LBT)^{1/3}$
(e) Sphericity : The sphericity, expresses (Kumar *et al.*, 2017)
(f) Ø = $(LBT)^{1/3}/L$, where " Ø is the degree of sphericity"
(g) Surface area : The surface area was calculated using the relationship which is given as follows(Kumar *et al.*, 2017).
Surface area = $(GMD)^2$
(h Length / Breadth ratio : It is the ratio of length to width of the grain
(i) Weight: Weight of the single grain obtained using grain analyser based on the grain dimensions and total grain mass.
(j) Area :Based on dimensions of the rice grain area was calculated in grain analyzer.
The basic dimensions extracted were subjected to PCA in STAR software package developed by IRRI.
Image Acquisition and Processing. Individual rice seed images were obtained with the help of LEICA MC 170 HD – Image analyzer, used to capture images with 10X magnification. Two hundred rice seeds were captured per variety and totally 2000 images were taken to create a dataset for processing Fig. 3.
Image processing has direct impact on classification results as it explains the preliminary image operations done to classify data as accurately as possible. With the assistance of the MATLAB application, the image was processed. The captured images were first transformed to grayscale and then to binary images followed by high intensity images (Fig. 4). These transformations were carried out in background by a python package Tensor Flow Backend. The original image was converted to grey scale image based on shaded and unshaded pixels. Binary image was generated based on the pixels; finally the images were subjected to classification model.

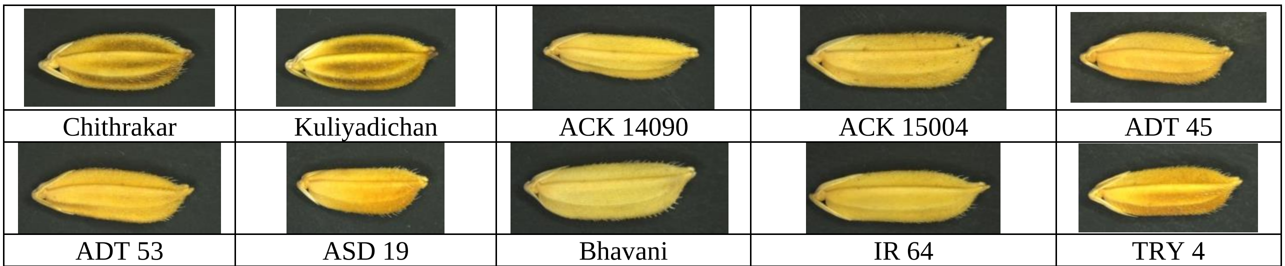

Fig. 3. Images obtained from Image Analyzer (LEICA).

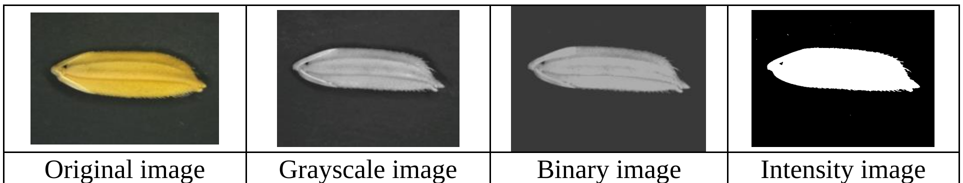

Fig. 4. Image Processing Stages.

Feature optimization and Classification. For further processing of input images, the entire feature set was optimized. Among the different dimensionality reduction techniques, Principal component analysis (PCA) yields precise results that reduce dataset redundancy and enhance classifier performance. Being a supervised learning algorithm, accepts hyperspectral pictures with an optimized feature set. The Optimized features set were fed to the Partial Least Square Regression model classifier. Data were separated into two categories for testing and training purposes. High discriminatory power was provided by a strong set of characteristics, which eliminates the need for complicated categorization techniques. Thus PLS regression increased classification accuracy, speed and particularly suited when the matrix of predictors had more variables than observations, and existence of multi-colinearity among X values.

Rice images have distinguishing characteristics. First, strong vertical edges are present along the boundaries of the image. Second, natural textures are difficult to observe. Third, it's outgrowth extensions like awn point and brush (hair on the husk), finally, colour of the grain. Thus, edges, texture, colour and extension details are considered as major factors for discriminating the rice varieties. To extract these features, the original HOG descriptors (focuses on the structure or the shape of an object) with additional colour information were obtained, and were referred as colour frequency and texture features computed from co-occurrence matrices. PLS is used as a dimensionality reduction technique to manage the high dimensionality that results from the combination of features. The following procedures are used in our detection method. The PLS model integrates and analyses the features collected using the original HOG, color frequency, and co-occurrence matrices for each detection window in the image, resulting in a low dimensional vector. The vector is classified using a straight forward and effective classifier.Then the performance of the PLS regression classifier is compared with SVM (Support Vector Machine) classifier with the same dataset.

RESULTS AND DISCUSSION

The Morphological features of rice seed such as length, breadth, thickness, geometric mean diameter, surface area, sphericity, L/B ratio and area for each rice variety is depicted in the Table 2.

Table 2: Mean and Standard deviation values for various seed characters of rice genotype.

Genotypes	Length (mm)	Breadth (mm)	Thickness (mm)	GMD (mm)	Sphericity (mm)	Surface area (mm)	L/Bratio	Area (mm)	Weight (mg)
Chithrakar	7.941±0.748	2.962±0.519	2.008±0.001	3.523±0.118	0.445±0.007	12.690±0.897	2.680±0.002	20.273±1.641	0.031±0.002
Kuliyadichan	8.715±0.528	2.588±0.460	2.008±0.001	3.497±0.260	0.401±0.026	12.544±1.884	3.367±0.633	22.001±2.754	0.033±0.004
TRY 4	7.144±0.377	2.389±0.269	2.008±0.001	3.230±0.079	0.454±0.011	10.448±0.519	2.990±0.170	14.901±1.777	0.018±0.001
ADT 53	7.359±0.632	2.188±0.253	2.008±0.001	3.181±0.187	0.433±0.007	10.134±1.264	3.363±0.158	14.213±1.956	0.018±0.002
ACK 14090	8.568±0.449	2.261±0.219	1.980±0.001	3.366±0.075	0.393±0.012	11.347±0.455	3.789±0.127	17.461±1.469	0.023±0.002
ACK 15004	7.941±0.389	2.962±0.222	2.008±0.001	3.523±0.140	0.445±0.001	12.690±0.885	2.680±0.072	20.273±1.291	0.031±0.002
ADT 45	7.776±0.448	2.098±0.220	1.642±0.001	2.987±0.045	0.385±0.018	8.940±0.804	3.706±0.278	14.711±1.497	0.020±0.002
ASD 19	7.920±0.550	2.187±0.193	2.008±0.001	3.259±0.101	0.412±0.020	10.635±0.284	3.621±0.428	15.598±1.596	0.020±0.002
IR 64	8.817±0.613	2.511±0.195	2.008±0.001	3.538±0.107	0.403±0.013	12.535±0.644	3.511±0.112	19.737±1.986	0.027±0.003
Bhavani	8.233±0.495	2.373±0.184	1.890±0.001	3.326±0.169	0.405±0.041	11.073±0.765	3.469±0.528	17.806±1.267	0.024±0.002

The genotype IR 64 (8.817) exhibited maximum seed length followed by Kuliyadichan (8.715). Chithrakar (2.962) and ACK 15004(2.962) had maximum seed breadth values. Mostly seed thickness was more or less similar for all the genotypes, as it contributed the least variation compared to other traits. Geometric mean diameter ranged from 2.987(ADT 45) to 3.538(IR 64). For sphericity, TRY 4 (0.454) genotypes exhibited the maximum value, whereas Chithrakar, Kuliyadichan and ACK 15004 recorded the maximum surface area, seed weight and area. The genotype, ADT 45 had the highest L/B ratio followed by ACK 14090. The mean values were fed in STAR software for PCA analysis in order to identify the traits contributing maximum variation among the genotypes.

The amount of variance explained by PCs defines the number of PCs to be considered for analysis. According to Rencher *et al.* (2002), at least 70% of the variance must be explained by PCs. The proportion of variance, cumulative proportion and eigen values are given in the table 3. Out of nine PCs, two exhibited more than 1 eigen values and contributed approximately 89.86% of all the variability (61.81% explained by PC1 and 28.05% by PC2) among the characters studied.

Table 3: Proportion of variance, cumulative proportion and eigen values of rice genotypes.

Statistics	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9
Proportion of Variance	0.6181	0.2805	0.0928	0.0073	0.0012	0.0001	0.0000	0.0000	0.0000
Cumulative Proportion	0.6181	**0.8986**	0.9914	0.9987	0.9999	1.0000	1.0000	1.0000	1.0000
EigenValues	**5.5631**	**2.5243**	0.8349	0.0659	0.0105	0.0010	0.0003	0.0000	0.0000

Scree plot, a line of eigenvalues of principal components, which displays the number of PCs that should be considered for analysis. From the scree plot and proportion value, it is clear that the maximum variation was observed in PC_1 and PC_2, hence the traits present in $PC_1$and PC_2 contribute more variation for diversity (Fig. 5).

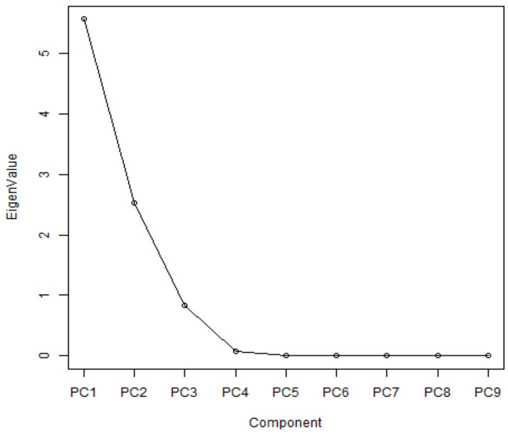

Fig. 5. Scree plot.

Traits contributions in different PCs are given in table 4. The results showed that the entire trait except L/B ratio exhibited positive values in PC_1, hence every trait other than L/B ratio contributed more for variation. In PC_2, traits other than breadth, thickness and sphericity recorded positive value. Therefore, trait such as length, surface area, geometric mean diameter, area and weight contributed significant variation than other traits as they possessed positive values in both PC_1 and PC_2. These traits could be used for varietal identification. Similar work on characterization of rice landraces were done in rice using agro-morphological traits (Keerthivarman *et al.*, 2019).

The first two PCs were plotted against each other in biplot to observe the relation among the genotypes and the various traits studied were depicted in figure6. Genotypes *viz.*, Kuliyadichan and IR 64 grouped in right top corner of the biplot showing positive values for both the PCs and the traits *viz.*, length, surface area, geometric mean diameter, area and weight were placed in same quadrant contributing maximum divergence.

The traits contributing maximum variation were taken into consideration in further classification process using classifiers. This work extracted spectral, textural and shape features of the rice grain images from the dataset containing sample images of 10 rice varieties obtained from image analyzer (LEICA). The images of entire dataset were classified as training (128) and testing (32) images, validated images (32) for each rice varieties in the ratio of 80:20:20.

The PLS regression model and SVM classifier were performed for the same dataset, where classification is made using the training and testing phase of the images. During training 80% of the images were trained and the remaining 20% of the images were tested. The performance measure of both models is described in Fig. 7.

Table 4: Contribution of different traits towards total variance.

Traits	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9
Length	0.2001	0.5478	-0.1238	0.3147	0.1350	0.0820	0.3975	0.5849	-0.1430
Breadth	0.3904	-0.1622	0.3035	0.2853	-0.5249	0.5901	-0.0234	0.0205	0.1518
Thickness	0.2635	-0.1903	-0.7836	-0.3764	-0.2038	0.2238	-0.0039	0.0954	-0.1950
GMD	0.4102	0.0817	-0.2068	0.4126	0.1036	-0.3019	-0.7079	0.0383	0.0875
Sphericity	0.1501	-0.5864	-0.0756	0.0955	0.3210	-0.1269	0.2850	0.3181	0.5631
Surface.Area	0.4173	0.0742	-0.1297	0.2160	-0.0643	-0.3057	0.4992	-0.6403	-0.0113
L/B ratio	-0.2694	0.4537	-0.3018	-0.0377	-0.1997	0.1109	-0.0296	-0.1436	0.7452
Area	0.3906	0.2156	0.1583	-0.3639	0.6259	0.4267	-0.0952	-0.2181	0.1141
Weight	0.3848	0.1700	0.3116	-0.5639	-0.3392	-0.4472	-0.0024	0.2600	0.1589

Table 5: Scores for rice genotypes in relation to two principal components (PC1 and PC2).

Genotypes	**Principal components**	
	PC1	**PC2**
Chithrakar	2.9751	-1.2727
Kuliyadichan	2.3227	1.6974
TRY 4	-1.209	-2.6927
ADT 53	-2.0713	-1.5470
ACK 14090	-0.5349	1.6557
ACK 15004	2.9750	-1.2727
ADT 45	-4.0046	0.9974
ASD 19	-1.5052	0.0367
IR 64	1.5447	1.6117
Bhavani	-0.4916	0.7861

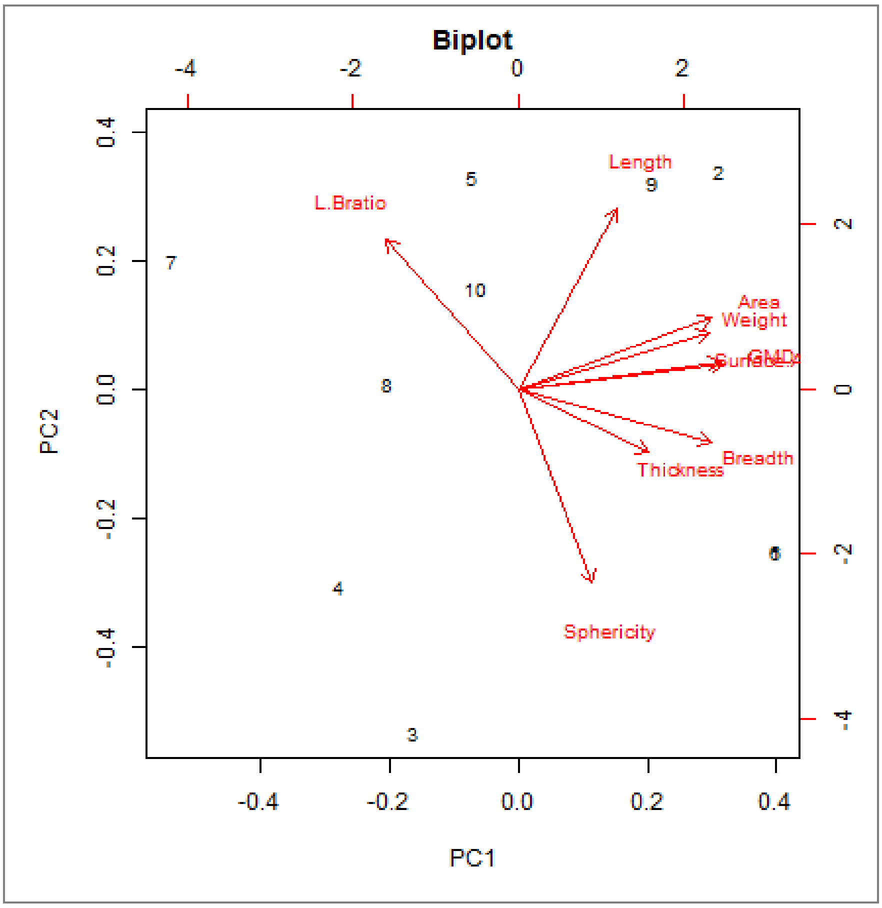

Fig. 6. Biplot for PC1 and PC2.

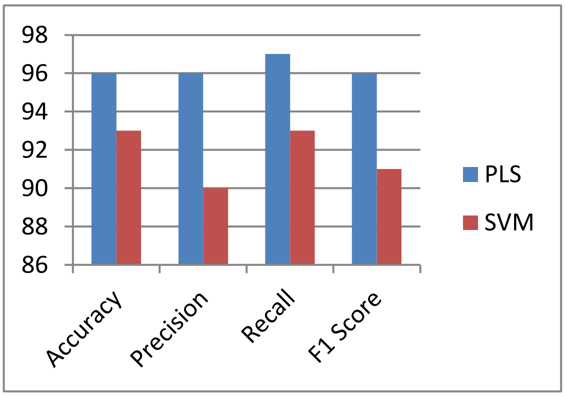

Fig. 7. Performance Measure.

The PLS had achieved an accuracy and precision of 96% displaying higher values compared to SVM (93%).Similar success rate of greater than 90% was obtained, when colour, shape, and morphological characteristics of rice were assessed simultaneously (Cinar *et al.*, 2019)

Based on the performance measure of both models, Partial Least Square Regression exhibited better performance than the Support Vector Machine classifier as reported earlier for classification of cloud types (Nandhini *et al.*, 2019). The rice genotypes can be identified based on the seed morphology and images using Machine learning tools as revealed by the previous study on classification of rice varieties using Artificial Intelligence Methods (Qiu *et al.*, 2018).

CONCLUSION

Ten rice genotypes used in this study were classified efficiently by using machine learning techniques. By comparing accuracy, precision, recall and F1 score of both the methods, PLS gives better performance than the SVM classifier. Traits such as length, surface area, geometric mean diameter, area and weight were the highly contributing trait for presence of variation among the genotypes. By using these classifiers, genotypes could be identified based on morphological features, visual characteristics and textural characteristics, as the accuracy and prediction are reliable. Thus, Machine learning tools is an alternative approach to identify the varietal purity based on seed morphological features and images.

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REFERENCES

Beebe, K. (1998). Pell, RJ: Seasholtz, MB.*Chemometrics: A Practical Guide* 1.

Cinar, I., and M. Koklu. (2019). Classification of rice varieties using artificial intelligence methods.*International Journal of Intelligent Systems and Applications in Engineering*, *7*(3), 188-194.

Fidalski, J., Tormena C. A. and Scapim, C. A. (2007). Espacialização vertical e horizontal dos indicadores de qualidade para um Latossolo Vermelho cultivado com citros. *Revista Brasileira de Ciência do Solo, 31,* 9-19.

Grobe, J. (2005). Aplicações da estatística multivariada na análise de resultados em experimentos com solos e animais. 2005. 145 f Dissertação (Mestrado em Agronomia)-Universidade Federal do Paraná, Curitiba.

Guzman, J.D., and E.K. Peralta (2008). Classification of Philippine rice grains using machine vision and artificial neural networks. World conference on Agricultural information and IT.

Hoang, V. T., D. P. Van Hoai, T. Surinwarangkoon, H. T. Duong, and K. Meethongjan (2020). A comparative study of rice variety classification based on deep learning and hand-crafted features. *ECTI Transactions on Computer and Information Technology (ECTI-CIT) 14* (1), 1-10.

Hong, P.T.T., T. T. T. Hai, V.T. Hoang, V. Hai, and T. T. Nguyen (2015). Comparative study on vision based rice seed varieties identification. 2015 Seventh International Conference on Knowledge and Systems Engineering (KSE).

Keerthivarman, K., S. J. Hepziba, R. Gnanamalar, and J. Ramalingam (2019). Characterization of rice (*Oryza sativa* L.) landraces based on agro-morphological traits. *Electronic Journal of Plant Breeding, 10* (2), 627-635.

Kumar, L., N. Mishra, S. Patel, D. Khokhar, and A. Lakra (2017). Rice puffing characteristics of some selected varieties. *Trends in Biosciences, 10* (30), 6263-6267.

Liu, Z. Y., F. Cheng, Y. B. Ying, and X. Q. Rao (2005). Identification of rice seed varieties using neural network. *Journal of Zhejiang University-Science B 6* (11), 1095-1100.

Nandhini, K., and Tamilpavai, G. (2019) Classification of cloud types using Partial least square regression. *International Journal for Science and Advance Research in Technology, 5*(11), 190 – 197

Piedade, G.N.d., L.V. Vieira, A.R. dos Santos, D. J. Amorim, M. D. Zanotto, and M. M. Sartori (2019). Principal component analysis for identification of superior castor bean hybrids. *Journal of Agricultural Science, 11* (9), 179.

Qiu, Z., J. Chen, Y. Zhao, S. Zhu, Y. He, and C. Zhang (2018). Variety identification of single rice seed using hyperspectral imaging combined with convolutional neural network. *Applied Sciences, 8* (2), 212.

Rencher, A.C., and W. Christensen. (2002). Méthods of multivariate analysis. a john wiley & sons. *Inc. Publication, 727*, 2218-0230.

Sakai, N., S. Yonekawa, A. Matsuzaki, and H. Morishima (1996). Two-dimensional image analysis of the shape of rice and its application to separating varieties. *Journal of Food Engineering, 27* (4), 397-407.

Sun, D. W. (2016). *Computer vision technology for food quality evaluation*: Academic Press.

Thissen, U., M. Pepers, B. Üstün, W. Melssen, and L. Buydens. (2004). Comparing support vector machines to PLS for spectral regression applications. *Chemometrics and Intelligent Laboratory Systems 73* (2), 169-179.

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