

A Machine Learning Framework for Wheat Seed Variety Classification Using GLCM-Based Texture Analysis and Feature Optimization

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Abstract—In Pakistan, wheat is one of the important crops, and the production of wheat is highly reliant upon the use of pure and certified seed varieties. Hence, wheat seeds should be properly identified to ensure the quality of the crop and better production. Farmers typically rely on a visual assessment of the varieties of seeds in practice. This technique is incorrect and prone to inaccuracies. Many seeds of wheat are very similar in shape and color. This wrong seed selection could lead to reduced yield and economic loss. To tackle this problem, this study proposes an automated machine learning based classification of wheat seed varieties. The experiments are carried out on six wheat varieties grown in Southern Punjab, Pakistan. This research utilizes the data obtained by taking digital images of wheat seeds under consistent lighting and a uniform background at three different resolutions: 256 x 256, 512 x 512, and 1024 x 1024. In seed analysis, texture is chosen to describe seed surface characteristics because texture information is best at differentiating visually similar seeds. These images are used to calculate the following features: Histogram Features, Texture Features, and Laws Texture Features using Spatial Gray Level Co-occurrence Matrices. These matrices are second-order statistics such as correlation, energy, contrast, and homogeneity calculated based on the relationship between the intensities of the pixels at various distances and orientations. Then, the derived features are optimized using Principal Component Analysis and Correlation Feature Selection. Five machine learning classifiers, namely LogitBoost (LB), BayesNet (BN), Classification Via Regression (CVR), Multi-Layer Perceptron (MLP), and Random Forest (RF), are employed. The classifiers are evaluated separately on the PCA-reduced and CFS-selected datasets for each image resolution. Classification accuracy and consistency were assessed. The experimental results indicated that the PCA optimized Dataset of 1024 x 1024 resolution and the Random Forest classifier gave excellent discrimination between the wheat varieties, and the classifiers achieved 96.4% accuracy for all the classes. The proposed system helps to minimize human judgment dependency and ultimately reduces the risk of misclassification at the early stage of cultivation. The method is non-destructive, economical. and applicable in agricultural applications.

Keywords—Gray-Level Co-occurrence Matrix (GLCM); Principal Component Analysis (PCA); Correlation-based Feature Selection (CFS); Random Forest (RF); BayesNet (BN)

I. INTRODUCTION

Wheat (*Triticum aestivum* L.) is an important cereal crop in the world and is a source of food for a large portion of the human population. Wheat is important in food production because of its versatility across different agro-climates, high nutritional content, and its broad use in foods, making it vital to global food security [1, 2]. In Pakistan, wheat is a major staple crop which plays a crucial role in rural livelihoods, agricultural productivity, and Pakistan's economic development. Wheat production has significantly improved due to the introduction of high-yielding wheat varieties, increased irrigation, use of fertilizers, and the use of modern cultivation methods since the Green Revolution, which has contributed to food security in the country [3]. However, the sustainability of wheat production is becoming a growing concern due to climate change, water scarcity, soil degradation, increasing temperatures, and increased occurrence of biotic stresses (such as pests and diseases) and abiotic stresses (such as drought, heat, and salinity) [4, 5].

In response to these difficulties, agricultural research stations have cultivated many wheat cultivars with greater yield capacity, disease resistance, drought resistance, and suitability to various environmental conditions [6]. As a result, a few wheat varieties have been grown throughout Pakistan, especially in the South of Punjab, where wheat farming is a critical part of the agricultural activities [7]. Careful choice of wheat cultivars is very important as they have different agronomic characteristics, growth requirements, stress tolerances, and yield potentials. Therefore, correct wheat variety identification and classification is crucial in agricultural production, varietal purity testing, wheat breeding, seed certification, and precision agriculture [8, 9].

The identification of varieties is traditionally done with the help of experienced wheat agronomists and seed analysts by manual inspection. These methods tend to be time-consuming, labour-intensive, subjective, and subject to human error, especially when differentiating morphologically similar cultivars [10, 11].

In recent years, there has been a growing demand for fast, accurate, and scalable classification approaches, which has encouraged the use of computer vision, digital image processing, and machine learning technologies in agricultural systems. These technologies can be used to automatically analyze the visual features of grains, including morphology, texture, color, shape, and structural characteristics. These features can help discriminate between different wheat varieties [12, 13].

Machine vision systems use vision equipment, sensors, and computational algorithms to accurately and consistently acquire and analyze visual information [14]. Machine vision systems can analyze a vast amount of data without getting tired or biased, which is very suitable for agricultural automation [11, 15]. This capability extends to image processing, where digital images are processed using image enhancement, image segmentation, feature extraction, and pattern recognition to transform the raw images into meaningful analytical information [13, 16]. The quantitative attributes derived from extracted features can be used by machine learning algorithms for classification and decision-making.

Over the past years, artificial intelligence has been used in crop classification in a way that has greatly enhanced its effectiveness. In recent years, machine learning models like Support Vector Machines (SVMs), ensemble classifiers, and deep learning models like Convolutional Neural Networks (CNNs) have achieved excellent performance in agricultural image analysis studies [8, 9]. These algorithms can be used to accurately classify wheat varieties and identify subtle differences in wheat morphology that may be difficult to visually distinguish from wheat images alone by learning discriminative patterns from wheat image sets [17, 18]. Therefore, image processing along with machine learning techniques has emerged as a viable approach for wheat classification where efficiency, accuracy, repeatability, and scalability are enhanced.

Although significant strides have been made in the field of agricultural machine vision, current research has mainly concentrated on the detection of diseases, monitoring of crop health, and binary classification, compared to the relatively limited work on the classification of wheat varieties in multiple classes with real-field image data sets and the development of sophisticated feature extraction techniques [19, 20]. Moreover, the establishment of advanced classification schemes that can differentiate the very similar wheat cultivars for a variety of conditions is an open research problem. Wheat is highly significant crop in Pakistan and as the demand for intelligent agricultural decision support systems is increasing, it is highly scientific and significant to develop an accurate and automated wheat classification framework.

Hence, this work aims to explore the use of machine learning and computer vision technologies for wheat variety classification. By integrating digital image processing, feature extraction, and advanced classification algorithms, the proposed framework aims to improve the accuracy and reliability of wheat classification. The approach is intended to support wheat variety identification and may have potential applications in seed certification and agricultural decision support.

II. LITERATURE REVIEW

With the advent of machine learning, computer vision, and deep learning, agricultural research has undergone a transformation, especially in the field of wheat seed and variety classification. Classification of wheat is essential to ensure varietal purity, crop management, seed certification, and better agricultural productivity. Practically, farmers' wheat seed identification methods are largely based on manual work and the expertise of experts. These methods are also time-consuming, subjective, and challenging to scale up. For this reason, automated image-based classification systems have been used. The classification is achieved by the use of digital image processing and machine learning algorithms to enhance its accuracy, efficiency and uniformity.[21, 22].

Initially researchers used handcrafted visual features of the wheat seed images such as color, shape, texture, area, perimeter, and geometric features. Wheat classification and seed quality assessment were often conducted with traditional machine learning algorithms like Support Vector Machines (SVM), Decision Trees, Random Forests, Naïve Bayes, and Artificial Neural Networks. The performance of these approaches was found to be encouraging, with classification accuracy frequently exceeding 90% [22-25]. SVM consistently performed better than other traditional classifiers in high-dimensional feature spaces and with limited training samples [21, 26, 27].

Wheat image analysis has also been largely influenced by texture-based feature extraction techniques. Gray-Level Co-occurrence Matrix (GLCM) descriptors and their related texture measures are broadly used to identify the discriminative visual patterns in wheat seed images and plant images. Several studies have demonstrated that texture features, in combination with machine learning classifiers, play a significant role in improving the classification result and also offer additional texture information beyond color and geometric measurements [28, 29]. Likewise, morphological and morphometric traits like kernel length, width, degree of kernel compactness, and groove dimensions are highly informative for wheat variety identification [26, 30].

Despite the limitations of handcrafted feature engineering, deep learning has emerged as a rapidly advancing field, thus moving research from manual feature engineering to automatic feature learning. In wheat classification, Convolutional Neural Networks (CNNs) are gaining popularity as the most prominent approach due to their capacity to extract complex visual features directly from raw images. Several CNN models are able to recognize tremendous classification accuracy on wheat seed datasets. A custom CNN architecture attained an accuracy of more than 97% for wheat classification [31], whereas transfer learning approaches with pretrained networks, including DenseNet201, MobileNet, and InceptionV3, revealed their effectiveness in improving classification performance [32]. More recent studies on Advanced CNN-based architectures have attained higher accuracy, exceeding 98% for wheat variety recognition [33-35].

Recently, there are also efforts on low-power deep learning algorithms for mobile devices and edge devices. Agricultural research is usually conducted in resource-limited environments, and decreasing the computational complexity without

compromising accuracy has become an important research goal. LWheatNet attained 98.59% classification accuracy with a model size of almost 1.33 MB [34]. Similarly, the G-PPW-VGG11 model for wheat field-based classification supports that lightweight networks can be used for real-time agricultural applications in achieving high accuracy. The studies indicate a shift towards more application-focused approach and smart farming [20].

Attention mechanisms and transformer-based architectures, which allow the model to focus on the most informative visual regions, have also improved the classification performance. Hybrid network models of CNN, attention modules, and recurrent networks have exhibited the best performance for learning delicate distinctions between wheat varieties having similar appearances. As an example, A hybrid Vision Transformer-CNN model attains an accuracy of 98.33% [36], and Xception-BiLSTM model achieves an accuracy of 97.73% [37]. Hard-voting groups also show good results with classification accuracy of up to 99% [33].

Hyperspectral imaging has also been identified as a potential non-destructive technique for wheat classification and for assessing wheat seed quality along with the RGB imaging. Hyperspectral sensors work differently from the standard imaging system. They are able to provide both spatial and spectral data, which are necessary for detailed characterization of wheat varieties. Multiple studies have combined hyperspectral imaging with machine learning algorithms, including SVM, Partial Least Squares Discriminant Analysis (PLS-DA), XGBoost, deep neural networks, and others, to deliver excellent classification accuracy [38-42]. The hyperspectral approaches show good performance, but they are costly to acquire and computationally intensive.

Another relevant research line is in the field of image segmentation and object detection techniques, which could be useful in enhancing the extraction of features, such as the isolation of wheat grains, spikes, and heads from the background. To meet the particular demands of agricultural production, several contemporary segmentation architectures have emerged to significantly enhance wheat object detection and wheat segmentation in real-world agriculture, including DeepLabV3+ [43], CBAM-HRNet [44], YOLOv8-HD [45] and semi-supervised encoder-decoder networks [46]. These advances enable more reliable feature extraction, resulting in improved classification performance.

In Pakistan, the study on the analysis of wheat using AI has significantly increased over the past few years. Local research has been done on wheat diseases, growth stage identification, yield prediction, and dataset development. A benchmark dataset with standardized images of major wheat varieties was presented, which is crucial for future machine learning research in Pakistan [47]. A hybrid MobileNetV2-DenseNet121 network was designed to obtain a recognition rate of about 99% for wheat growth stages [48]. Deep learning and image processing methods have been effectively used in wheat disease detection and yield prediction in the field and through remote sensing [49-51].

Although there are enormous advances in wheat classification studies, there are still some critical questions that

have not been answered. Most of the previous studies have used publicly available international datasets or laboratory settings, which may not apply to local agricultural conditions [22, 25, 26]. Furthermore, Pakistani local wheat variety image datasets have been used in a limited number of studies [47]. Although deep learning, transformer-based, and ensemble methods have shown high classification accuracies, many of these approaches require considerable computational resources. This reduces their suitability for deployment on mobile devices and in resource-constrained agricultural environments [20, 33, 36]. Additionally, the focus of most of the existing studies is only on classification performance, and little attention is paid to the translation of classification results into practical recommendations for agronomic operations that can be used directly by farmers in their decision-making processes.

Hence, robust and efficient machine learning models are required to achieve precise Pakistani wheat variety classification using image-based data. Such systems should also support practical agricultural decision-making by linking variety classifications with crop management. These can contribute to precision agriculture and sustainable wheat production.

III. METHODOLOGY

A. Proposed Methodology

The main goal of the study is to propose an automated method of identifying wheat seed varieties based on digital image data. The proposed framework is depicted in Figure 1 that describes the entire process of classifying wheat seed varieties. These six steps represent the entire process.

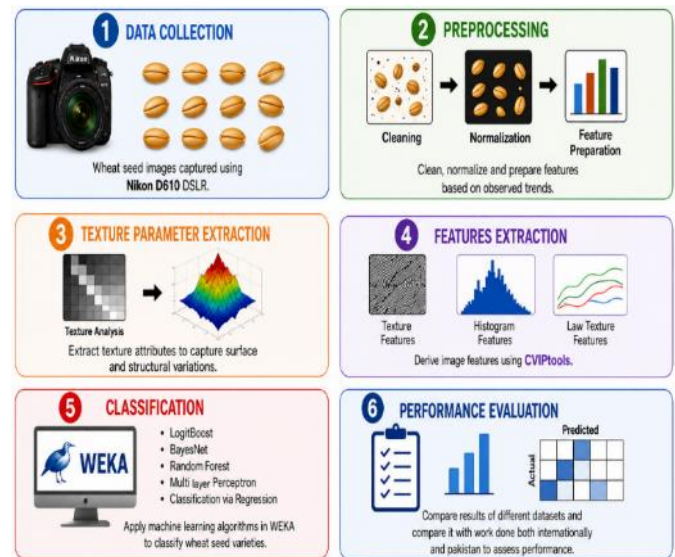


Fig. 1. Proposed methodology framework.

B. Study Area and Wheat Varieties

A total of six wheat varieties were used in the study, which are commonly grown in Southern Punjab, Pakistan, namely Akbar-19, Dilkash-20, Inqalab-91, Sadiq-21, Nawab-21 and Ghazi-19. Wheat seed samples were gathered from Bahawalpur, Multan, and Dera Ghazi Khan districts. These varieties were carefully chosen because of their agricultural importance and widespread cultivation in these areas.

C. Image Acquisition

Wheat seeds images were captured by using a Nikon D610 DSLR camera equipped with a 24-megapixel sensor under controlled studio lighting. Each of the 300 images was a single physical sample of seed, and 50 samples were taken from each of the six varieties: 50 x 6 = 300 images. So, no repeated images of the same physical seed were present throughout the dataset. Environmental variability was minimized by maintaining a fixed camera setup, a uniform background, and consistent lighting throughout the image acquisition process. Sample images of each variety used in this research are shown in Figure 2.



Fig. 2. Wheat seed images.

D. Image Preprocessing

The captured images were resized to three different resolutions: 256×256, 512×512, and 1024×1024 pixels to explore the effect of image scale on classification accuracy. RGB images were converted into grayscale images to simplify the computation required while maintaining structural and texture information. Image enhancement and normalization techniques were applied to improve contrast and reduce noise. Preprocessing enhanced image quality and normalized the dataset for analysis. Given an image $I(x, y)$, normalization is computed as:

$$I_n(x, y) = \frac{I(x, y) - \mu}{\sigma} \quad (1)$$

where μ is the mean intensity and σ denotes the standard deviation. This step helps to minimize illumination variations and improve relevant features. Noise reduction techniques were also applied to improve image clarity.

E. Feature Extraction

CVIPtools software was used for feature extraction. Three types of descriptors were extracted: histogram features, Gray-Level Co-occurrence Matrix (GLCM) texture features, and Laws texture features. Five regions of interest (ROIs) on individual seeds were selected randomly from each image to capture local texture variations, as tabulated below. Based on ROI circle size in Table 1, nine datasets comprising 91 features (Histogram, Texture, and Laws Texture) were extracted.

TABLE I. SUMMARY OF ROI USED FOR EACH DATASET

Sr. No	Datasets	ROI Circle Radius Size
	256 x 256	12 Pixels 14 Pixels 16 Pixels
	512 x 512	14 Pixels 16 Pixels 18 Pixels
	1024 x 1024	16 Pixels 18 Pixels 20 Pixels

F. Histogram Features

Histogram analysis represents the intensity distribution of image pixels [52]:

$$p(i) = \frac{n_i}{N} \quad (2)$$

where n_i is the number of pixels with intensity i and N is the total number of pixels.

Mean:

$$\mu = \sum_{i=0}^{L-1} i \cdot p(i) \quad (3)$$

Variance:

$$\sigma^2 = \sum_{i=0}^{L-1} (i - \mu)^2 p(i) \quad (4)$$

Entropy:

$$H = - \sum_{i=0}^{L-1} p(i) \log p(i) \quad (5)$$

G. Gray-Level Co-occurrence Matrix (GLCM) Features

GLCM was employed to quantify spatial relationships between neighboring pixels. Texture features were computed in four orientations (0°, 45°, 90°, and 135°). The principal Haralick descriptors used in this study include Contrast, Correlation, Homogeneity, Energy (Angular Second Moment), and Entropy [53].

$$P(i, j) = \frac{\text{Frequency of pixel pair } (i, j)}{\text{Total number of pairs}} \quad (6)$$

Derived features include:

Contrast:

$$\text{Contrast} = \sum_{i,j} (i - j)^2 P(i, j) \quad (7)$$

Energy:

$$\text{Energy} = \sum_{i,j} P(i, j)^2 \quad (8)$$

Correlation:

$$\text{Correlation} = \frac{\sum_{i,j} (i - \mu_i)(j - \mu_j) P(i, j)}{\sigma_i \sigma_j} \quad (9)$$

Homogeneity:

$$\text{Homogeneity} = \sum_{i,j} \frac{P(i, j)}{1 + |i - j|} \quad (10)$$

These measures capture structural and spatial properties of wheat seed textures.

H. Laws Texture Features

Laws texture energy measures were extracted using convolution masks derived from the one-dimensional kernels L5, E5, S5, W5, and R5. These filters capture texture patterns associated with level, edge, spot, wave, and ripple structures. Symmetric masks were combined to reduce feature redundancy and improve computational efficiency.

- L, E, S, W, R represent:
 - L (Level): Average or smooth intensity in the image.
 - E (Edge): Edge detection (intensity changes) for texture.
 - S (Spot): Identifies spot-like patterns in the image.
 - W (Wave): Captures wave or oscillatory patterns.
 - R (Ripple): Identifies fine ripple or repetitive texture.

Law's texture energy measures use convolution masks to extract local texture information (Laws, 1980). The masks are formed using 1D vectors such as:

Level (L5): [1 4 6 4 1]

Edge (E5): [-1 -2 0 2 1]

Spot (S5): [-1 0 2 0 -1]

The 2D mask is generated as:

$$\text{Mask} = V_i^T \cdot V_j \quad (11)$$

Texture energy is computed as:

$$E = \frac{1}{MN} \sum_{x,y} |I(x,y) * \text{Mask}| \quad (12)$$

where *denotes convolution.

I. Feature Optimization

Principal Component Analysis (PCA) and Correlation-based Feature Selection (CFS) were used separately to reduce the dimensionality and remove redundant information from the extracted feature sets. PCA was used to reduce the size of the feature space while retaining the major variance in the data, whereas CFS was used to select attributes with high relevance and low inter-correlation. For each image resolution, PCA and CFS were applied separately to the complete extracted feature dataset, and separate data files were generated for the PCA-optimized and CFS-optimized feature sets. The resulting datasets contained 25 PCA features and 21 CFS-selected features, respectively. These optimized datasets were subsequently used for classification with the selected machine learning algorithms in WEKA. The classification performance was evaluated using 10-fold cross-validation. Thus, PCA and CFS were performed before the cross-validation stage and were not independently fitted within each training fold.

In general, the extracted feature vector is:

$$X_{opt} = [f_1, f_2, \dots, f_m] \quad (13)$$

where:

X_{opt} = optimized feature vector after feature reduction.

$f_1, f_2, \dots, f_m$ = selected features.

m = number of retained features after optimization.

J. Classification Models

Five supervised machine learning algorithms implemented in WEKA 3.8.2 were evaluated: LogitBoost, BayesNet, Classification via Regression, Multi-Layer Perceptron (MLP), and Random Forest using default settings. In order to ensure uniformity, the same configurations were applied to all feature-optimized datasets for performance comparison. The classification performance was evaluated using 10-fold cross-validation. The selected algorithms have been used in agricultural classification tasks. These models learn a mapping function:

$$f: X \rightarrow Y \quad (14)$$

where Y denotes the class label of wheat seed varieties.

K. Performance Evaluation

The 10-fold cross-validation was performed on the PCA-optimized and CFS-optimized datasets after the respective feature-selection procedures had been completed. The classification performance was measured by the following performance metrics: Accuracy, Precision, Recall, and F1-score. The classifiers were compared based on these performance measures to determine the most effective classifier. The classification results were also compared with recent studies from Pakistan and other countries that have been reported in the literature. The evaluation of the performance of the models is performed with classification measures:

Accuracy:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (15)$$

Precision:

$$\text{Precision} = \frac{TP}{TP+FP} \quad (16)$$

Recall:

$$\text{Recall} = \frac{TP}{TP+FN} \quad (17)$$

F1-Score:

$$F1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \quad (18)$$

A confusion matrix is used to visualize classification performance. Comparative evaluation is carried out among classifiers and benchmarked with existing national and international studies.

IV. RESULTS

Six Pakistani wheat varieties were considered: Akbar-19, Dilkash-20, Ghazi-19, Inqalab-91, Nawab-21 and Sadiq-21. Digital images of these varieties were taken and used to evaluate the proposed wheat seed classification system. The experiments were carried out using three image resolutions (256×256, 512×512, and 1024×1024 pixels) to explore the effect of image quality on classification performance. GLCM having Texture features, Histogram features, and LBP texture features were obtained for each ROI in wheat seed regions.

Principal Component Analysis (PCA) and Correlation-based Feature Selection (CFS) were used for dimensionality reduction and feature selection, respectively. PCA was performed in WEKA using a cumulative variance retention threshold of 95% (-R 0.95), resulting in 25 principal components. CFS was performed using CfsSubsetEval with BestFirst search in the forward direction and default search parameters, resulting in 21 selected features. CfsSubsetEval evaluates feature subsets by considering the correlation between the selected features and the class while reducing redundancy among the selected features. The resulting PCA and CFS feature sets were used separately for classification at each image resolution.

The optimized feature sets were then classified using different machine learning algorithms. Previous research in this field has also reported that image-based feature extraction and machine learning provide an effective approach for automated wheat variety identification [24, 54].

The classification accuracy varied with the dimensionality reduction and feature selection methods. The major variance patterns were preserved, and important discriminative texture information was retained by PCA, giving better results than CFS. While CFS reduced the number of features, some information related to the seed surface characteristics was lost. The results showed that there are some subtle differences in the texture of the different wheat varieties and that the ability to preserve these differences is essential for the correct classification.

The performance of the machine learning classifiers varied with the selected features and image resolution in the 10-fold cross-validation experiments. Higher-resolution images generally delivered higher classification accuracy. This may be because they kept more detailed information about seed texture, shape, and surface patterns.

A. Classification Performance Analysis Using PCA Optimized Features

Table 2 presents classification performance of five machine learning classifiers using PCA-optimized features extracted from wheat seed images at three different resolutions (256×256, 512×512, 1024×1024).

TABLE II. ACCURACY COMPARISON OF CLASSIFIERS (PCA OPTIMIZED)

Classifier	Accuracy (%) Dataset 256 x 256	Accuracy (%) Dataset 512 x 512	Accuracy (%) Dataset 1024 x 1024
LogitBoost	86.00	91.73	92.40
BayesNet	84.07	92.13	88.80
ClassificationViaRegression	88.53	92.67	94.20
MultilayerPerceptron	87.60	91.53	93.80
RandomForest	92.80	94.67	96.40

The performance of five classification machine learning algorithms is presented for the three different resolution images of wheat seeds extracted from the images using PCA in Table 2. The corresponding classification accuracies are shown in Figure 3. The results reveal that the image resolution has a positive effect on the classification accuracy since the higher the image

resolution, the more discriminative texture and structural information of the wheat seed variety could be obtained. The results also reveal that feature representation and the selection of the corresponding learning algorithm are crucial for classification accuracy.

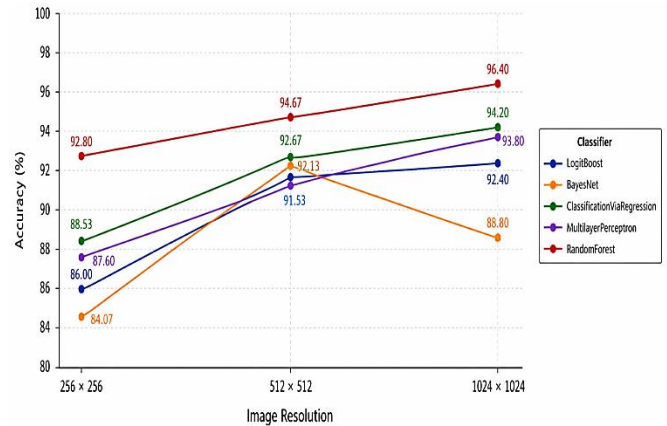


Fig. 3. Classification accuracy of different classifiers (PCA optimized).

Random Forest amongst all classifiers, has shown the highest accuracy for all image resolutions, with accuracies of 92.80%, 94.67%, and 96.40% for 256×256, 512×512, and 1024×1024 datasets, respectively. Random Forest outperforms other methods because it follows the ensemble learning method, with multiple decision trees working together to enhance the accuracy of classification and minimize errors.

The performance of ClassificationViaRegression was also found to steadily improve with increasing resolution of the images, with the results of 88.53%, 92.67%, and 94.20%, respectively. Likewise, LogitBoost and MultilayerPerceptron showed higher accuracy with higher-resolution images, suggesting that the higher-resolution images provided better feature representation. BayesNet performed well at 512×512 resolution but showed lower accuracy at 1024×1024 resolution, indicating a possible limitation in the ability of the model to capture higher dimensional relationships between the image feature dimensions.

The overall results indicate that PCA preserved important discriminative features in the wheat seed images. The combination of PCA and Random Forest achieved the best classification performance, and it is observed that it achieves the highest accuracy in the highest resolution data (96.40%). The results presented here emphasize the necessity of using image quality, feature optimization, and classifier selection in developing reliable wheat seed classification systems.

B. Classification Performance Analysis Using CFS Optimized Features

Table 3 shows the classification performance of five machine learning classifiers, trained with features optimized by CFS on the wheat seed images with three different image resolutions: 256×256, 512×512, and 1024×1024 pixels.

The results shown in Table 3 indicate that both the selected feature subset and the learning algorithm had influenced the classifier performance. CFS-based feature selection resulted in

lower classification accuracy as compared to PCA optimization. Figure 4 shows a graphical representation of their classification accuracy results. This indicates that some important discriminative information essentials for wheat variety classification was lost during feature reduction.

TABLE III. ACCURACY COMPARISON OF CLASSIFIERS (CFS OPTIMIZED)

Classifier	Accuracy (%) Dataset 256 x 256	Accuracy (%) Dataset 512 x 512	Accuracy (%) Dataset 1024 x 1024
LogitBoost	70.53	73.87	71.53
BayesNet	67.67	67.53	68.80
ClassificatoinViaRegression	79.07	77.33	75.80
MultilayerPerceptron	65.47	68.93	73.60
RandomForest	85.27	84.33	75.47

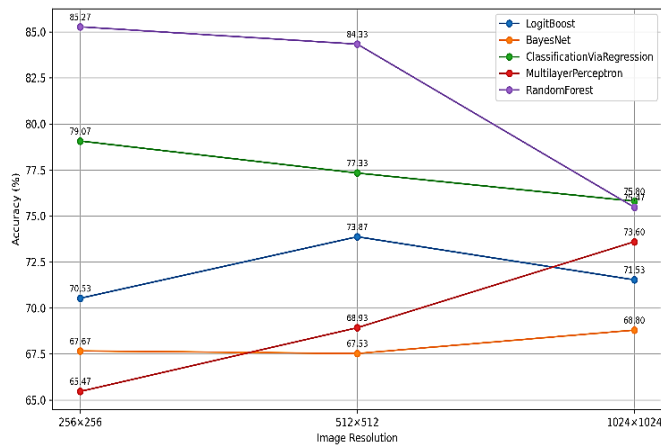


Fig. 4. Classification accuracy of different classifiers (CFS optimized).

In comparison, LogitBoost performed relatively stably on the image resolutions with an accuracy of 70.53%, 73.87% and 71.53% for 256×256, 512×512 and 1024×1024, respectively. In addition, BayesNet delivered similar results with a range of 67.53%-68.80%, indicating some consistency but not as effective as the other classifier in modelling complex relationships among the selected seed features.

ClassificationViaRegression achieved accuracies of 79.07%, 77.33%, and 75.80% for all the three datasets. However, its accuracy decreased slightly with increasing image resolution. This suggests that the CFS-selected features did not fully keep the additional information available in higher-resolution images. In contrast, MultilayerPerceptron showed gradual improvement from 65.47% to 73.60%, indicating better utilization of additional feature information at higher resolutions.

Random Forest achieved the highest accuracy for the 256×256 and 512×512 datasets, with accuracies of 85.27% and 84.33%, respectively. However, its performance decreased to 75.47% for the 1024×1024 dataset. This reduction suggests that the CFS-selected feature subset was less effective in representing complex patterns from higher-resolution images. Overall, the results confirm that although CFS reduced the feature dimensionality, PCA optimization retained more

informative features and provided superior classification performance for wheat seed variety classification.

C. Performance Comparison of Both PCA and CFS Optimized Features

Table 4 and Table 5 report the performance of the proposed model and baseline methods with various evaluation measures. These metrics provide complementary information for overall classification accuracy, class-wise prediction performance, and discriminative ability. This allows a more comprehensive comparison of model effectiveness.

TABLE IV. ACCURACY COMPARISON OF CLASSIFIERS (PCA OPTIMIZED)

Classifier	Resolution	Kappa Statistic	Weighted F-Measure	ROC Area
LogitBoost	256×256	0.8320	0.860	0.982
LogitBoost	512×512	0.9008	0.917	0.995
LogitBoost	1024×1024	0.9088	0.924	0.994
BayesNet	256×256	0.8088	0.841	0.980
BayesNet	512×512	0.9056	0.921	0.996
BayesNet	1024×1024	0.8656	0.888	0.991
ClassificatoinViaRegression	256×256	0.8624	0.885	0.985
ClassificatoinViaRegression	512×512	0.9120	0.932	0.995
ClassificatoinViaRegression	1024×1024	0.9304	0.968	0.992
MultilayerPerceptron	256×256	0.8512	0.876	0.976
MultilayerPerceptron	512×512	0.8984	0.915	0.990
MultilayerPerceptron	1024×1024	0.9256	0.938	0.992
RandomForest	256×256	0.9136	0.928	0.994
RandomForest	512×512	0.9360	0.947	0.997
RandomForest	1024×1024	0.9568	0.964	0.998

TABLE V. ACCURACY COMPARISON OF CLASSIFIERS (CFS OPTIMIZED)

Classifier	Resolution	Kappa Statistic	Weighted F-Measure	ROC Area
LogitBoost	256×256	0.6464	0.703	0.943
LogitBoost	512×512	0.6864	0.739	0.952
LogitBoost	1024×1024	0.6584	0.708	0.942
BayesNet	256×256	0.612	0.675	0.933
BayesNet	512×512	0.6104	0.677	0.938
BayesNet	1024×1024	0.6256	0.68	0.926
ClassificatoinViaRegression	256×256	0.7488	0.789	0.965
ClassificatoinViaRegression	512×512	0.728	0.773	0.963
ClassificatoinViaRegression	1024×1024	0.7096	0.747	0.954
MultilayerPerceptron	256×256	0.5856	0.655	0.909
MultilayerPerceptron	512×512	0.6272	0.691	0.918

MultilayerPerceptron	1024×1024	0.6832	0.728	0.942
RandomForest	256×256	0.8232	0.852	0.974
RandomForest	512×512	0.812	0.843	0.977
RandomForest	1024×1024	0.7056	0.753	0.949

The Random Forest classification rate was 96.4% but was also supplemented with other evaluation parameters such as Precision, Recall, F1-Score, Specificity and AUC-ROC presented in Tables 4 and 5. These metrics provide alternative information about the accuracy of the classifier in correctly predicting positive and negative cases while considering false-positive and false-negative rates and in properly separating classes. The overall high values for all these metrics justify the classification rate reported as 96.4% for the Random Forest classifier and give evidence of good and reliable classification.

D. Comparison with International Research

The results obtained were compared with previous international wheat classification studies. Kayabaşı et al. [54] achieved approximately 93% accuracy using texture and morphological features with artificial neural networks. Basati et al. [24] reported around 90.20% accuracy using color, morphology, and texture features with decision tree classification. Singh et al. [55] reported 97.70% accuracy using advanced feature representation and fuzzy clustered random forest. Lüy et al. [28] achieved 82.20% accuracy by using GLCM texture features and grain characteristics as mentioned in Table 6.

TABLE VI. COMPARISON WITH INTERNATIONAL STUDIES ON WHEAT SEED CLASSIFICATION USING TEXTURE/IMAGE FEATURES AND MACHINE LEARNING

Study	Features Used	Classifier	Accuracy (%)	Comparison with Present Study
Kayabaşı et al. (2017)	Image texture and morphological features	ANN	93.00	Present study achieved higher accuracy (96.40%) using PCA and RandomForest
Basati et al. (2018)	Color, morphology, and texture features	Decision Tree (J48)	90.20	The present study improved classification accuracy by more than 6%.
Singh et al. (2020)	Visual grain characteristics	Fuzzy Clustered Random Forest	97.70	Slightly higher than the present study; however, it focused on grain grading rather than classification of multiple wheat varieties.
Lüy et al. (2023)	GLCM texture features and grain characteristics	Machine Learning	82.00	The present study substantially outperformed the reported results that time.
Present Study	GLCM texture and intensity features + PCA	RandomForest	96.40	The present study achieved 96.40% accuracy among reviewed texture-based varietal classification studies.

Studies are noted in Table 6, with the difference among them in respect to the number of wheat classes, the number of datasets, the setup of acquiring images, image preprocessing, and the way the studies are validated. All of this can have significant impact on classification accuracy and on the validity of direct one-on-one comparisons. The reported accuracies are therefore listed, in particular, to provide a benchmark in this research. Compared with these studies, the proposed PCA-based Random Forest framework achieved competitive performance while using a comparatively simple and computationally efficient machine learning approach.

E. Comparison with Pakistani Research Studies

The proposed method was also compared with recent studies conducted in Pakistan, as shown in Table 7.

TABLE VII. COMPARISON WITH RESEARCH CONDUCTED IN PAKISTAN

Study	Research Focus	Method	Accuracy (%)	Comparison with Present Study
Nawaz et al. (2025)	Development of Pakistani wheat seed dataset	Dataset Creation	N/A	Provides a dataset but not a classification framework.
Yasar et al. (2024)	Bread wheat variety classification	CNN + SVM	94.00	GLCM features were not used.
Yasar et al. (2024)	Bread wheat variety classification	ResNet18s	97.57	GLCM features were not used.
Usman et al. (2024)	Wheat seed disease classification	CNN	98.43	Different tasks focusing on disease detection rather than variety classification. Further, CNN-based methods are more accurate, but they normally require more data, GPU resources, and long training time. A quantitative comparison of computational resources was not performed in the present study.
Ashraf et al. (2023)	Wheat disease recognition	CNN	93.00	Different application domain.
Present Study	Six Pakistani wheat varieties	PCA + RandomForest	96.40	One of the highest accuracies reported using traditional machine-learning techniques.

The performance of the proposed wheat seed classification framework was compared with recent studies conducted in Pakistan, as summarized in Table 7. Existing studies have mainly focused on wheat variety classification using deep learning approaches or wheat disease recognition, whereas the present study focuses on automatic classification of six Pakistani wheat varieties using texture-based features and traditional machine learning. Further, the accuracy reported is a contextual benchmark for wheat seed classification research in Pakistan. But caution should be taken in making direct one-to-one comparisons due to the differences in the size of the data sets, wheat varieties, the way the images were taken, the preprocessing methods, and how the images were validated. These factors may influence the accuracy in the classification and can have an impact on the comparability of accuracy values reported.

Nawaz et al. [47] developed a Pakistani wheat seed image dataset, which provides an important resource for future research; however, the study did not present a complete classification framework. Yasar et al. [56] achieved 94.00% and 97.57% accuracy using CNN-SVM and ResNet18 models, respectively, for bread wheat variety classification. However, these approaches relied on deep learning architectures and did not utilize GLCM-based handcrafted texture features. Similarly, Usman et al. [51] and Ashraf et al. [49] reported high accuracies using CNN models, but their studies focused on wheat disease detection rather than variety identification.

In comparison, the proposed PCA-optimized Random Forest framework attains an accuracy of 96.40% for six Pakistani wheat varieties. The results show that the proposed approach presents competitive performance with deep learning-based approaches, requiring comparatively lower computational complexity using handcrafted features and a Random Forest classifier. A quantitative comparison of computational complexity with deep learning approaches was not performed in this study. The results highlight the potential of optimized texture features along with machine learning algorithms for wheat seed variety classification.

F. Research Contributions

This work provides a framework for wheat seed variety classification using image acquisition, image preprocessing, texture and intensity-based feature extraction, feature dimensionality reduction and selection, and machine learning. The framework can support research in agricultural image analysis and wheat seed classification. The framework proposed is applicable to small and medium-sized datasets in the agricultural context and can be adapted to other classification problems of crops. The comparison of five classifiers (LogitBoost, BayesNet, ClassificationViaRegression, MultilayerPerceptron, and RandomForest) shows that the choice of a particular classifier, as well as feature optimization, has a pronounced effect on the quality of the classification result. The wheat variety identification results demonstrated that the PCA-optimized RandomForest model gave the highest accuracy of 96.40%; thus, it is effective in wheat variety identification tasks. This study offers fresh empirical data on the texture features of wheat varieties grown in South Punjab, Pakistan, and fills the gap of wheat seed image datasets and classification studies in

the region. The proposed method shows that the handcrafted texture features and the traditional machine learning algorithms can accurately distinguish wheat seed varieties without being destructive, quickly, and cheaply. The proposed framework has potential applications in seed identification, varietal verification, and agricultural image analysis. It may also provide a basis for future research involving deep learning, hybrid feature extraction, and larger agricultural datasets.

V. CONCLUSION

In this study, a complete image-based wheat variety classification framework based on machine learning techniques was presented. Whereas the previous work was performed on benchmark datasets like the UCI Wheat Seeds dataset, this study is based on a real-world image dataset of six wheat varieties from Pakistan, namely Akbar-19, Dilkash-20, Ghazi-19, Inqalab-91, Nawab-21, and Sadiq-21. The use of locally cultivated wheat varieties with similar visual characteristics makes the classification problem more difficult and practically relevant. The study provides a detailed image-based classification framework for Pakistani wheat varieties. It also addresses the limited availability of local wheat seed image datasets.

Five machine learning classifiers, including LogitBoost, BayesNet, ClassificationViaRegression, MultilayerPerceptron, and RandomForest, were systematically compared in their performance, with identical experimental conditions. The results showed that the choice of classifiers has a remarkable impact on the classification accuracy, with the highest accuracy of 96.40% achieved by PCA-optimized features with RandomForest. This study also examined the influence of the image resolution, by comparing the performance of image datasets with resolutions of 256×256, 512×512 and 1024×1024, with higher resolution images generally yielding better classification results as more discriminative texture and intensity information was available.

One of the key findings of this research is that handcrafted features used for texture and intensity are employed instead of deep learning-based features extraction. The results show that traditional machine learning methods can achieve high classification accuracy using handcrafted texture and intensity features. The present study did not quantitatively evaluate computational requirements or compare them with deep learning models. Therefore, computational efficiency should be investigated separately in future work. In addition, the comparison of PCA and CFS feature optimization methods demonstrated that PCA preserved more informative features and that it gave better classification results when identifying wheat seeds.

VI. LIMITATIONS

Overall, the proposed framework was able to provide good classification performance, but there are some limitations that should be considered. The dataset used includes six varieties of wheat from Pakistan and was sampled under controlled imaging conditions; thus, the model needs to be tested with more varieties, different regions, and different environmental conditions. Second, the image acquisition process was conducted under relatively controlled imaging conditions, which may induce some variations in illumination, background

noise, seed orientation, and image quality in an actual agricultural environment that can impact the classification performance. Third, the study is primarily based on handcrafted texture and intensity features, which can achieve good classification results, but the performance of the proposed handcrafted-feature approach was not directly compared with deep learning-based feature extraction in this study. In addition, the data size is relatively small, especially when compared to the large-scale deep learning applications. Future work needs to be directed towards building larger and more diverse wheat seed image datasets and testing the hybrid or deep learning approach to gain robustness and scalability.

VII. FUTURE WORK

The proposed framework provides a trustworthy, inexpensive, and efficient solution for wheat variety classification. This performance achieved shows its possible use in seed certification, verification of variety, grain quality, and smart systems in agriculture. The dataset developed, methodology, class performance evaluation, and experimental results will serve as a benchmark for future research on deep learning-based frameworks, hybrid feature extractors, seed quality analysis, and large-scale agricultural automation in the context of agriculture in Pakistan and other developing countries.

ACKNOWLEDGMENT

The authors would like to express their sincere gratitude to the Department of Information Technology, The Islamia University of Bahawalpur, for providing the facilities and support required to complete this research. The authors also thank all individuals who assisted in the collection and preparation of the wheat seed dataset. Their support and valuable contributions are greatly appreciated.

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