A Comparative Study of Machine Learning Algorithms for Paddy Variety Classification Using Digital Image Processing

Dr Jagadesh Krishna[2], Praveen. B. S[1], and Thatchayeni. E[1]

[2] Associate Professor, Department of BCA In Artificial Intelligence, SBRR Mahajana First Grade College (A), Pooja Bhagavat Memorial Mahajana Education Centre, Mysuru – 570016, India,

[1] Assistant Professor, Department of BCA In Artificial Intelligence, SBRR Mahajana First Grade College (A), Pooja Bhagavat Memorial Mahajana Education Centre, Mysuru – 570016, India,

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ABSTRACT

Paddy is the world's second-largest cereal crop in terms of production area, and almost half of the world's population relies on it as its primary food source. Seed quality and varietal purity are critical for yield, yet different paddy seed varieties look very similar, so manual identification by experts is slow, subjective and expensive, and mixing or adulteration of varieties in the market lowers the economic value of rice. This paper presents a machine learning based system for the automatic classification of five paddy varieties, namely 1001, Jaya, Jyothi, Kuruva and Small, which are commonly cultivated in the Old Mysore region. Images of single paddy kernels were acquired under fixed lighting conditions with a smartphone camera and cleaned using background removal. Three complementary descriptors, namely color histogram (CH), gray level co-occurrence matrix (GLCM) and local binary pattern (LBP), were extracted and concatenated into a single feature vector, which was then normalized and reduced with principal component analysis (PCA) before being fed to six classifiers: support vector machine (SVM), random forest (RF), decision tree (DT), k-nearest neighbor (KNN), Gaussian naive bayes (GNB) and gradient boosting (GB). Experiments were conducted on two datasets of 525 images each, the original and the cropped versions, using an 80:20 train-test split. The SVM classifier with the combined CH+GLCM+LBP features, feature normalization and PCA achieved the highest accuracy of 98.09% on dataset 1 and 97.14% on dataset 2, outperforming the individual feature descriptors and the other classifiers. The proposed system provides a reliable and efficient solution for seed purity testing and variety identification, enabling farmers to improve crop yield and market value.

Keywords: color histogram, gray level co-occurrence matrix, local binary pattern, paddy variety classification, principal component analysis, support vector machine

I. INTRODUCTION

Paddy is the world's second-largest cereal crop in terms of production area, and it serves as the primary food source for almost half of the world's population. Agriculture is the backbone of the Indian economy: around 65% of the population lives in rural areas and agriculture employs more than 55% of the labour force. By 2050, India will require approximately 584 million tons of paddy and Karnataka alone will require about 137.9 million tons, while the national paddy area is expected to shrink to roughly 44 million hectares. Many variables contribute to this increasing demand, and seed quality is one of the most important among them. Experiments indicate that the use of high-quality, genetically pure paddy seed can boost yield by 15% to 20%.

Mixing of different paddy kinds in the rice market leads to adulteration, lowers the economic value of rice and reduces buyer-seller trust. Differentiating paddy seed varieties is challenging because the kernels of different varieties look very similar. If a farmer cultivates the wrong variety by presuming that the seed is the desired one, the overall productivity suffers, because different cultivars require different soils, growing methods and maturation periods. Facilities for seed purity testing rely on human experts, which takes a considerable amount of time and money.

To address these issues, researchers have focused on automatic seed grading through image processing and computer vision. Several descriptors have been used for a single kernel, including geometric, morphological, color and texture features. Geometric features alone do not provide good accuracy, morphological features may fail when the collection contains images captured in different positions, and statistical image features are often affected by scale and rotation. Combining complementary descriptors therefore offers a more reliable alternative, and shape and texture variations across varieties make them useful features for classification.

In this paper, we propose a machine learning pipeline for paddy variety classification in which images of single kernels are acquired with a smartphone camera, cleaned by background removal and described by a combination of color histogram (CH), gray level co-occurrence matrix (GLCM) and local binary pattern (LBP) features. The concatenated feature vector is normalized and reduced with principal component analysis (PCA), and then classified by six classifiers. The main contributions of this work are:

1) A curated and balanced image dataset of five regionally important paddy varieties (1001, Jaya, Jyothi, Kuruva and Small), comprising 525 original images and 525 cropped images, collected under controlled conditions.

2) A combined feature representation that fuses color (CH) and texture (GLCM and LBP) descriptors into a single feature vector, followed by feature normalization and PCA.

3) A systematic evaluation of three model configurations (raw features, normalized features and normalized features with PCA) with six classifiers, over both datasets.

4) An accuracy of 98.09% on dataset 1 and 97.14% on dataset 2 with the SVM classifier, which is the best performance among all the configurations studied.

The rest of the paper is organized as follows: Section II reviews the related work, Section III describes the dataset, Section IV presents the proposed methodology, Section V discusses the results and analysis, and Section VI concludes the paper.

II. LITERATURE REVIEW

Several studies have addressed seed and grain classification with machine learning. Mach Bah Uddin et al. [1] presented a computer vision-based system for identifying paddy seed varieties using T20-HOG and Haralick textural features to handle illumination, scale and rotational variations, and trained a neural network on the BDRICE and VNRICE datasets, reporting an accuracy of 99.28% with precision, recall and F1-score above 98%.

Kiratiratanapruk et al. [2] reviewed and developed machine learning techniques for the automatic grading of paddy rice seeds, where preprocessing steps such as seed orientation and quality screening were found to be crucial; models such as SVM and InceptionResNetV2 reached accuracies of up to 99.24%. Maheswari and Renukadevi [3] evaluated paddy seed image classification on 540 real-time images captured with a digital camera and compared SVM, KNN and a proposed random evaluation technique, where the proposed method achieved accuracies in the range of 95.80% to 98.68% across fifteen varieties.

Dheer and Singh [4] compared linear discriminant analysis, logistic regression, KNN and naive bayes classifiers on six features extracted from 100 samples of each rice variety with a 70:30 train-test split, and found KNN to be the most effective with an accuracy of 99.16%. Köklü et al. [5] classified five rice varieties (Arborio, Basmati, Ipsala, Jasmine and Karacadag) from 75,000 grain images and 106 derived features, reporting 99.87% accuracy with an artificial neural network, 99.95% with a deep neural network and 100% with a convolutional neural network. The same study evaluated the models with sensitivity, specificity, F1 score, false positive rate and false negative rate derived from the confusion matrices.

Sundram et al. [6] described a deep learning approach for rice varietal identification in which normalization, augmentation, batch normalization and dropout are used to improve the generalization of convolutional neural

networks, while optimization algorithms such as stochastic gradient descent and Adam are explored to train the model parameters. Kappali et al. [7] studied paddy disease identification with segmentation techniques combined with SVM and KNN classifiers, and concluded that the classification accuracy depends heavily on the quality of the segmentation. Saxena et al. [8] analysed 75,000 samples of five rice varieties with 107 features, selected the top 20 features with a random forest classifier, and reported 99.85% accuracy for random forest and 99.68% for decision tree on a 70:30 split.

Most of these works target well-known benchmark datasets or commercial varieties. Limited attention has been given to the region-specific varieties grown in the Old Mysore region of Karnataka, and no single study so far combines color histogram, GLCM and LBP descriptors with feature normalization and PCA across six classical classifiers for such varieties. Classical machine learning pipelines are also lightweight and inexpensive compared with deep learning, which makes them suitable for deployment on modest hardware in field conditions. These observations motivate the present work.

III. DATASET

The paddy varieties used in this work were collected from the Rice Mill at Arakere in Mandya district. Five varieties that are locally known as Kuruva, Jaya, Jyothi, 1001 and Small were collected, and with the help of experienced guides and farmers the seeds were stored separately by labelling the five varieties to avoid cross-contamination. Purified paddy of each variety was then taken to the experimental area for sampling.

In the experimental lab, cleaned single kernels were placed on a thick white sheet and images were acquired with a smartphone (OPPO Reno10 Pro 5G, rear camera 50 MP, Qualcomm Snapdragon 778G) at an average height of 15 to 17 cm under fixed lighting conditions. The images were saved in JPG format. After image acquisition, the rembg library in Python was used to remove the background and obtain a uniform white background for further processing. The single-kernel arrangement ensures that every image contains exactly one sample of one variety, which removes the need for instance separation at a later stage and keeps the ground-truth labels unambiguous.

In total, 105 samples of resolution 3072×4096 were collected from each class, giving 525 images for dataset 1, as shown in Table I. For dataset 2, 105 samples from each class were cropped to 1212×881 pixels, giving another 525 images, as shown in Table II. Both datasets are balanced, with an equal number of samples for every variety. Sample images of the five varieties before and after cropping are shown in Fig. 1 and Fig. 2, respectively.

Table I. *Dataset 1 paddy variety data collection statistics*

Variety	Description	Samples	Resolution
Kuruva	Locally adapted, drought resistant	105	3072×4096
Jaya	High yielding, short growth cycle	105	3072×4096
Jyothi	Medium duration, disease resilient	105	3072×4096
1001	Hybrid, high yield, climate tolerant	105	3072×4096
Small	Small grain, unique texture	105	3072×4096
Total		525	

Table II. *Dataset 2 paddy variety data collection statistics*

Variety	Description	Samples	Cropped size
Kuruva	Locally adapted, drought resistant	105	1212×881
Jaya	High yielding, short growth cycle	105	1212×881
Jyothi	Medium duration, disease resilient	105	1212×881
1001	Hybrid, high yield, climate tolerant	105	1212×881

Small	Small grain, unique texture	105	1212×881
Total		525	

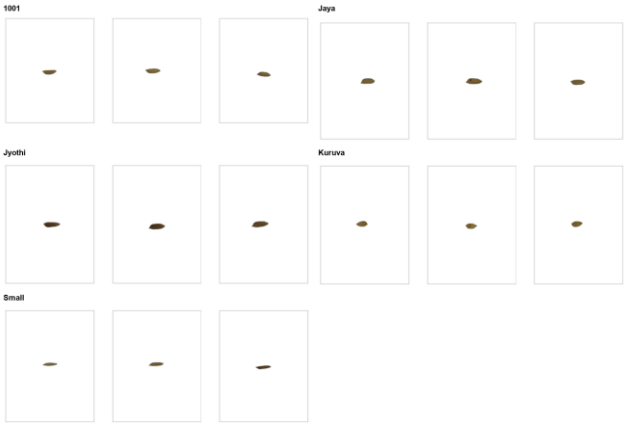

Fig. 1*. Sample images of the five paddy varieties in dataset 1 (1001, Jaya, Jyothi, Kuruva and Small).*

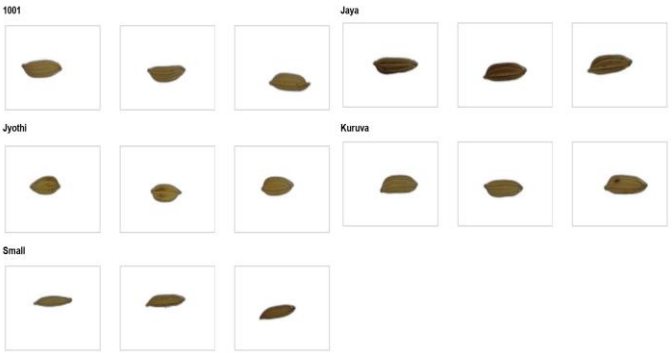

Fig. 2. *Sample images of the five paddy varieties in dataset 2 after cropping.*

A few challenges were faced during data collection. Paddy seeds of all varieties were rarely available at a single rice mill, so the seeds had to be collected from multiple mills. Different varieties sometimes get mixed at the mill, so each variety was stored separately in plastic covers to prevent cross-contamination, and experts were contacted for guidance in identifying the varieties. Since the images were captured under fixed lighting and at a fixed height on a plain white sheet, the illumination differences between the samples are small and the remaining background variation is removed in the pre-processing stage.

IV. PROPOSED METHODOLOGY

The proposed system follows a standard classification pipeline that consists of data acquisition, pre-processing, feature extraction, feature normalization, dimensionality reduction and classification. The overall architecture of the proposed paddy variety classification model is shown in Fig. 3.

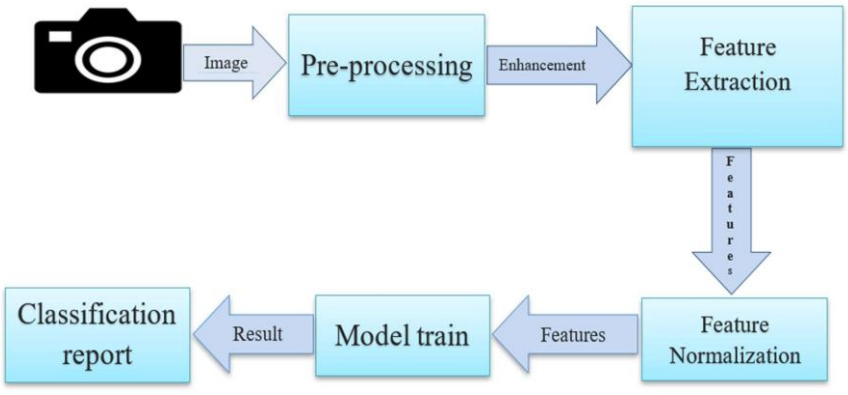

Fig. 3. *Architecture of the proposed paddy variety classification model.*

The objectives of the proposed system are:

1) To acquire and label a balanced image dataset of five paddy varieties under controlled conditions.

2) To extract complementary color and texture features from every kernel image and combine them into one feature vector.

3) To study the effect of feature normalization and dimensionality reduction on the classification accuracy.

4) To compare six classifiers on the same features and identify the best configuration for paddy variety classification.

5) To provide a solution that is light enough to be deployed on modest hardware for practical use by farmers and seed testing laboratories.

A. Pre-processing

The raw images contain significant noise in the background, so the rembg library, a machine learning based background removal tool, is applied to isolate the foreground kernel and replace the background with a uniform white one, as shown in Fig. 4. Each kernel is then cropped from the image so that only the grain region is used for feature extraction, and the resulting images are resized to a constant resolution so that all samples share the same dimensions.

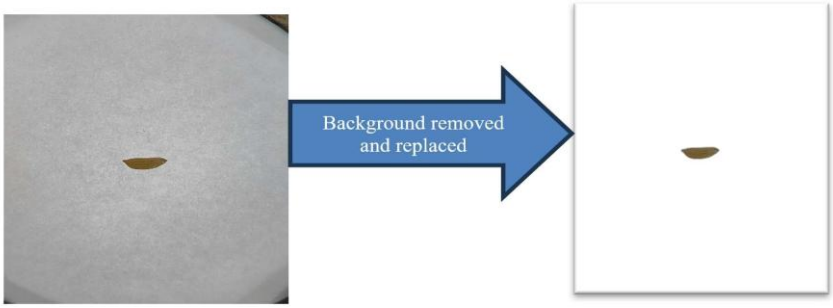

Fig. 4. *Background removed paddy variety images.*

B. Feature Extraction

Three complementary descriptors are extracted from every image and concatenated into a single feature vector.

Color Histogram (CH): a color histogram describes the distribution of the pixel intensities in each color channel. It captures the appearance and shade of the kernel, which differ slightly but consistently across varieties, as illustrated in Fig. 5.

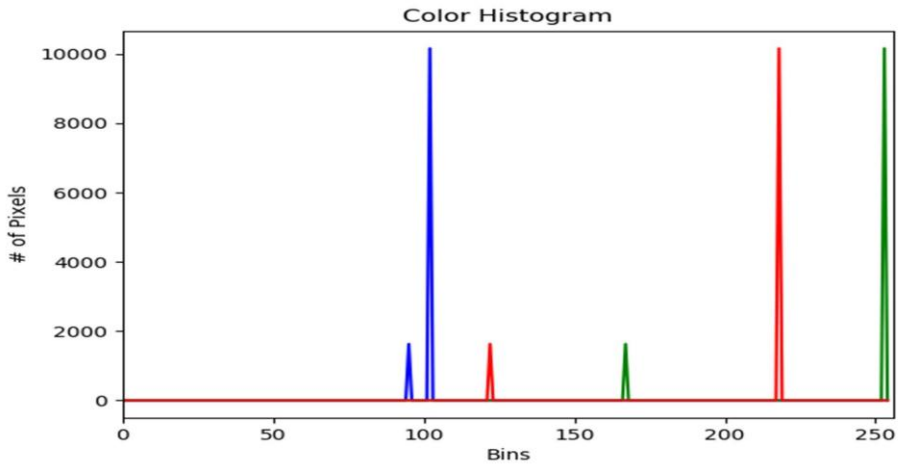

Fig. 5. *Example of an RGB color histogram.*

Local Binary Pattern (LBP): LBP labels the pixels of an image by thresholding the neighborhood of each pixel against its centre value and represents the result as a binary code, which makes it a compact and illumination invariant texture descriptor, as shown in ***Fig. 6.***

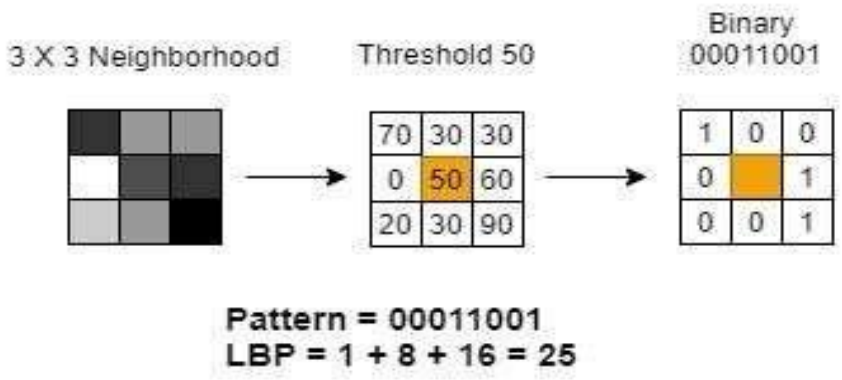

Fig. 6. *Example of the working of the local binary pattern.*

Gray Level Co-occurrence Matrix (GLCM): the GLCM tabulates how often pairs of pixels with given intensities occur at a given offset. Texture measures such as contrast, correlation, energy and homogeneity are computed from the matrix for several directions, as shown in Fig. 7. Contrast measures the local intensity variation, correlation measures the linear dependency of neighbouring pixels, energy (angular second moment) measures the uniformity of the image, and homogeneity gives high weight to the near-diagonal entries of the matrix. Together these measures capture the grain surface texture that is not represented by the color histogram.

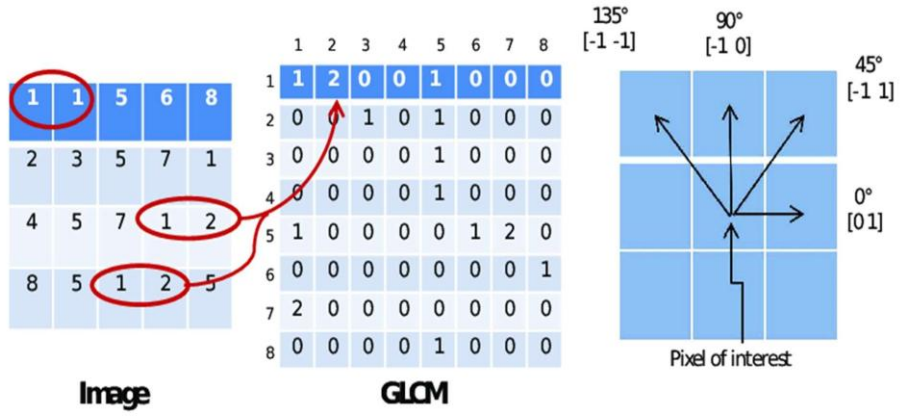

Fig. 7. *Example of the working of the gray level co-occurrence matrix.*

C. Feature Normalization

The features extracted from different descriptors exist on different scales, which can bias the classifiers. Four normalization techniques are studied in this work: standard scaling (z-score), min-max scaling, max-abs scaling and mean normalization. In z-score normalization, each feature value is transformed as

$$z = (x-\mu) / \sigma \qquad (1)$$

where x is the feature value, μ is the mean and σ is the standard deviation of that feature over the training set, so that every feature has zero mean and unit variance. In min-max scaling, the values are rescaled to the range [0, 1] as

$$x_{norm} = (x-x_{min}) / (x_{max}-x_{min}) \qquad (2)$$

where the minimum and the maximum values of the feature over the training set are used for the rescaling. In max-abs scaling, each feature is divided by the largest absolute value that the feature takes:

$$x_{scaled} = x / max(|x|) \quad (3)$$

and in mean normalization the feature is centred by its mean and scaled by the range of the feature as

$$x_{scaled} = (x-\mu) / (x_{max}-x_{min}) \quad (4)$$

All four techniques are applied in the experiments and their effect on the classification accuracy is reported in Section V.

D. Dimensionality Reduction

The concatenated feature vector can be large and may contain correlated features. Principal component analysis (PCA) is therefore applied to project the data onto the directions of maximum variance while retaining most of the information, which removes redundancy and reduces the training time of the classifiers, as illustrated in Fig. 8.

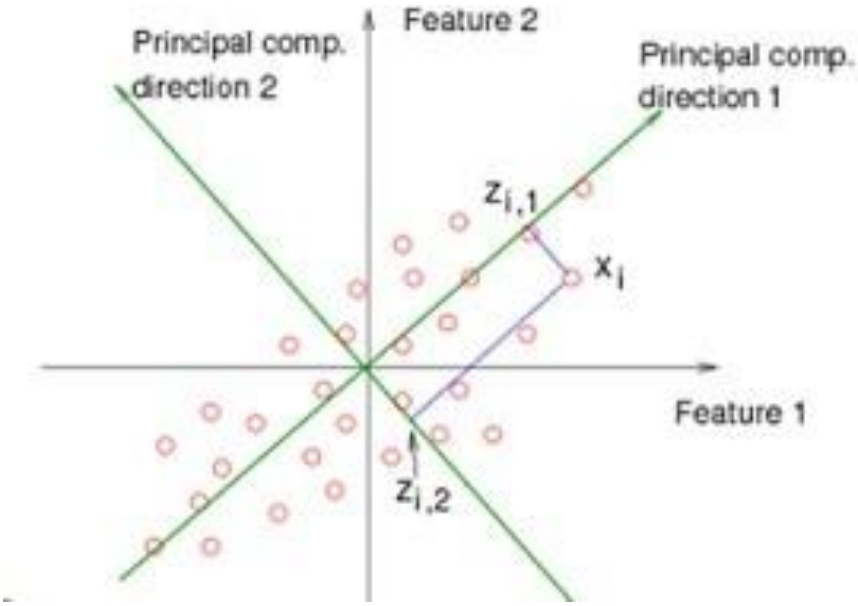

Fig. 8. *Illustration of principal component analysis.*

E. Classifiers

Six standard classifiers are used. The support vector machine (SVM) finds the optimal hyperplane that maximizes the margin between classes and can handle non-linear boundaries with kernel functions. The k-nearest neighbor (KNN) classifier assigns a label by majority vote of the k closest training samples. The decision tree (DT) splits the feature space with a sequence of threshold tests. The random forest (RF) ensemble averages the predictions of many decorrelated trees. The Gaussian naive bayes (GNB) classifier applies Bayes' rule with independent Gaussian feature assumptions. Gradient boosting (GB) builds trees sequentially, each correcting the errors of the previous ones. Depending on the geometry of the decision boundary, the SVM can use a linear, a polynomial or a radial basis function kernel, and the same classifiers are used for both paddy datasets so that the results can be compared directly.

F. Experimental Setup

Each dataset is divided into training and test sets in the ratio 80:20, as shown in Fig. 9, and the trained models are evaluated with classification accuracy on the held-out test set. Three configurations are studied for both datasets: (i) features without normalization and without PCA, (ii) features after normalization, and (iii) features after normalization and PCA. Each configuration is evaluated with a single feature descriptor as well as with

all possible combinations of CH, GLCM and LBP, using the six classifiers. Every model is trained on the training partition only, and the test partition is used once for reporting the final accuracy, which keeps the evaluation unbiased.

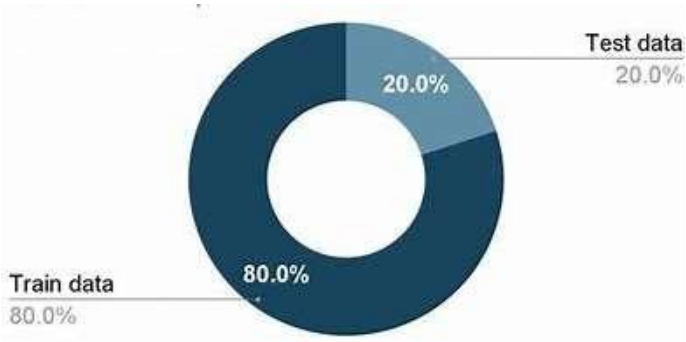

Fig. 9. *Train-test split of the dataset (80:20).*

V. RESULTS AND ANALYSIS

A. Paddy Variety Classification (Dataset 1)

This section presents the experimental results of the proposed system. Classification accuracy is used as the evaluation metric because the five classes of both datasets are balanced, so the accuracy directly reflects the share of test samples that are assigned to the correct variety. The results before feature normalization (dataset 1) are given in Table III. With raw features, gradient boosting performs best for the color histogram (96.19%) and the SVM performs poorly (81.90%), which shows that the classifiers are sensitive to the different scales of the extracted features.

Table III. *Results before feature normalization (dataset 1), accuracy in %*

Feature	SVM	RF	DT	KNN	GNB	GB
CH	81.9	94.28	90.47	92.38	83.8	96.19
LBP	72.38	86.66	86.66	87.61	83.8	89.52
GLCM	83.8	90.47	89.52	88.57	87.61	92.38

Table IV gives the results after feature normalization for dataset 1. Normalization improves the accuracy of every classifier, and the SVM gains the most: its accuracy rises from 81.90% to 94.28% with CH and to 97.14% with the combined features. The combined CH+GLCM+LBP vector yields 97.14% with both SVM and KNN and 97.14% with gradient boosting.

Table IV. *Results after feature normalization (dataset 1), accuracy in %*

Feature	SVM	RF	DT	KNN	GNB	GB
CH	94.28	94.28	91.42	85.71	81.82	95.23
LBP	90.47	86.66	87.61	87.61	83.8	91.42
GLCM	94.28	90.47	89.52	91.42	88.57	94.27
CH+GLCM	97.14	95.23	92.38	97.13	87.16	97.14
CH+LBP	97.14	95.23	93.33	93.33	80	96.19
LBP+GLCM	94.28	89.52	90.47	91.42	87.64	92.38
CH+GLCM+LBP	97.14	92.38	91.42	97.14	87.61	97.14

The confusion matrix of the SVM with the combined features after normalization is shown in Fig. 10.

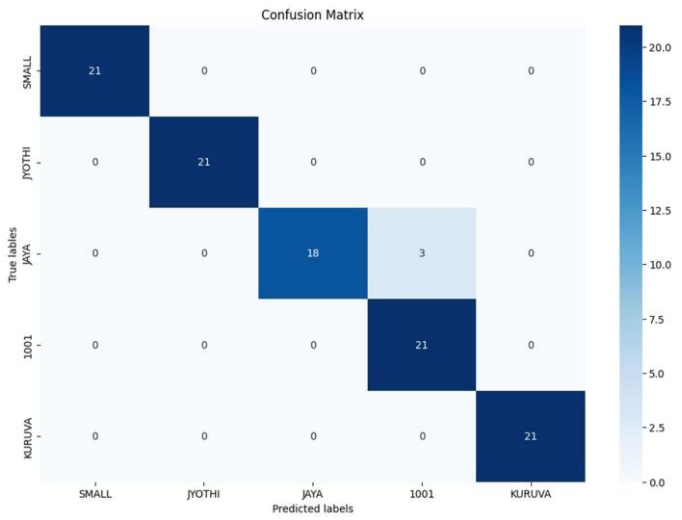

Fig. 10. *Confusion matrix of CH+GLCM+LBP with the SVM classifier after feature normalization (dataset 1).*

Table V reports the results after applying PCA on the normalized features of dataset 1. PCA further improves the performance of the SVM, which reaches 98.09% with CH+GLCM and with CH+GLCM+LBP, the highest accuracy obtained in this study.

Table V. *Results after applying PCA (dataset 1), accuracy in %*

Feature	SVM	RF	DT	KNN	GNB	GB
CH	92.38	93.33	74.28	85.71	92.38	74.28
LBP	90.47	89.52	85.71	86.66	89.52	88.57
GLCM	94.28	95.27	85.72	89.52	91.42	92.38
CH+GLCM	98.09	95.23	91.42	97.13	92.38	96.19
CH+LBP	95.23	93.33	85.57	92.38	82.85	94.29
LBP+GLCM	95.23	95.23	90.47	90.47	92.38	90.47
CH+GLCM+LBP	98.09	94.28	95.43	96.19	91.42	97.14

The classification accuracies of the six classifiers with the CH features before normalization, after normalization and after applying PCA are compared in Fig. 11.

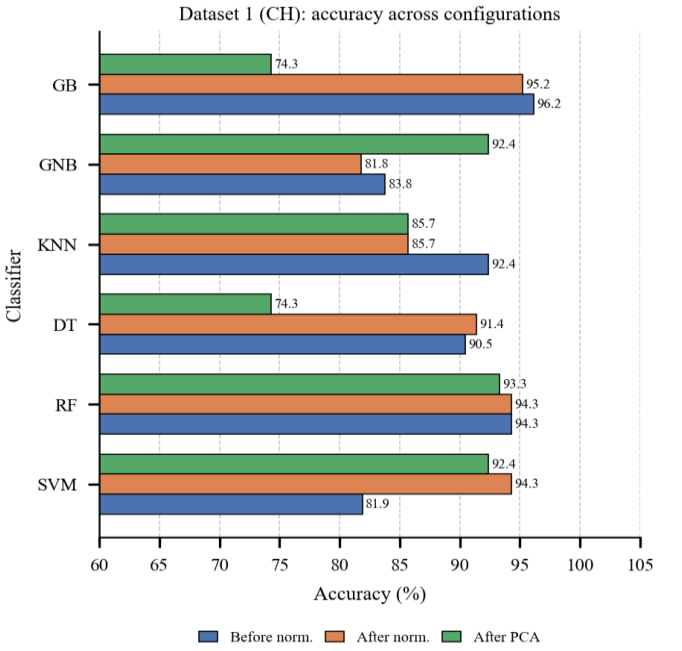

Fig. 11. *Comparison of classifier accuracies with CH features across the three configurations (dataset 1).*

The confusion matrix of the SVM classifier with the combined features after PCA is shown in Fig. 12.

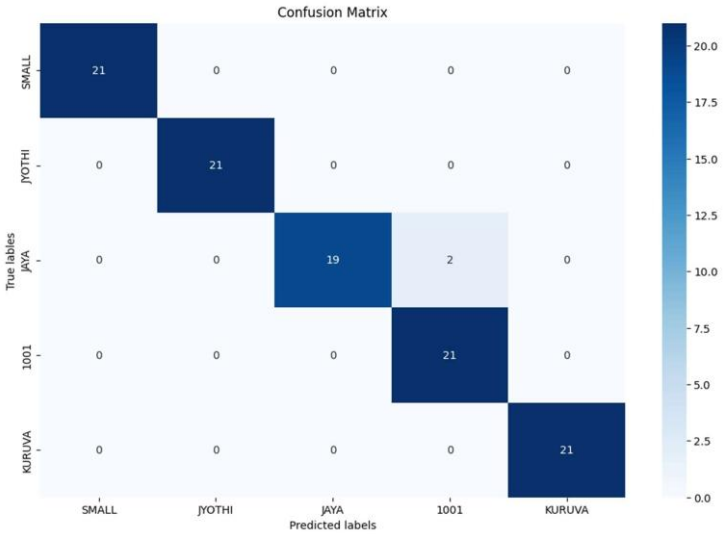

Fig. 12. *Confusion matrix of CH+GLCM+LBP with the SVM classifier after applying PCA (dataset 1).*

B. Paddy Variety Classification (Dataset 2)

The same experiments were repeated on the cropped dataset 2. Table VI gives the results before feature normalization, where gradient boosting again leads with 96.19% for CH, while the SVM reaches only 79.04%. The trend observed on dataset 1 therefore repeats on the cropped images as well.

Table VI. Results before feature normalization (dataset 2), accuracy in %

Feature	SVM	RF	DT	KNN	GNB	GB
CH	79.04	94.28	90.47	93.33	80	96.19
LBP	66.66	88.57	84.76	83.8	81.9	92.38
GLCM	86.66	89.52	87.61	83.8	80.95	89.52

Table VII gives the results after normalization, in which the combined CH+LBP vector achieves 97.14% with the SVM, and Table VIII gives the results after applying PCA, where the SVM reaches 97.14% with CH+GLCM, CH+LBP and CH+GLCM+LBP.

Table VII. *Results after feature normalization (dataset 2), accuracy in %*

Feature	SVM	RF	DT	KNN	GNB	GB
CH	95.23	89.52	92.38	93.33	82.24	96.19
LBP	89.52	88.57	84.76	84.76	81.9	92.38
GLCM	91.42	89.52	87.61	89.52	80.95	88.57
CH+GLCM	95.23	91.42	92.38	92.38	91.42	95.23
CH+LBP	97.14	89.52	94.28	96.19	87.61	94.28
LBP+GLCM	94.28	89.52	90.47	91.42	87.61	92.38
CH+GLCM+LBP	97.14	91.42	93.33	92.38	90.47	95.23

Table VIII. *Results after applying PCA (dataset 2), accuracy in %*

Feature	SVM	RF	DT	KNN	GNB	GB
CH	94.28	90.47	78.09	95.23	68.57	88.57
LBP	86.66	83.8	76.19	85.71	88.57	82.19
GLCM	89.52	88.57	82.85	86.66	83.8	83.8
CH+GLCM	97.14	93.33	88.57	92.38	84.76	90.47
CH+LBP	97.14	91.42	83.8	95.23	83.8	89.52
LBP+GLCM	95.23	95.23	90.47	90.47	92.23	90.47
CH+GLCM+LBP	97.14	94.28	88.57	91.42	84.76	91.42

The same comparison for the cropped dataset 2 is given in Fig. 13, where the same trend of improvement after normalization is again visible.

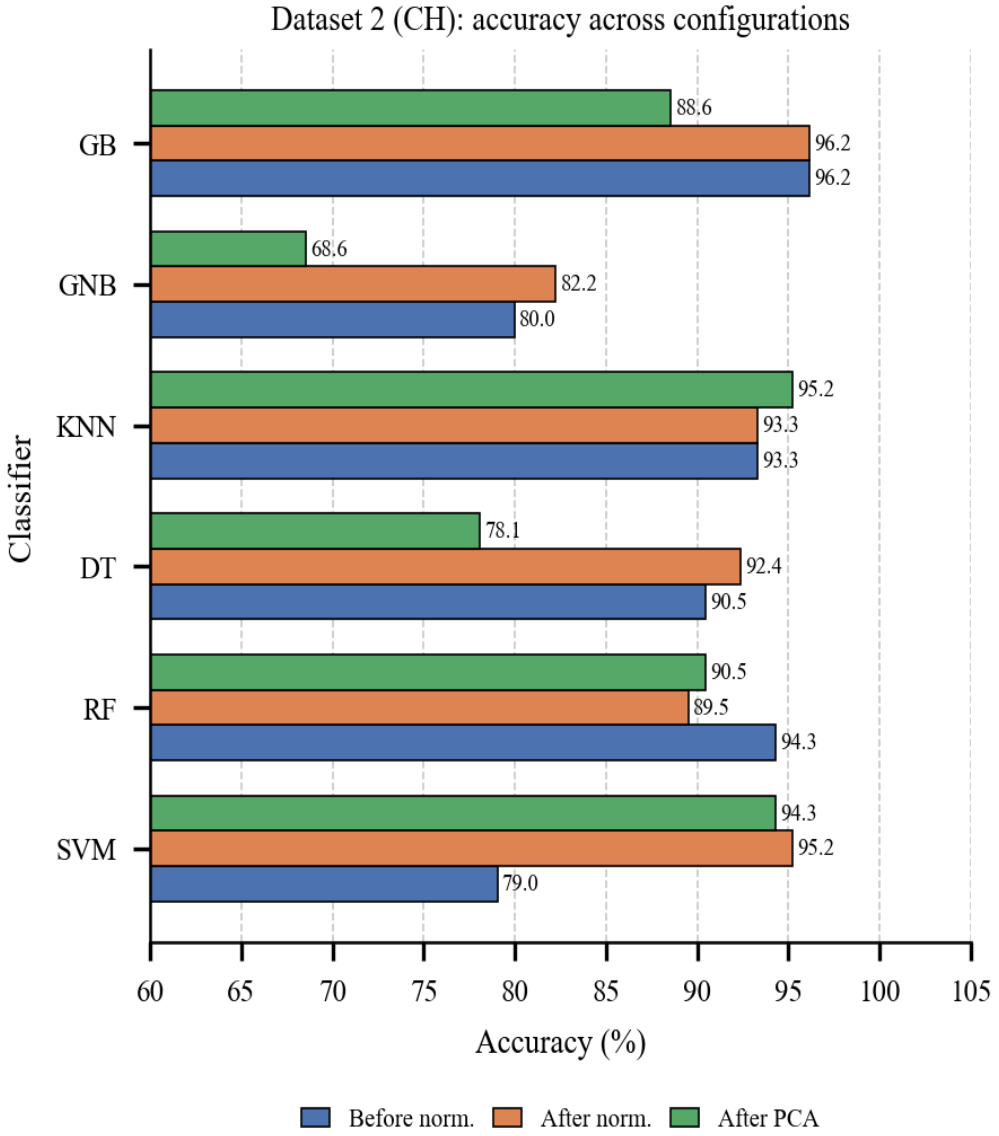

Fig. 13. *Comparison of classifier accuracies with CH features across the three configurations (dataset 2).*

The confusion matrix of the SVM classifier with the combined features after PCA on dataset 2 is shown in **Fig. 14.**

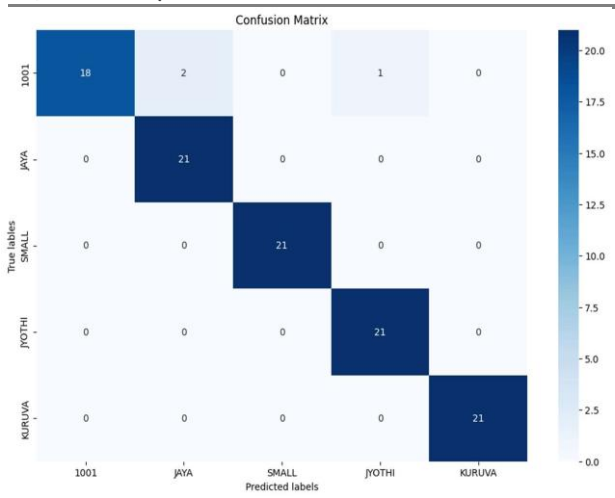

Fig. 14. *Confusion matrix of CH+GLCM+LBP with the SVM classifier after applying PCA (dataset 2).*

C. Comparison with Deep Learning Models

For comparison, six pre-trained deep learning architectures were also fine-tuned on the augmented paddy dataset. The resulting accuracies were 83.23% for VGG16, 82.78% for VGG19, 75.28% for ResNet50v2, 88.45% for InceptionV3, 77.25% for MobileNetV2 and 82.35% for DenseNet121, as summarized in Table IX. All of these results are well below the 98.09% obtained by the proposed classical pipeline, which can be attributed to the very small size of the dataset.

Table IX. *Accuracy of pre-trained deep learning models on the augmented dataset*

Model	**Accuracy (%)**
VGG16	83.23
VGG19	82.78
ResNet50v2	75.28
InceptionV3	88.45
MobileNetV2	77.25
DenseNet121	82.35

The accuracy of the proposed classical pipeline in comparison with the fine-tuned deep learning models is illustrated in Fig. 15.

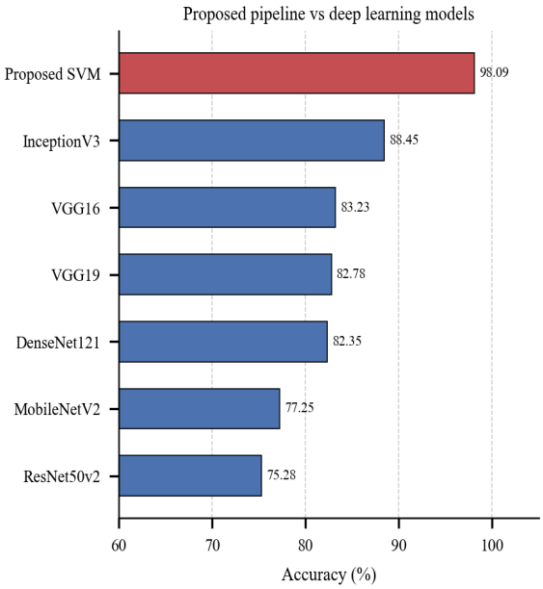

Fig. 15. *Accuracy comparison of the proposed SVM pipeline with pre-trained deep learning models.*

D. Discussion

The main observations from the experiments can be summarized as follows. First, feature normalization has the largest effect on the SVM, whose accuracy improves by more than 15 percentage points on both datasets, because the SVM optimizes a margin that is sensitive to feature scales. Second, the combination of color and texture descriptors is consistently better than any single descriptor, which confirms that CH, GLCM and LBP carry complementary information. Third, PCA removes redundant features and lifts the best accuracy from 97.14% to 98.09% on dataset 1. Finally, gradient boosting is the strongest classifier on raw features, while SVM is the best overall classifier once the features are normalized and reduced. Further, the decision tree is the classifier that degrades most after PCA (74.28% with CH on dataset 1), because its axis-aligned splits are sensitive to the rotated features, whereas the margin-based SVM and the ensemble methods make better use of them. Gaussian naive bayes is consistently weaker on the combined features, which indicates that the independence assumption is not satisfied by the correlated color and texture descriptors.

The effect of the feature combination on the SVM accuracy after PCA is summarized in Fig. 16, which confirms that the combined descriptors consistently outperform the individual ones.

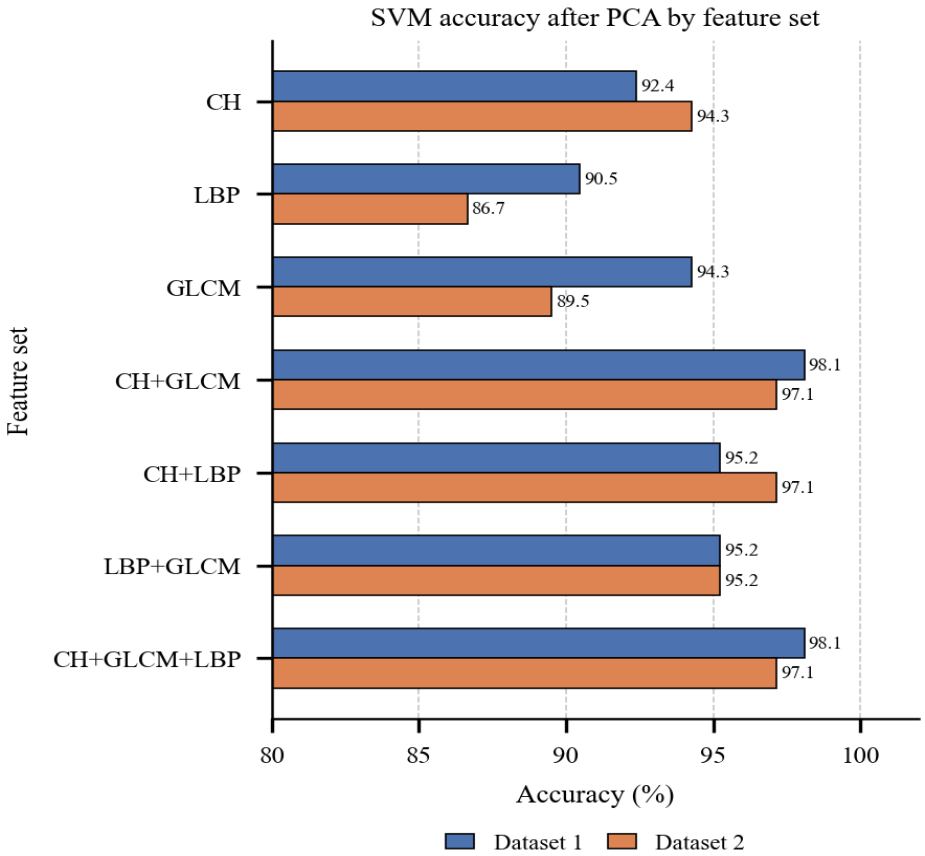

Fig. 16. *SVM accuracy with individual and combined feature sets after PCA on both datasets.*

VI. CONCLUSION AND FUTURE WORK

This paper presented a machine learning approach for the classification of five paddy varieties using color and texture features. Images of single kernels were acquired under controlled conditions, cleaned with background removal, and described by combining color histogram, GLCM and LBP descriptors. The features were normalized and reduced with PCA before classification with six classifiers. The experiments show that the combination of features with normalization and PCA, fed into the SVM classifier, performs best, reaching 98.09% accuracy on dataset 1 and 97.14% on dataset 2. The results also show that normalization is essential for the SVM and that combined descriptors are always better than a single descriptor. The proposed system therefore offers a reliable and efficient solution for seed purity testing, and it helps farmers to confirm the variety they cultivate and to obtain the price their produce deserves.

The future work of this project is listed below:

1) Increasing the size of the dataset for better performance of the trained models.

2) Including additional classes to prepare a larger and more representative dataset.

3) Segmenting each paddy seed in a scattered arrangement and feeding the segments to an SVM for real-time prediction.

4) Collecting more extensive and diverse datasets so that the models generalize well to different varieties and varying environmental conditions.

5) Incorporating data augmentation techniques to simulate different scenarios and improve model robustness.

6) Employing clustering techniques for paddy seed segmentation based on similar features and storing the segmented results in corresponding folders.

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