A Deep Convolutional Neural Network Approach To Rice Grain Purity Analysis

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Abstract. Traditional rice grain classification is costly, time-consuming and requires sophisticated human expertise. Besides, computer vision based methods are still based on predefined morphological features that are often not transferable across different types of grains. In this paper, the feasibility of automated feature extraction for rice grain purity analysis has been demonstrated using a Convolutional Neural Network (CNN) based deep learning approach. Due to lack of benchmark datasets, the paper defines a dataset with technician-verified, labeled images of different types of rice grains with a background of uniform illumination. Moreover the paper also proposes architecture of a CNN for automated rice grain feature extraction. The performance of a classifier trained on these features is compared to classifiers trained on morphological features used by modern computer vision approaches. It is found that in this dataset, the proposed method can detect the presence of native and foreign grains in a given sample of rice grains with superior accuracy which is at least 25% better in case of multiclass classification scenario.

Keywords: Convolutional Neural Network, Rice Grain, Morphological Features, Deep Learning, Computer Vision.

1 Introduction

The selection of grains for analysis is typically carried out in two steps of Nine-Spoon method to pick 9 spoonful of rice from different places and Quadrant Method to analysis samples that are divided into different quadrants. The final readings are so sensitive that even variations of ~4% of the same characteristic are considered vastly different. At times, even two technicians with different levels of expertise may generate a different report for the same sample. It is an immensely time-consuming and expensive process. Machine learning has been successfully used in several applications like healthcare or intrusion detections [1-2]. Machine vision techniques have started to be utilized very often in analysing rice grains by many researchers. Yao et al. [3] developed an automatic inspection and image processing unit to evaluate rice chalkiness and shape using a camera and a light box. They calculated the chalkiness of a grain using an automatic multi-threshold method based on maximum entropy, and also estimated rice grain shape parameters by finding the Minimum Enclosing Rectangle (MER). Their objective analysis methods were strongly correlated with manual estimations by trained technicians [3]. Devi et al. used Canny Edge Detection to extract morphological features to classify grains on their predicted lengths [4]. Their method was tested on four different samples of rice grains and the accuracy of the predictions was within 2% of manual calculations [4]. In a similar case, research considered the problem of the touching of grains in image pre-processing by using the Shrinkage algorithm [5]. In an attempt to replace the industry standard Satake RSQI10A grain scanner software, Ali et al. enumerated similar morphological features of rice grains in their low-cost solution [6]. The results from such projects paved the way for an objective, appearance-based quantifier that would be superior and more reliable than manual inspection. Although several works used other features like shape, texture, color features to generate optimal morphological features for grains and achieved good accuracy, these features are also depended on rice specific expertise knowledge [7-9] and are not often transferable to different rice categories. Moreover, no publicly available database exists that has technician-verified, classified image samples of different categories of rice grains with uniform illumination background. Because of the intrinsic limitations of classical and previous automated methods, this work proposed a deep learning based system to, demonstrate the potential of convolutional neural networks (CNNs) for automated transferable feature extraction and classification of rice grains. Apart from the methodology, the paper also defines a dataset with technician-verified, labeled images described in data collection section.

2 Materials and methods

2.1 Data Collection

This paper defines a rice grain dataset with the help of specialists from rice distributors and retailers in India that is available for research[1]. After obtaining a significant random sample using the *Nine-Spoons* and *Quadrant Methods*, the rice grains were scanned using a generic Flat-Bed Scanner (FBS). The images were all scanned with a black background at 300 ppi as depicted in Figure 1. The dataset contains the rice varieties most commonly found in North-India. The total number of available images for each grain category and the total individual grain samples that were extracted from these images are summarized in Table 1. Initially, the dimension of every image was 3507x2550 pixels, with around

[1] https://github.com/Mushahid2521/Rice-Grain-Purity-Analysis-Using-Deep-Learning

100 to 200 individual rice grains in each image as depicted in figure 1. The grains were manually placed far apart from each other so as to avoid the algorithm from considering multiple grains as a single grain. All samples were scanned using a similar arrangement.

Table 1. Summary Samples in Dataset

Grain Type	Total Images	Grain Samples
PR	192	15,277
1121	155	17,345
Sharbati	51	13,596
1401	52	12,559
1509	105	17,262
Sona Masoori	24	4,024
RH-10	17	3,852
Sugandha	59	11,933

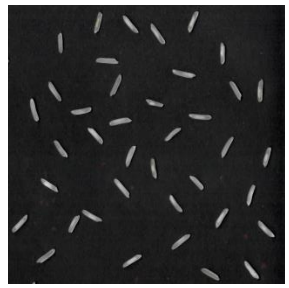

Fig. 1. Scanned Image Example

2.2 Pre-Processing

The scanned rice grain image (SI), was first segmented into individual grain images. Canny Edge Detection algorithm was employed to detect the grain boundaries [10]. SI was first converted into a grayscale image. Noises were reduced using *Gaussian Smoothing*. *Sobel kernel* was used to find intensity gradients in the horizontal (G_x) and in the vertical direction (G_y) of the image. Edge gradient (G) and each pixel direction (Θ) was computed according to equations 1 and 2 followed by *Non-Maximum Suppression*to get binary image with thin edges.

$$G = \sqrt{{G_x}^2 + {G_y}^2} \tag{1}$$

$$\Theta = \frac{G_y}{G_x} \tag{2}$$

Finally, *Hysteresis Thresholding* performed thresholding twice using an upper threshold (maxVal=100) and lower threshold (minVal=100) based on validation.

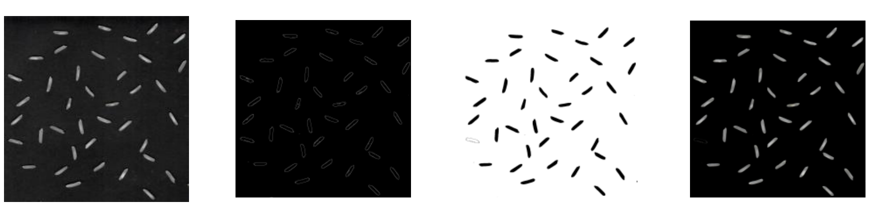

Fig. 2.a. Input Scanned Image (SI)

Fig. 2.b. Canny Edge Detection

Fig. 2.c. Grain Extraction Mask

Fig. 2.d. Final Output

Fig. 2. Edge Detection for individual grains

The next step in the process is to find and grab contours (boundary of a grain) from the output of the previous step. On a white colour mask, contours of black colour were drawn using the tuples that we grabbed in the previous step. This made the image binary with the colours Black (0) in place of the grains and White (255) as the background. The mask was then used to extract the grains from the SI. The contour values were also used to generate the Minimum Enclosing Rectangles (MER) around the grains and crop them into individual grain images (CI). The progress of this process is depicted in figure 2 using cropped images for visual clarity. When the grains were cropped from the SI, the CI were of different sizes. To feed into a predictive model, these images were resized to same length and width by padding the CI of the grains with black pixels (0). Considering different height and width of the grain images, we have used a size of 128X128 pixels as the Standard Dimensions for individual grain images. Since, fewer samples and a lot of model parameters often lead to overfitted deep learning models, data augmentation was performed. Original images were rotated in different angles to obtain around 24,000 individual grains for every class.

2.3 Morphological Feature Extraction

Quantifiers that represent size namely: the length (l_r) and width (w_r) of minimum enclosing rectangle (MER), the length of the Major Axis (l_{a1}) and Minor Axis (l_{a2}), length of the grain considering it an ellipse (l_e), the perimeter (p), the area of each grain (A), the area of a shape (A_S) and the area of the MER (A_R) were selected. These basic features were combined into six complex features (equation 3-8) that contributed significantly in rice grain classification and were subjected to normalization before use [9].

$$\textit{Area} \text{ by } \textit{Perimeter} \text{ ratio} = \frac{A}{p} \tag{3}$$

$$\text{The ratio of } \textit{Area} \text{ to the total of Area and Perimeter} = \frac{A}{A+p} \tag{4}$$

$$\text{Aspect Ratio: Ratio of } \textit{Major Axis} \text{ length to } \textit{Minor Axis} \text{ length} = \frac{l_{a1}}{l_{a2}} \tag{5}$$

$$\text{Rectangularity} = \frac{A_S}{A_R} \tag{6}$$

$$\text{Equivalent Diameter} = \sqrt{\frac{4A}{\pi}} \tag{7}$$

$$\text{Shape Factor 3} = \frac{A}{l_{a1} \times l_{a2}} \tag{8}$$

2.4 Convolutional Neural Network Architecture

The input of the proposed CNN architecture is a 128 by 128 image patch. The kernel size in each layer was chosen to be minimal. The samples of CI for each type of grain were passed through four pairs of Convolution and Max-Pooling layers. In the first two Convolution layers, a 5×5 filter size was used, and in the next two layers a 3×3 filter size was used. The number of filters in the Convolution layers is respectively 6, 16, 64 and 128 as depicted in Figure 3. In the Max-Pooling layers, a 2×2 pool size was used. Due to faster convergence and non-saturating values in gradient descent compared to sigmoid functions, Rectified Linear Unit (ReLU), computing $f(z) = \max(0,z)$, on corresponding weighted sum z, was used as an activation function for all the layers. A Softmax function on corresponding input x computing $f(x)=(1+e^{-x})^{-1}$ was used in the last *dense* layer for classification, computing the class probabilities. A 40% *dropout* was used between the last two dense layers to reduce *overfitting*. The loss function used was Categorical Cross-Entropy (CE) as given in Equation 9.

$$\text{CE}=-\sum_i^C t_i \, log \, log \, f(s)_i \quad (9)$$

Where, for C classes, t_i is the ground truth and *f(s)* is the corresponding activation. The model was trained with *Adam* optimizers because of its faster convergence. The network architecture is depicted in figure 3. The hyperparameter selection was performed based on cross validation as discussed in result section. Figure 4 show an example with different types of grains arranged in different rows and corresponding identification as drawn by the program. The purity of the rice sample is calculated as the percentage of native grains in the sample by count.

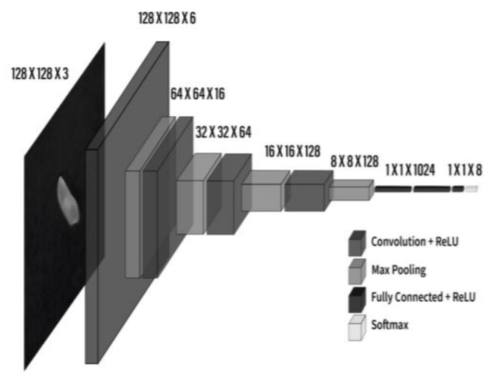

Fig. 3. Convolutional Neural Network Architecture

Fig. 4. Program's Prediction

3 Results and Discussion

To compare the outcome of the proposed approach with traditional approach, morphological features of samples were classified using classifiers kNN[11], Decision Tree(DT)[11] and Artificial Neural Network(ANN)[12]. For parameter selection process, 900 samples were selected and used in a 3 fold cross validation fashion. The value of k was selected as 3 for kNN based on best average validation accuracy of 39% as depicted in figure 5. Similarly, for ANN classification, the number of nodes was selected as 140 with best average accuracy of 49% as depicted in figure 6.

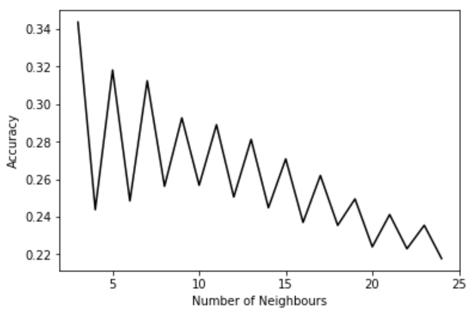

Fig. 5. kNN parameter(k) selection.

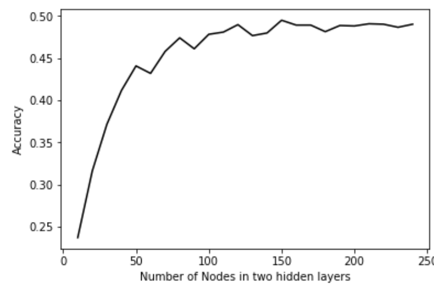

Fig. 6. Hidden layer nodes selection for ANN.

Structural parameter selection in the CNN setup, is enlisted in Table 2 for selection of total convolutional layers and dropout. With 3 Layers the network performs better for training data compared to others (4 or 5 layers) which comes with a cost of lower validation accuracy. It indicates possible overfitting as it has less parameters compared to 4 or 5 convolutional layer setup. A 5 convolutional layer setup shows poor performance compared to 4 layer setup in both training and validation data. Thus 4 convolutional layers were used for further experiment. Without dropout in fully connected layers the selected model performs better for training data since dropout is used to reduce overfitting, but without dropout the model achieves same accuracy with lower standard deviation for validation data. Thus 4 convolutional layer with dropout is proposed for this experiment.

Table 2. Average Performance for parameter selection of CNN

Experiments	Training Accuracy	Validation Accuracy
Without Dropout(4 Convolution layers)	64±2.2	42 ±1.6
With Dropout(4 Convolution layers)	62 ±6.5	42 ±0.9
Convolutional Layers 5	48 ±8.4	42 ±0.4
Convolutional Layers 4	62 ±6.5	42 ±0.9
Convolutional Layers 3	78 ±2.6	40 ±0.5

In the same experimental setup as the validation environment, with 3000 test samples for each category and rest as train data, average classification accuracy of the kNN, Decision Tree and ANN classifier on manual morphological features are listed in table 3.These experiments are based on the selected parameters as discussed previously. While latest machine vision approaches often using ANN with morphological features [8-9], the accuracy of those features for this dataset has been found to be poor. Besides classifiers like decision tree and kNN also depicts poor performance on those features. On the other hand, proposed convolutional features with ANN classifier provide a better accuracy of 77% on the same test data.

Table 3. Rice Grain Classification Accuracy

Experiments	Average Testing Accuracy (%)
DT on Morphological Features	52
kNN on Morphological Features	48
ANN on Morphological Features [6-7]	51
Proposed Approach (Convolutional Feature + ANN)	77

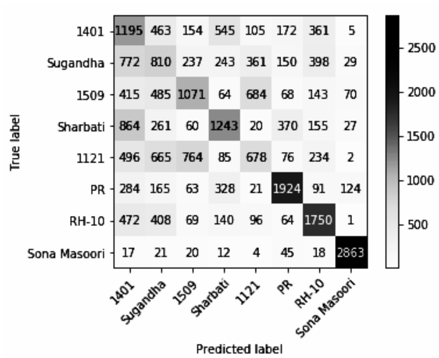

Fig. 7(a). Confusion Matrix for KNN

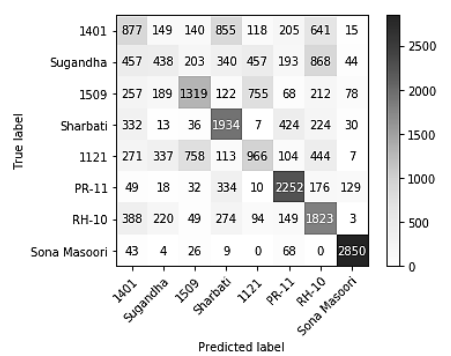

Fig. 7(b). Confusion Matrix for Decision Tree

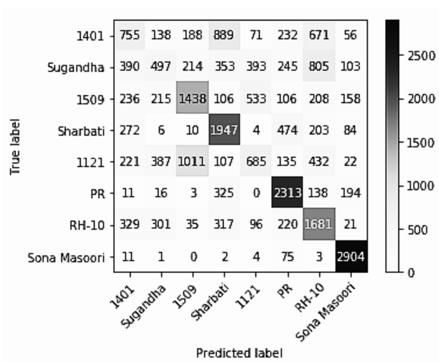

Fig. 7(c). Confusion Matrix for Neural Network

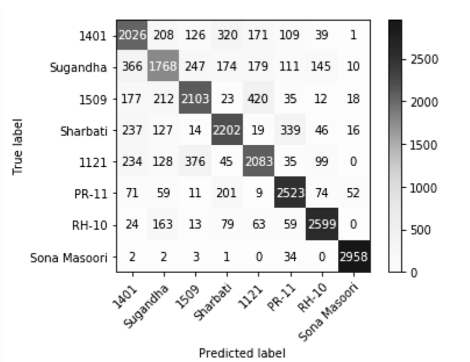

Fig. 7(d). Confusion Matrix for CNN

The confusion matrices for test data classification are given in figures 7. From the comparison of the confusion matrix, it can be concluded that some grain types could be classified with high accuracy using the morphological features but some would not. In these cases, a CNN works considerably well. Further experiment reveals that if the model is formulated into binary-classification, then the accuracy increases to 81% for all grain types. CNN based extracted features are highly transferable. It extracts specific as well as generic features in the intermediate layers [13]. These features learned from one type of grain samples can be tuned to identify a different category of grain samples. Thus the performance of CNN is better across different categories of rice grains. This is clear from the confusion matrices that CNN classifies at least around 1760 samples of every category correctly while performance of others may drop significantly up to 430 for particular categories. In Table 4, the precision, recall and F1 scores for different classifiers are enumerated for comparison in multi class classification scenario which also elucidates the success of CNN.

Table 4. An Objective Comparison of Different Classifiers

Type of Grains	KNN			Decision Tree			ANN			CNN		
	Precision	Recall	F1	Precision	Recall	F1	Precision	Recall	F1	Precision	Recall	F1
PR	0.67	0.64	0.66	0.65	0.75	0.7	0.61	0.77	0.68	0.79	0.83	0.81
1121	0.34	0.23	0.27	0.40	0.32	0.36	0.38	0.23	0.29	0.67	0.74	0.71
Sharbati	0.47	0.41	0.44	0.49	0.64	0.55	0.48	0.65	0.55	0.73	0.77	0.75
1401	0.26	0.40	0.32	0.33	0.29	0.31	0.34	0.25	0.29	0.67	0.68	0.67
1509	0.44	0.36	0.39	0.52	0.44	0.47	0.50	0.48	0.49	0.79	0.62	0.69
Sona Masoori	0.92	0.95	0.94	0.90	0.95	0.93	0.82	0.97	0.89	0.98	0.99	0.98
RH-10	0.56	0.58	0.57	0.42	0.61	0.49	0.41	0.56	0.47	0.86	0.9	0.88
Sugandha	0.25	0.27	0.26	0.32	0.15	0.20	0.32	0.17	0.22	0.67	0.64	0.66

4 Conclusion

This paper proposed a CNN based rice grain classification approach that is more accurate compared to morphological features used by earlier researchers to identify foreign grains in a given sample of rice grains. Compared to manual human expertise based approach as discussed in introduction, this proposed method is consistent and fast. Moreover an expert defined dataset has been introduced for experiment and a neural-network based approach was suggested on automated deep convolutional features due to its superior accuracy. In the test dataset, the total classification accuracy was 77% which increases up to 82% in binary classification settings which is better than the some modern approaches. Apart from the ad-mixture, which represents the impurity of a rice sample, there are other factors such as percentage of Pin-Broken grains, Damaged and Discoloured (DDC) grains, immature grains, and Chalky grains. These factors together influence the sale and purchase of a particular batch of milled rice. Extended research may consider identifying the other 4 important factors and building low-cost, full-service software that is time-efficient and objective.

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