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A Comparative Study on Rice Grain Classification Using Convolutional Neural Network and Other Machine Learning Techniques

Anurag Bhattacharjee[1], Ksh Robert Singh*[2], Takhellambam Sonamani Singh[3], Subir Datta[4], Subhasish Deb[5], Usham Robinchandra Singh[6], Ghaneshwori Thingbaijam[7]

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Abstract: Rice is the paramount concern crop in India, and it can be difficult to discern between the many types available. The sort and quality of grain are swiftly ascertained by visual inspection in the present grain-handling system. It takes human abilities to distinguish between different varieties of rice, and this process can be labor-intensive and time-consuming. Furthermore, the classification task may differ from person to person due to the subjectivity of human perception of images. Thus, digital image processing may be used to get around all of these problems. Several convolutional neural networks namely, Googlenet, Resnet50, Alexnet, and EfficientnetB0, as well as other parametric and non-parametric classifiers namely, K-Nearest Neighbours (KNN), Linear Discriminant Analysis (LDA), Naïve Baise (NB), Support Vector Machine (SVM), Decision Trees (DT) and Back Propagation Neural Network (BPNN) are used to classify eight distinct sorts of rice grains. In this work, 800 samples of eight distinct varieties of rice make up the image data set. It is found that CNN models, can achieve classification accuracy up-to 68.20%. However, classification based on other classifiers using texture features provides accuracy as high as 96.75%. It is observed that, other classifiers perform a more accurate classification of rice as compared to that of CNN models.

Keywords: *Convolutional Neural Network, Image Processing, Rice grain, Texture Feature*

1. Introduction

Rice is a crucial agricultural commodity on a global scale, serving as a staple food for billions and forming the basis of many cultures and cuisines. Cultivated for thousands of years, rice has shaped civilizations, economies, and diets globally. It provides a rich source of carbohydrates, vitamins, and minerals, and its gluten-free nature makes it accessible to those with dietary restrictions. Millions of farmers depend on rice cultivation for their income, aiding in rural development and poverty reduction. Thus, rice is not only a symbol of cultural heritage and culinary diversity but also a cornerstone of sustainable agriculture and socio-economic development worldwide.

1.1. Need for classification of Rice

Different varieties of rice have unique qualities in taste, texture, aroma, and cooking properties. Classifying rice ensures that producers and consumers get the desired quality and characteristics. It aids in market segmentation, helping producers target specific consumer preferences and niche markets. Classification is also crucial for agricultural research and development. Researchers study various rice varieties to understand their genetic traits, nutritional content, disease resistance, and agronomic characteristics. This research helps breed new varieties with desired traits, contributing to food security.

1.2. Related work

Numerous research works have endeavoured to tackle issues related to classification within the agriculture industry. Numerous

studies [1–8] have looked into different approaches to rice grain and corn seed classification, such as image pre-processing methods and machine learning algorithms including KNN, SVM, and ANN. The research encompasses a broad spectrum of subjects, including variety classification, fault identification, and quality assessment, and the accuracy percentages range from 39% to 100%. Fascinatingly, some of this study doesn't explicitly address training or testing dataset representation, which could hinder reproducibility and comparative analysis. Furthermore, the challenge of precisely placing grain kernels to prevent contact or overlap is highlighted by attempts to classify food grains using Probabilistic Neural Network (PNN) and image processing techniques [9]. However, by using colour and texture data in conjunction with Back Propagation Neural Network (BPNN), a study on bulk grain photography demonstrates how to circumvent

[1,2,4,5] Department of Electrical Engineering, Mizoram University, Mizoram -796004,India.
ORCID ID : 0009-0003-3837-3291
ORCID ID : 0000-0003-0318-8988
ORCID ID : 0000-0003-1550-1425
ORCID ID : 0000-0001-8596-9811
[3] Department of Computer Science and Engineering, MIT, Manipur University, Manipur-795003, India
ORCID ID : 0000-0001-6839-362X
[6] Department of Computer Science, South East Manipur College, Manipur-795135, India.
ORCID ID : 0000-0001-7795-4759
[7] Department of Electronics and Communication Engineering, MIT, Manipur University, Manipur-795003, India.
ORCID ID : 0009-0003-1670-9532
** Corresponding Author Email: robert_kits@yahoo.co.in*

this time-consuming process and reach 90% classification accuracy [10]. One area of research to be addressed is the classification of rice grain types and plant seed kernels using convolution neural networks (CNN) and image processing [11–16]. While some research focus on single-kernel images, which present special challenges due to the lack of touching or overlapping grain kernels, others compare the findings with CNN models that have already been trained. It's interesting to note that fewer class labels in a classification problem make it easier. The research review highlights that manual grain identification and classification is laborious and subjective, necessitating the development of robust digital image processing and computer vision-based techniques. It is highlighted that the new technique of feature extraction is time-consuming and necessitates prior knowledge of image descriptors. Yet having too many features could result in redundancy, underscoring the need of feature selection in enhancing the efficacy of categorization. Conversely, Convolutional Neural Networks (CNNs) offer architecture specifically designed to identify patterns and characteristics in images. The goal of this study is to evaluate several pre-trained CNN models and other classifiers efficacy in rice grain variety categorization. Through the identification of optimal techniques for rice sample classification, this work seeks to enhance bulk rice sorting systems.

2. Methodology

This section involves acquiring images of eight different types of bulk rice grains. This step is followed by texture features extraction using Gray level Co-occurrence Matrix (GLCM) and Gray Level Run-length Matrix (GLRLM). This section also highlights different classifiers consider in this study.

2.1. Data Collection

A smart phone was used to snap high-resolution, JGP-formatted pictures of eight distinct varieties of rice in favorable lighting conditions. Figure 1 displays sample pictures of eight varieties of rice. The eight distinct types of rice were represented in this picture by the letters A, B, C, D, E, F, G, and H respectively.

Fig 1. Sample images of eight types of rice

2.2. Texture feature extraction methods

Grey level co-occurrence matrix: The GLCM method is utilized to capture the texture details of an object. It involves expressing the frequency of pixel pairs in a matrix along one direction. To expedite processing, input images are quantized to a gray scale of 64, necessitating a 64*64 GLCM. Pixel pairs are assessed for occurrence at angles of 0°, 45°, 90°, and 135°.The mean of the four GLCM matrices is computed. Nine statistical properties: Mean, Variance, Range, Energy, Entropy, Contrast, Inverse difference moment, Homogeneity, Correlation are then extracted from the resulting GLCM. A sample of GLCM extracted features values using MATLAB software is shown in table 1.

Grey Level Run Length Matrix (GLRLM): GLRLM analysis uses eleven statistical properties to characterize image textures. These properties include Run Percentage, Gray Level Non-Uniformity, Short Run Emphasis, Long Run Emphasis, Low Gray Level Run Emphasis, High Gray Level Run Emphasis, Run Length Non-Uniformity, Short Run Low Gray Level Emphasis, Short Run High Gray Level Emphasis, Long Run Low Gray Level Emphasis, and Long Run High Gray Level Emphasis. Each property quantifies different aspects of texture patterns, providing detailed insights into the texture characteristics of the image. A sample of GLRLM extracted feature values is shown in table 2.

2.3. Selected CNN models and Classifiers

Googlenet, Alexnet, Resnet50, and Efficientnet-B0 are the models that were chosen as they are compelling choice for image classification tasks.

i)**GoogLeNet**: GoogLeNet is known for its innovative inception modules, which use filters of various sizes in each layer to capture diverse features efficiently. These modules have parallel convolutional pathways with different kernel sizes for multi-scale feature extraction. It also includes reduction blocks that down sample feature maps while increasing depth. With 22 layers of convolutional, pooling, fully connected layers, and inception modules, GoogLeNet balances efficiency and accuracy.

ii)**AlexNet:** AlexNet revolutionized deep learning with its pioneering eight-layer architecture, including five convolutional layers and three fully connected layers. It showed the potential of convolutional neural networks (CNNs) for image classification. Using ReLU activation functions and max-pooling for down-sampling, AlexNet efficiently learns hierarchical features. Its use of dropout regularization prevents overfitting, improving generalization. Additionally, data augmentation techniques like random cropping and horizontal flipping enhance robustness. Despite being simpler than later models, AlexNet achieved great success in image classification and paved the way for further advancements in deep learning.

iii)**ResNet-50:** ResNet-50 extends ResNet-18 to 50 layers, using more residual blocks for better feature representation. Skip connections help propagate gradients during training, while identity mappings within residual blocks preserve information flow, allowing deeper network training. With its rich architecture of residual blocks, convolutional layers, batch normalization, activation layers, and skip connections, ResNet-50 effectively captures complex hierarchical features

iv)**EfficientNet-B0:** EfficientNet-B0 uses MBConv blocks with depth-wise separable and pointwise convolutions to capture multi-scale features efficiently. Its architecture balances model size and accuracy through compound scaling, adjusting network width, depth, and resolution uniformly. Some variants include Squeeze and excitation (SE) blocks to enhance feature recalibration. With 290 layers mostly made up of MBConv blocks, EfficientNet-b0 excels in generalization across diverse datasets while optimizing computational efficiency.

v)**K-Nearest Neighbors (KNN)**: KNN classifies a data point based on the majority class of its k closest neighbors. It doesn't require a training phase but stores all training data for comparison during prediction. While KNN is simple, it can be computationally demanding for large datasets, and its performance is significantly affected by the choice of k.

Table 1. Extracted GLCM features values

Type of Rice	F1	F2	F3	F4	F5	F6	F7	F8	F9
A	29.11272	0.78587	0.002969	0.380278	12.09677	0.302449	0.000298	6.41E-07	0.006591
B	31.54356	0.704466	0.003418	0.36817	12.10354	0.293627	0.000302	7.49E-07	0.007009
C	41.39048	0.673507	0.002912	0.350224	12.09524	0.27608	0.000297	6.28E-07	0.006682
D	30.42986	0.675497	0.003778	0.374709	12.1648	0.30655	0.000305	8.35E-07	0.007416
E	41.25949	0.649262	0.002937	0.338865	12.25022	0.262023	0.000301	6.32E-07	0.006685
F	33.3603	0.714578	0.00334	0.365178	12.23788	0.292287	0.000303	7.29E-07	0.007007
G	33.581	0.797247	0.002596	0.367466	12.24681	0.291055	0.000297	5.51E-07	0.006542
H	29.49548	0.781341	0.002933	0.373876	12.2936	0.295187	0.000301	6.31E-07	0.006635

Table 2. Extracted GLRLM feature values

Types of rice	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11
A	0.00105	1750.181	7863.583	372.4351	1.135703	0.75854	2.384261	0.000902	0.001878	1270.507	4535.664
B	0.000761	1949.567	6420.367	422.2443	1.027813	0.713783	2.703937	0.000621	0.001584	1322.925	5708.862
C	0.000749	2004.261	6795.36	388.9323	1.010234	0.7483	2.693218	0.000631	0.001514	1420.198	6014.028
D	0.00078	1845.288	5980.009	440.7625	0.998125	0.701603	3.108954	0.000626	0.001836	1227.489	6263.164
E	0.753545	2.463932	386.8227	6849.983	1.001797	0.000784	1973.238	0.00067	1389.017	0.001438	5500.012
F	0.698868	2.993646	437.5108	6049.935	1.008203	0.000809	1978.735	0.000662	1303.57	0.001749	6543.569
G	0.732238	2.61723	406.7444	6674.903	1.025625	0.00068	2161.541	0.000561	1505.871	0.001379	6184
H	0.739996	2.623528	394.685	7095.224	1.074531	0.000933	1732.524	0.00078	1230.449	0.001861	4908.101

vi)**Linear Discriminant Analysis (LDA):** LDA finds the best linear combinations of features to separate classes, assuming normally distributed features and equal class covariances. It is effective for high-dimensional data but is sensitive to the above assumptions.

vii) **Naive Bayes (NB):** Bayes' theorem-based probabilistic classifier NB assumes feature independence given the class. It calculates conditional probabilities and class priors from training data. While computationally efficient, its strong independence assumption can limit performance, particularly in text classification.

viii)**Backpropagation Neural Network (BPNN):** BPNN adjust weights through forward and backward propagation, learning complex patterns with non-linear activation functions. They require substantial labeled data and computational power, suitable

for complex applications but resource-intensive.

ix)**Support Vector Machine (SVM**): Using the biggest margin, SVM determines which hyperplane best divides the classes. By utilizing kernel functions to handle both linear and non-linear data, it seeks to improve generalization and prevent overfitting, particularly in high-dimensional fields.

x)**Decision Tree**: Decision trees create a structure akin to a flowchart by segmenting data into subsets according to characteristics that yield the best information gain or lowest Gini impurity. They might overfit, but they are simple to comprehend. They function better when pruning and ensembling are used.

2.4. Training Phase

For CNN, we have used four pre-trained Convolutional Neural Networks- GoogleNet, Resnet50, EfficientNetB0 and Alexnet. All these networks consist of many layers and are trained on millions of images to classify 800 classes of images. This study considers 10% of total images for training and 100% for testing. Some of the layers of these neural networks need to be fine-tuned according to our dataset. Layers such as fully Connected layer, SoftMax layer and classification layers are adjusted.

The used algorithm is shown below:

Algorithm:

1 Load data set using image data store with specified folder structure for labels.

2 Split data in to training and testing sets (10-100 split ratio).

Load the pre-trained network and define network layers.

4 Define training options for the network. (‘sgdm’,’Maxepoch’,10.’InitialLearnRate’,0.01,’ ValidationData’, trainingdata.’ValidationFrequency’,1,)

5 Train the network using training data and defined options.

6 Validate and test the trained model on the testing dataset:

7 Predict classes for testing images.

8 Display images with predicted classes.

9 Calculate accuracy.

10 Plot confusion matrix to evaluate model performance on testing data.

For other Classifier, first we have extracted different features value using GLCM and GLRLM method then by using 10% of these values, we trained the classifiers. For training the used algorithm is shown below:

Algorithm:

1 Load the dataset containing images of different types of rice, ensuring balanced representation across classes.

2 For each image in the dataset. Extract texture features using GLCM and GLRLM.

3 Store the extracted features along with their corresponding class labels.

4 Train the classifiers using the 10% extracted texture features and their respective class labels.

5 Test the classifiers with 100% dataset.

3. Results and Discussion

This study compares the performance of four different pre-trained CNN models to that of other six different classifiers. A grand total of 800 images were captured, 100 images obtained for each distinct variety of rice. All the CNN models and other classifiers are trained using 10% of total data. Figure 2 shows the training progress of resnet50, where the validation accuracy is shown by the dotted black line; the training accuracy and loss are indicated by the blue and red lines, respectively. After training, 100% of the images are used to test the classifier models. It is found that the accuracy of the Googlenet, Resnet50, Alexnet, and EfficientnetB0 are 66.6%, 68.2%, 59.4%, and 65.2% respectively. In case of other classifiers namely, NB, KNN, LDA, SVM, Decision tree and BPNN the accuracies are 65.6%, 69%, 91.8%, 47.5%, 78.3%, and 92% respectively (using GLCM base texture features). The classification accuracies of the above six classifiers using GLRLM features are 71.1%, 69.75%, 96.75%, 92%, 86.6%, and 91% respectively. Figure 3 displays the confusion matrix for Resnet50 classifier.

Table 3 summarizes the performance of each classifier for classifying different varieties of rice using a total of 800 images (100 per class). Thus, this table indicates the numbers of correctly predicted classes for all the classifiers considered in this work. Additionally, figure 4 illustrates a comparison classification graph between CNN models and other classifiers. This study aims towards comparing the performance of CNN classifiers to that of other classifiers using texture features as input. It is learnt that feature extraction task is not required for CNN classifiers as the same is taken care by convolution layers and max pool layers. In the case of other classifiers, GLCM and GLRLM based texture features are utilized for the classification task. Results indicate that classification based on texture features produce improved result as compared to CNN models considered in this work. It is also learnt classification using GLRLM based texture features is found more suitable as compared to GLCM. Results show that LDA classifier is capable of attaining maximum classification accuracy of 96.8% using GLRLM. It is also observed that performance of BPNN is comparatively better and consistent as compare to other classifiers.

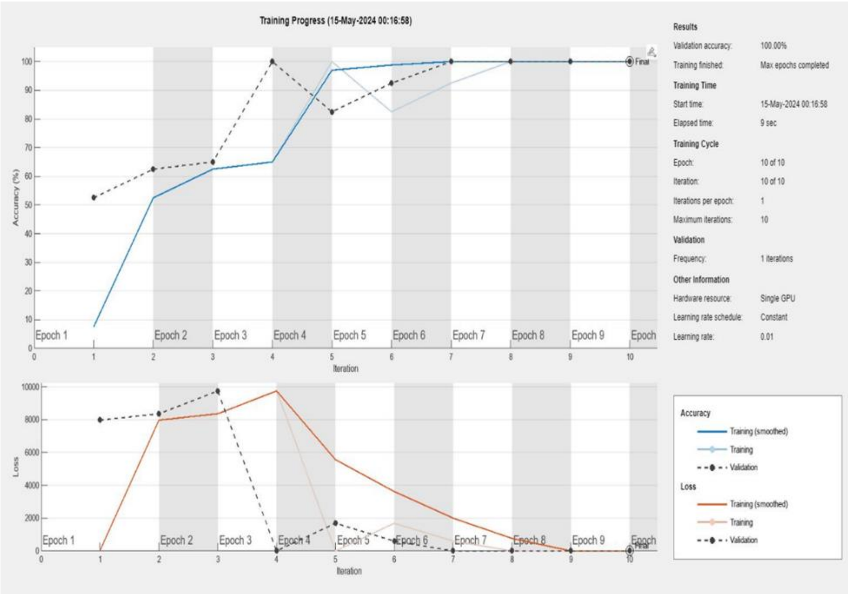

Fig 2. Training progress plot for Resnet50

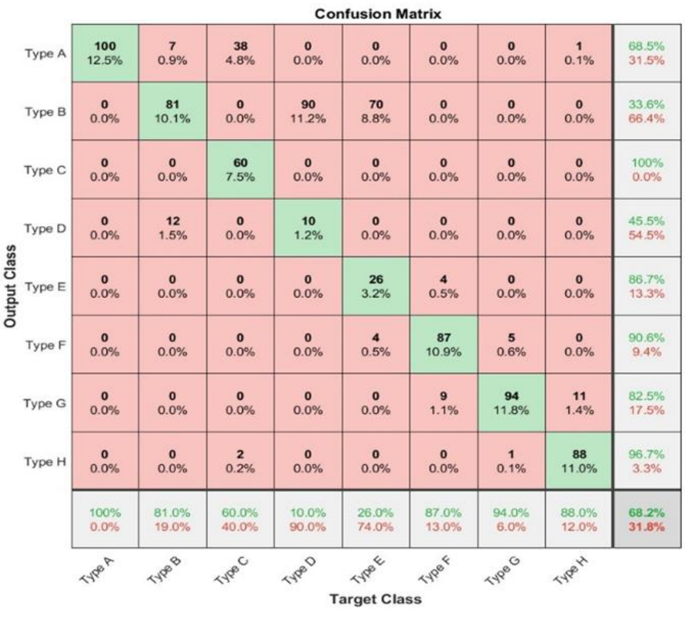

Fig 3. Confusion matrix for Resnet50

Table 3. Performance of each Classifier

Types of rice	GoogleNet	ResNet50	Alexnett	EfficientNetb0	NB		KNN		LDA		SVM		DT		BPNN	
					GLCM	GLRLM	GLCM	GLRLM	GLCM	GLRLM	GLCM	GLRLM	GLCM	GLRLM	GLCM	GLRLM
A	100	100	100	93	76	62	84	82	95	97	92	100	75	100	92	92
B	73	81	21	67	62	57	58	82	93	97	50	95	73	69	92	85
C	100	60	11	100	67	91	83	46	96	100	75	93	87	100	94	95
D	32	10	86	98	85	69	87	58	100	94	63	82	86	85	100	94
E	100	26	100	10	79	62	76	83	100	100	40	83	88	84	93	90
F	10	87	9	100	41	73	58	82	73	89	18	100	69	83	94	89
G	99	94	100	25	72	67	56	65	85	98	27	92	72	82	89	87
H	19	88	48	29	43	88	50	60	93	99	18	100	79	91	89	96

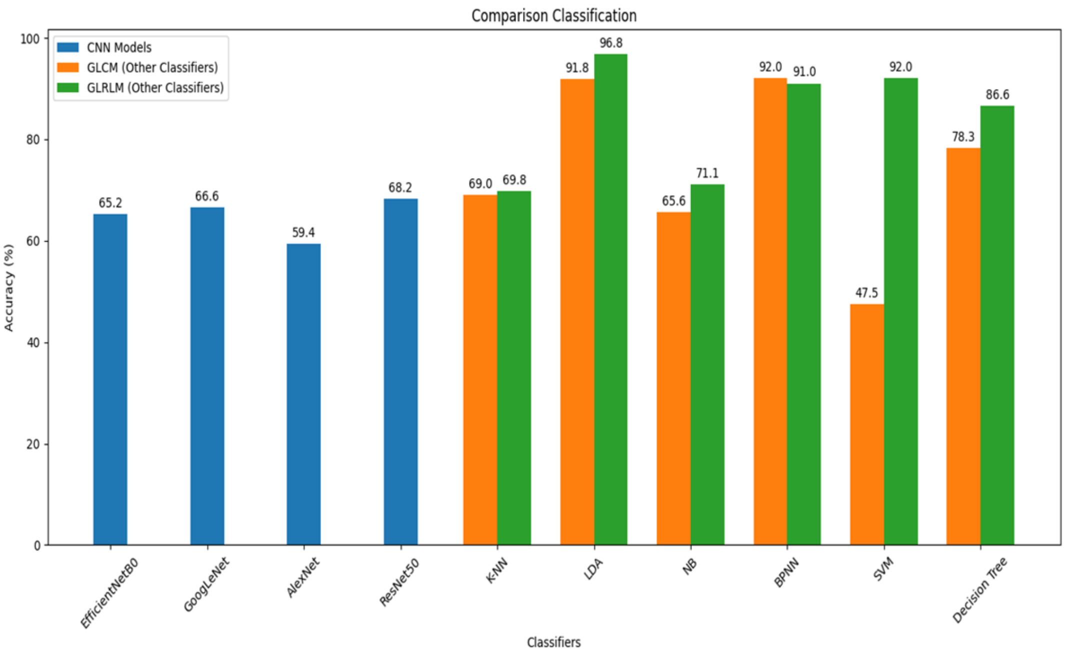

Fig 4. Classification performed of CNNs and other classifiers

4. Conclusion

Classification of eight different varieties of rice grain is carried out using different machine learning techniques and the results are compared. This study suggests that classification using engineered features (GLCM and GLRLM based texture features in this study) is found more suitable for classification of rice grain as compared to pre-trained CNN classifiers. This may be due to that fact that some part of human intelligence is imparted during feature extraction in the case of classification using engineered features. This study also suggests that BPNN and K-NN classifiers are found equally good on both the texture features (GLCM and GLRLM). However, the performance of BPNN is comparatively better and consistent as compare to other classifiers.

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Author contributions

Anurag Bhattacharjee: carried out the work using different pre-trained convolution neural networks. **Ksh. Robert Singh:** performs texture feature extraction (using GLCM and GLRLM) and also organized the whole manuscript. **Takhellambam Sonamani Singh**: carried out the literature survey of this work. **Subir Datta and Subhasish Deb:** contribute towards data collection and image acquisition task. **Usham Robinchandra Singh and Ghaneshwori Thingbaijam:** carried out the classification task using different conventional classifiers other than CNNs.

Conflicts of interest

The authors have no conflicts of interest.

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