Implementation of ML Algorithm for Mung Bean Classification using Smart Phone

Mubarak Almutairi[1], Mutiullah[2], Kashif Munir[3], and Shadab Alam Hashmi[4]

[1] College of Computer Science and Engineering, University of Hafr Albatin, Saudi Arabia

[2,3,4]Faculty of Computer Science and Information Technology, Khwaja Fareed University of Engineering and Information Technology, Rahim Yar Khan, Pakistan

Corresponding author: Mubarak Almutairi (e-mail: almutairi@uhb.edu.sa).

Abstract This work is an extension of my work presented a robust and economically efficient method for the Discrimination of four Mung-Beans [1] varieties based on quantitative parameters. Due to the advancement of technology, users try to find the solutions to their daily life problems using smartphones but still for computing power and memory. Hence, there is a need to find the best classifier to classify the Mung-Beans using already suggested features in previous work with minimum memory requirements and computational power. To achieve this study's goal, we take the experiments on various supervised classifiers with simple architecture and calculations and give the robust performance on the most relevant 10 suggested features selected by Fisher Co-efficient, Probability of Error, Mutual Information, and wavelet features. After the analysis, we replace the Artificial Neural Network and Deep learning with a classifier that gives approximately the same classification results as the above classifier but is efficient in terms of resources and time complexity. This classifier is easily implemented in the smartphone environment.

Keywords: *Mung-Beans, Textural Features, Fisher's Co-efficient; Linear Discriminant, Artificial Neural Network, Smart Phone.*

I. INTRODUCTION

Mung bean plays a vital role in a balanced and healthy diet due to their protein-rich edible grains and nutritional contents. It is a warm-season leguminous plant mainly grown as crop rotation with cereals like rice and wheat. It contains 59% carbohydrate, almost 20-24 percent protein, 4 percent fiber, vitamin (A, B, C, and E), and a good source of folate and dietary fiber. They also supply a significant amount of iron, potassium, calcium, and magnesium [1, 2]. From this, it may be concluded that it is considered a good source of protein for vegetarians, and it has evolved for different food products such as snacks, sweets, dhals, and savory foods.

Mung-Beans is used to prevent cancer similar to other beans because of zero cholesterol and contain protease inhibitors. It is a more attractive food for diabetic persons due to deficient glucose levels and can fight high blood pressure and cardiovascular disease risk factors. It has also appeared as a good diet for those people who desire to reduce their weight. It contains a range of phytonutrients that are considered anti-inflammatory and antimicrobial, helpful to resist harmful viruses, bacteria, irritations, rashes, colds, etc., and enhance immunity [3]. It includes few oligosaccharides that cause flatulence which makes it easily digestible. Hence it is a good diet for children and patients with delicate digestive systems [2].

Mung-Beans crop is being cultivated twice a year because of its short maturity time (around two months). Firstly, it is produced during February and secondly in June and July, in the subcontinent, making it economically valuable for the farmers. A good yield, adequate rainfall is needed, from filling the flowers to a late pod. Maturity, tiny seed versus large seed types, upright versus prostrate growth habits, and the essential attributes are considered the seed color when the variety is selected. Usually, larger seeds are preferred that have a glassy, green color [4]. The virus-free and healthy seed, disease-resistant, early developing, short duration, and constant development are the reproducing destinations, and such assortments are being created. The early maturing cultivars with germplasm from national and international resources have been developed [1].

Manuscript received November 5, 2021
Manuscript revised November 20, 2021
https://doi.org/10.22937/IJCSNS.2021.21.11.12

TABLE I Some Mung-Beans Varieties Developed in Pakistan

Year of release	Variety	Institution
1991	NM-51	NIAB
1993	NM-92	NIAB
2000	Chakwal-97	BARI
2006	Azri-06	AZRI, Bhakkar
2006	NM-06	NIAB
2006	Chakwal-06	BARI
2013	NM-13	NIAB
2016	BWP-16	BWP

The above-discussed seed selection parameters in Table 1 are related to the post sowing process. Therefore, before the sowing, selecting appropriate seed variety is one of the basic requirements to avoid the wastage of valuable resources such as; field area, fertilizers, labor, time, etc. Discrimination or identification is a trivial procedure for the selection of good seeds from the available varieties. Still, for this purpose up to now, any simple scientific approach is not public.

Traditionally, varietal Discrimination is done by skillful experts who differentiate the seeds based on visual examination. An expert and proficient person checks the non_measureable parameters like physical kernel texture, color, size, and shape to analyze with his experience and tell the variety's name. Still, it is a highly inconsistent, tedious, and subjective method [5] that is affected by the experience of individuals [6]. According to Anami et al., the decision-making capabilities of experts can be seriously affected by health conditions such as eyesight, work conditions, work pressure, and fatigue [7]. Moreover, the experts may not be more familiar with newly launched or all varieties. So, a system free from all these factors is required to be developed. Four types of Mung-Beans have been differentiated based on quantitative parameters instead of qualitative parameters for handling all said issues.

In this paper, Section 2 presents a brief survey of literature regarding the Discrimination of different types of seeds. Section 3 consists of data acquisition, pre-processing, extraction, selection, and reduction of quantitative parameters used for kernel discrimination. Section 4 contains results and discussions of this developed system, and Section 5 provides the conclusion.

II. LITERATURE REVIEW

The use of information technology in artificial intelligence (free from all above-mentioned human limitations) is an alternative tool for this purpose. During the last few years, several types of research done and provided many approaches to use this approach for rapid and consistent classification/discrimination of seeds. Recently, Kurtulms et al. [8] have used color and shape features to classify eight varieties of pepper seeds with a soft computing approach. Using the ANN classifier, they received an accuracy of 84.94%. With the implementation of the same features, Li et al. have classified four maize varieties with an accuracy of 94.5% [9]. Similarly, using image processing techniques, Sbanci et al. have characterized wheat grains, like bread and durum, based on visual features. The simplified ANN classifier achieves the best result with a mean absolute error of $9.8*10^{-6}$ [10]. Zapotoczny also worked for the Discrimination of wheat kernels by using similar features and achieved an accuracy of 98%-100% [11]. Huang et al. [12]and Zhang et al.[13], have employed hyperspectral images for the classification of maize varieties of different years. The photos are in the spectral range of 380-1030 nm. The reported accuracy is 94.4% and 98.89%, respectively. Using geometrical features Abdullah and Quteishat have differentiated wheat seeds with an accuracy of 95% with ANN classifier [14]. A mixture set of color, shape and texture features has been employed by Pandey et al. as input to ANN to classify wheat and gram seeds and received an average accuracy of 95% [15].

Neelam and Gupta classified four rice varieties with the implementation of color and morphological parameters, where Mahalanobis is used as a classifier [16]. Birla and Singh [17] worked for quality analysis of rice using morphological parameters by machine vision approach. Similar parameters (shape and color) have been employed by Chen et al. [18] to discriminate five corn varieties. Ghamari for the varietal Discrimination of chickpea seeds [19] and Mebatsion et al. [20] were used to classify five cereal grains barley, oat, rye, Canada Western Amber Durum wheat seeds, and Canada Western Red Spring wheat seeds.

Undoubtedly, all the studies cited above are fast, accurate, and based on different image processing approaches but mainly focus on the features measured per kernel basis. Such experiments are only feasible to be performed in a controlled environment. Still, it would be challenging to employ a common former, to whom it is generally concerned, because of complex setup requirements. Moreover, Visen et al. developed algorithms for classifying grains based on such images that are more complex. Due to many pre-processing steps, such as segmentation, background removal, object extraction, etc. [21], some researchers used images of bulk samples to avoid these complications and make the situation simpler.

The Discrimination of five wheat varieties using the samples of bulk grain images is the potential of the machine vision approach investigated by Shahid et al. [22]. For this purpose, 26 statistical texture features are deployed to the ANN classifier and achieved an average accuracy of 97%. With an accuracy of 99.22%, five varieties of barley are classified by Zapotoczny based on bulk sample images [23]. The nine varieties of Iranian wheat using similar images are distinguished by Pourreza et al., [24] with the help of different computer vision approaches and obtained an average accuracy of 98.15%. Brenda et al. [25] worked on the Intra-regional classification of grape seeds produced in Mendoza province (Argentina) by multi-elemental analysis and chemometrics tools. Michael et al. [26] classified cowpea beans using multi-elemental fingerprinting combined with supervised learning.

Up to the best of our literature survey, none of the researchers has worked to differentiate Mung-Beans varieties as in Table 1, which cannot be classified/distinguished easily, even by an expert person due to similar geometrical morphological properties different types. This work aims to develop an economically efficient system, free from all human limitations, to have consistent results for the classification of Mung-Beans. More accurately, in a short time, without any complex laboratory arrangement, based on objective features (statistical texture features) rather than subjective features (shape and color), which many researchers have already employed to classify other seeds.

III. MATERIALS AND METHODS

A. Image Acquisition

This research's experimental material comprises Mung-Beans of four varieties; NM-92, NM-13, BWP-16, and Azri-06. Sample images of each type is given in Fig. 1. It is necessary to take pure seeds without any outliers, and a mixture of other seeds is required. So, instead of taking the sample of two-kilogram seeds of each variety from the open market, we obtained them from Agriculture Regional Research Centre, Bahawalpur Region, Punjab, Pakistan. In this study, we have the intention to employ superficial information retrieved from images of bulk samples, such as statistical textural parameters. These statistical texture features are used by many researchers in various image classification applications [28]. If the size of texture primitives is small and the difference of gray level among the adjacent primitives is significant, such texture is known as fine texture. So, to meet the conditions of such a texture, image acquisition is conducted at the vertical height of 10 feet from the sample beans by a Nikon digital camera, model; COOLPIX with Resolution property of camera approximately ten megapixels. Images are acquired mid-noon on a clear sunny day to maintain the uniform light intensity and have a minimum inter kernel shadow effect. Ten images of each variety are taken while reshuffling the sample after each image, to change the kernels (beans) randomness. Finally, a data set of colored images of 40 (10×4), having 2736×3648 dimensions and 24 bits depth in.JPG format, is created.

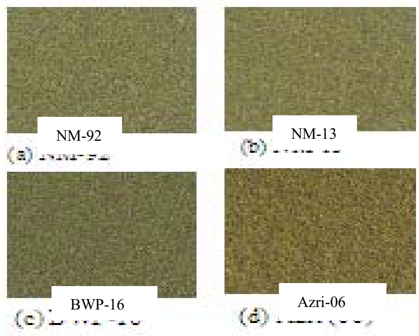

FIGURE 1. (a)-(d) show sample images of Mung-Bean varieties BRM (311), BRM (307), BRM (303), Azri (06

B. Pre-processing

Required meaningful statistical textural features from the acquired images of samples seeds must undergo some given below pre-processing steps.

Microsoft Picture Manager crops the area containing beans in each image. In this way, sample images of 300×400 pixels are obtained (cropped image of each variety is presented in Fig. 1). The software Mazda [29] used for features extraction only works for BMP format. We convert all acquired images into the required format (8-bit images) by Photoshop-7 because we are interested in extracting first-order, second-order statistical data textural parameters from these images to have logical results.

All possible superficial information in the form of statistical textural parameters, 12 non-overlapping sub-images or regions of interest (ROIs), with pixel dimensions of 16×16, 32×32, and 64×64, are developed in each image.

According to Shahid et al. [23], 64×64 dimensions provide better results in classification. We apply the different classifiers on different features selected by fisher analysis, Mutual Information, Probability of Error POE, and the Convex Principle Features selection method provided by Mazda software-generated texture features [30]. From each feature's selection method, we take ten features and five features obtained from the convex principle features selection method. These features are used in nave-based, Logistic regression model, multiclass classifier, and random forest Supervised classification techniques to achieve acceptable accuracy in the Mung-Beans types' classification. The complete detail of each classifier is given in the next section.

C. Supervised Classifier

Machine learn automatically using the labels of each instance given to the algorithms. Algorithms assign the labels to the new data according to the pattern founds in the data. These classifiers can be divided as; two categories

i. Classification means to group the things are instances based on some common characteristics found in data or attributes. For example, Sentiment Analysis, Spam detection, and dog breed detection
ii. Regression model means to fit the linear or quadratic equation or higher-order for the prediction. The simple linear equation is given below.

$$Y = a + bX \tag{1}$$

Here, Y is a dependent variable you want to predict like price, X is an independent variable like no of books, b is the unit cost of book or rate of change in variable X, and 'a' is the starting point or y-intercept.

In a linear equation, more independent variables may have affected the independent variable Y. So, each variable has its own coefficient, which shows the unit change in that independent variable.

Logistic regression is another form of linear regression in which independent variables are nominal or categorical data like yes/No, and the dependent variable is binary. This means to say output can be classified in two categories, which is decided by thresh hold value using the sigmoid function. P = 1/(1+ e^(-y)) and thresh-hold value can be calculated as ln(p/(1-P))=a+bx where p is the probability of one event and 1-p = probability of other event means ~p

D. K-nearest neighbor

K-NN is a non-parametric and lazy learning algorithm. It classifies the new cases based on the distance functions or similarity matrix. Where K is considered the number of nearest neighbors, it should be odd to get a better result. The scaling factor plays an essential role in the classification procedure.

If in the dataset we have binary features, then, in this case, hamming distance is used. If the dataset within the class is high variance, it is observed that the classification rate is poor. If the variability found in different categories is high, the classification rate is excellent, and various distance measures give different results.

KNN performs well with a small number of input variables (p) but struggles if the number of input variables is vast.

E. Support Vector Machine

Support Vector Machine is a well-known classifier used for classification by finding the hyperplane that maximizes the margin between two classes. Hyperplane boundary is drawn by transforming the variables using some linear algebra. Support Vector Machine is categorized in various classes concerning algebra.

i) Linear Support Vector Machine
ii) Polynomial Support Vector Machine. In this type, the polynomial degree should be defined and used for curved lines separation between two classes of input space.
iii) Sigmoid-kernel, it is similar to Logistic Regression, is used for binary classification

Radial Basses function (RBF) is used to create a non-linear combination of your features to separate your samples into higher dimensional features space to separate your classes

F. Naive Bayes Classifier

It is actually based on the Bayes theorem with some assumption like between the features, i.e., it assumes that all the features found in the class are independent to each other, meaning no one feature changes their value due to other feature value even if there is found any dependent feature in the class. Gaussian Nave Bayes is used to classify the objects used in the normally distributed data of feature.

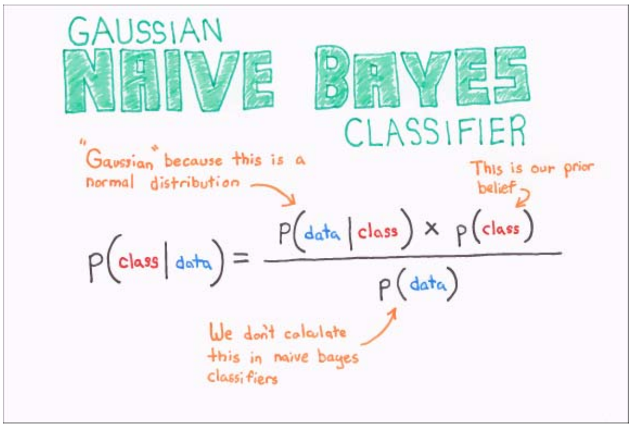

FIGURE 2. Formula of Naïve Bayes Classifier

Step 1 Calculate the prior probability as formula given in fig. 2

P (Class) = # of samples in the class / Total # of all samples

P (yellow class) = 11/18 from figure 3

P (blue) = 7/18

Step 2. Calculate the marginal Likelihood

P (data) = # of samples in observation/Total no.of observations

P (Data) =5/18

Step 3. Calculate Likelihood

P (data/class) = number of similar observations to the class/Total no. of points in the class.

P (Data /blue) =1/7

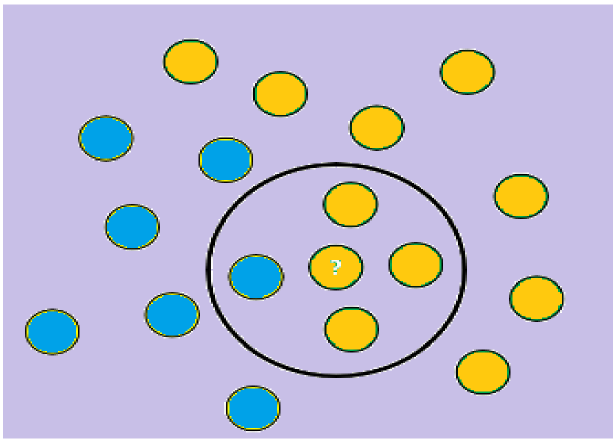

FIGURE 3. Graphical representation of Likelihood classifier

P (Data /yellow) =4/11

So Posterior Probability given in Fig. 2 for each Class is for data shown in Fig. 3

P= (Blue / data) = (1/7*7/18)/5/18 =0.2

P= (Yellow/data) = (4/11*11/18)/5/18 =0.8

So the output of classification of the above data is yellow because the posterior probability of yellow class is greater than the posterior probability of blue class. Mathematically we can write this as.

P (Class2 / data) > P(Class1 / data) where Class2 is yellow and Class1 is blue

G. Decision tree classification

Classification and regression model can be represented in the form of a tree structure in which each level is a composition of decision node and leaf node with the help of Entropy and information gain for the building of decision tree, where Entropy is the measurement of the amount of uncertainty which is.

$E(S) = \sum_{i=1}^{c} p_i \ln p_i$

Entropy calculates the homogeneity in the sample if the sample belongs to one class. Entropy becomes zero, and if the sample has more variability or belongs to two classes, then Entropy becomes one. Information gain is used to rank the features at each level of the tree structure first. We take that feature which can help to classify the majority of the instances in either class. A disadvantage of the tree structure is that the model becomes overfit when it tries to fit a model at a deeper level. Random Forest is the best example of a tree base decision model.

H. Features Reduction Methods

Linear Discriminant Analysis (LDA) is the most commonly used features reduction technique that can map the features that can minimize the variability within the class and maximize the variation between class to class mathematically we can define as. Let $X_i^{(k)}$ denote the ith pattern in class i, i=1,2,...,Mk , k=1,2,...,Nc. Define the within-class scatter matrix Cw as

$$C_W = \frac{1}{M} \sum_{k}^{Mc} \sum_{i}^{mk} (x_i^{9k0} - \mu^k)(x_i^{9k0} - \mu^k) \quad (2)$$

Where μ(k) is the mean vector of class k. Similarly, define the between-class scatter matrix CB. as

$$C_B = \frac{1}{M} \sum_{k=1}^{N} M_k (\mu^k - \mu)(\mu^k - \mu)^T \quad (3)$$

Where μ μμ μis the mean vector of the pooled data. The total scatter matrix is, then

$$C_T = \frac{1}{M} \sum_{k=1}^{Mc} \sum_{i=1}^{Mc} (x_i^k - \mu)(x_i^k - \mu)^T \quad (4)$$

The goal of linear discriminant analysis is to find a linear transform matrix Φ such that the ratio of determinants is maximized [27]

$$\left| \frac{\phi C_T \phi}{\phi C_W \phi} \right| \quad (5)$$

IV. RESULTS AND DISCUSSION

At first attempt, those mentioned above statistical textural features are extracted from ROIs having window size 64×64 pixels. For this purpose, a total (100×4) of 400 ROIs are developed. The data of the five most significant features shown in Table 2, selected by Convex Principal Feature Selection approach, when deployed to PCA and LDA, is clustered with an accuracy of 80.02% and 81.42%. The data of the five most significant features presented in Fig. 2 and Fig. 3 is clustered with 89.55% and 96.59% accuracy by PCA and LDA, respectively. Due to the size constraints of input data images, it is impossible to develop a handsome amount of sub-images greater than 64×64, to have reliable statistical results

TABLE 2

SELECTED FEATURES BY CONVEX PRINCIPAL FEATURES SELECTION METHOD

No.	Features
1	WavEnLL_s-4
2	WavEnLL_s-4
3	WavEnLL_s-4
4	WavEnLL_s-4
5	WavEnLL_s-4

As these features showed the best data clustering capability with an accuracy of 96.59% with the *LDA* approach, these are the most significant statistical textural parameters that may be used for further analysis.

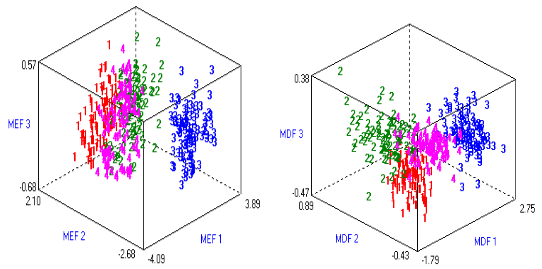

FIGURE 4. PCA and LDA data representation in clusters

Two disjoint data sets with a 70% /30% ratio for training and testing purposes, respectively, are developed. In this way, the five features mentioned above are listed in Table 2.' data from 400 ROIs have been deployed to train the classifier. Using a random forest tree classifier, we received an average accuracy of 98.17% during the training phase. Average 7 ROIs have been misclassified, as shown in Table 3. NM-92 and BWP-16 are classified approximately with 100% accuracy in the testing phase. Classification accuracy for NM-13 is 87%, and for AZRI-06, it is 88%, as given in Table 3. Class scattered in nonlinearly projected features space for test dataset is shown in Table 3. In this way, the system produced an average accuracy of 93.25% for all four varieties.

TABLE 3

CONFUSION MATRIX FOR SYSTEM PERFORMANCE DURING THE TRAINING PHASE

Classes	NM-92	NM-13	BWP-16	AZRi-06
NM-92	98	1	0	1
NM-13	2	87	0	11
BWP-16	0	0	100	0
AZRi-06	8	4	0	88

Graphical interpretation of the above data is given in Fig. 5.

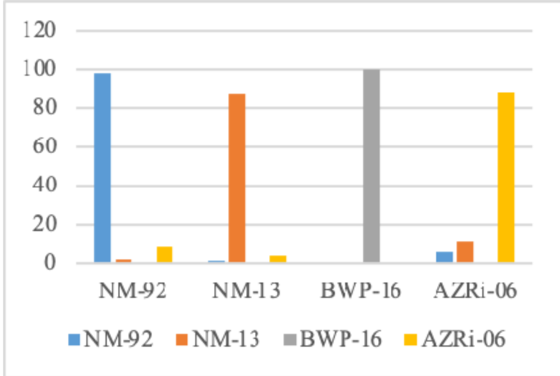

FIGURE 5. Analysis report of the training dataset

The empirical analysis is carried out using different classifiers with various features set. For this purpose, reduced features were obtained by Fisher analysis' F", Mutual Information, "MI" Probability of Error, "POE" F+MI+POE, and Convex-Principal features selection model. These are applied on different supervised classifier as shown in table 4 with corresponding accuracy rate we analyzed that Convex-Principal features selection give the highest accuracy with logistic and multiclass classifier

TABLE 4

CONFUSION MATRIX OF SYSTEM OUTPUT FOR THE TESTING PHASE

Classifier /Features	F	MI	POE	Combine	Convex
Nave Base	68	69	87	82	88.7
Logistic	87	73	90	85	93.5
Multi Class Classifier	88	74	89	87	93.3
Random Forest	78	72	90	90.2	92

A comparison of each classifier in terms of accuracy is given below in Fig.6. By using a time-series graph. It clearly shows that convex features have the highest accuracy.

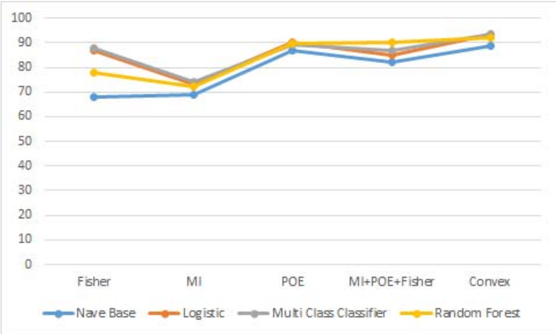

FIGURE 6. **Performance of various supervised classifiers with each feature set**

Second, to find which classifier takes minimal time to compute the result, we do the empirical analysis of the time needed by each classification model. The results in the table show that the logistic regression model and Multiclass Classifier have the worst time complexity on thirty features. In contrast, the Nive Base classifier shows the consistency of all features and the classifier. It means the nave base classifier is reliable and has the least time complexity with a considerable classification rate. The time complexity of each features model and classifier is given in Fig. 7.

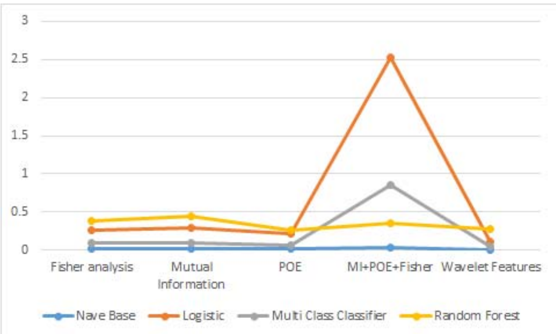

FIGURE 7. Performance of the various supervised classifier

V. CONCLUSION

In this study, various classifiers are implemented, trained, and tested using more than four hundred quantitative parameters (statistical texture features). Then, ten or five of them were selected by various features selection methods such as fisher, Mutual Information, Probability of Error, and Convex Principal of the feature selection method to differentiate four Mung-Beans varieties. The best results, 98.17% and 93.25%, for training and testing, respectively, are received by using the five most relevant features by taking the Convex-Principal method extracted from ROI (64×64). The result shows that the Logistic regression model has the highest accuracy. However, it is inconsistent in terms of time complexity. So Naive Base classifier is found consistent on all sizes of features selected by different feature selection methods. Its classification rate .5 percent is less from higher accuracy so it can be used in any environment with less computational resources. In five selected features, all features are extracted are belong to second-order parameters [28].

In the future, an Android application can be built using the features mentioned above using the nave base classifier. As a result, laymen and former can quickly learn the different varieties of Mung-Beans by using his simple Android handset.

ACKNOWLEDGMENT

We acknowledge the co-operation of Agriculture Regional Research Centre, Bahawalpur Region, Bahawalpur. Khwaja Fareed University of Engineering and Information Technology, Rahim Yar Khan, Pakistan, provides a pleasant atmosphere and resources to complete this work.

REFERENCES

[1] P. K. Dahiya, A. R. Linnemann, M. A. J. S. Van Boekel, N. Khetarpaul, R. B. Grewal, and M. J. R. Nout, "Mung Bean: Technological and Nutritional Potential," Crit. Rev. Food Sci. Nutr., vol. 55, no. 5, pp. 670–688, 2015.

[1] P. K. Pakistan. (2015, 12-06-2016). *Mungbean crop pulse in Pakistan*. Available: http://edu.par.com.pk/wiki/pluses/mung-bean/

[2] Z. Anwer. (2007, 10-06-2016). *Mungbean -- a rich source of protin*. Available: PAKISSAN.com

[3] D. Axe. (2016, 20-06-2016). *Mung Beans Nutrition & Its Big Benefits*. Available: https://draxe.com/mung-beans-nutrition/

[4] E. S. Oplinger, L. L. Hardman, A. R. Kaminski, S. M. Combs, and J. D. Doll, "Mungbean," University of Wisconsin-, MadisonMay,1990.

[5] Mahajan, Shveta, Das, Amitava, Sardana, and H. Kumar, "Image acquisition techniques for assessment of legume quality," *Trends in Food Science & Technology,* vol. 42, pp. 116-133, 2015.

[6] M. A. S. a. S. J. Symons, "A machine vision system for grading lentils," *Canadian Grain Commission* vol. 43, pp. 7.7-7.14, 2001 2001.

[7] B. S. a. D. G. S. Anami, "Improved Method for identification and classification of foreign boundries mixed food grain image sample," *ICGST- International Journal on Artificial Intelligence and Machine Learning,* vol. 9, pp. 1-8, 2009 2009.

[8] F. Kurtulmus, I. Alibas, and I. Kavdir, "Classification of pepper seeds using machine

vision based on neural network " *Int. J. Agric. and Biol. Eng.* , vol. 9, pp. 51-62, 2016.

[9] D. Li, Y. Liu, and L. Goa, "Research of maize seeds classification recognition based on the image processing," *International Journal of Signal Processing, Image Processing and Pattern Recognition* vol. 9, pp. 181-190, 2016.

[10] K. Sabanci, A. Kayabasi, and A. Toktas, "Computer vision based-method for classification of wheat grains using artificial neural networks " *Journal of Science Food Agric.*, 2016.

[11] P. Zapotocnzy, "Discrimination of wheat grain varieties using image analysis and multidimensional analysis texture of grain mass " *International Journal of food properties,* vol. 17, pp. 139-151, 2014.

[12] M. Huang, J. Tang, B. Yang, and Q. Zhu, "Classification of maize seeds of different years baased on hyperspectral imaging and model updating," *Computers and Electronics in Agriculture* vol. 122, pp. 139-145, 2016.

[13] X. Zhang, F. Liu, Y. He, and X. Li, "Application of hyperspectral imaging and chemometric calibrations for variety discrimination of maize seeds " *Sensors,* vol. 12, pp. 17234-17246, 2012.

[14] A. A. Abdullah and M. A. Quteishat, "Wheat seeds classification using multi-layer perceptron artificial neural network " *International Journal of Electronics Communication and Computer Engineering* vol. 6, pp. 307-309, 2015.

[15] N. Pandey, S. Krishna, and S. Sharma, "Automatic seed classification by shape and color features by using machine vision technology," *Internatoinal Journal of Computer Applications Technology and Research* vol. 2, pp. 208-213, 2013.

[16] Neelam and J. Gupta, "Identification and Classification of Rice varieties using Mahalanobis Distance by Computer Vsision " *Journal of Scientific and Research Publications* vol. 5, pp. 1-5, 2016.

[17] R. Birla and P. A. Singh, "An efficient method for quality analysis of rice using machine vision system " *Journal of Advance Information Technology* vol. 6, pp. 140-145, 2015.

[18] X. Chen, Y. Xun, W. Li, and J. Zhang, "Combining discriminant analysis and neural networks for corn variety identification " *Computers and Electronics in Agriculture,* vol. 71, pp. 548-553, 2010.

[19] S. Ghamari, "Classification of chickpea seeds using supervised and unsupervised neural networks," *African Journal of Agricultural Research* vol. 7, pp. 3193-3201, 2012.

[20] H. K. Mebatsion, J. Paliwal, and D. S. Jayas, "Automatic classification of non-touching cereal grains in digital images using limited morphological and color features," *Computers and Electronics in Agriculture,* vol. 90, pp. 99-105, 2013.

[21] N. S. Visen, J. Paliwal, J. D.S., and N. D. G. White, "Image analysis of bulk grain samples using neural networks," *Canadian Biosystems Engineering,* vol. 46, pp. 7.11-7.15, 2004.

[22] M. Shahid, M. S. Naweed, E. A. Rehmani, and Mutiullah, "Varietal discrimination of wheat seeds by machine vision approach " *Life Science Journal* vol. 11, pp. 245-252, 2014.

[23] P. Zapotocnzy, "Application of image texture analysis for varietal classification of barly " *International Agrophysics,* vol. 26, pp. 81-90, 2012.

[24] A. Pourreza, H. Pourreza, M. Abbaspur-Fard, and H. Sadrina, "Identification of nine iranian wheat varieties by texture analysis," *Computers and Electronics in Agriculture,* vol. 83, pp. 102-108, 2012.

[25] B. V. Canizo, L. B. Escudero, M. B. Pérez, R. G. Pellerano, and R. G. Wuilloud, "Intra-regional classification of grape seeds produced in Mendoza province (Argentina) by multi-elemental analysis and chemometrics tools," *Food chemistry,* vol. 242, pp. 272-278, 2018.

[26] M. Pérez-Rodríguez, J. E. Gaiad, M. J. Hidalgo, M. V. Avanza, and R. G. Pellerano, "Classification of cowpea beans using multielemental fingerprinting combined with supervised learning," *Food Control,* vol. 95, pp. 232-241, 2019.

[27] A. Materka and P. Szypinski, "MaZda User's Manual MaZda 4.6. download link; 1999–2006," ed, 2009.

[28] R. M. Haralick, K. Shanmugam, and I. Distein, "Texture Features for Image Classification," *IEEE Transactions on System, Man and Cybernetics,* vol. SMC-3, pp. 610-621, 1973.