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Comparison of Multi-class SVM and CNN for classification of similar looking Indian rice variety

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ABSTRACT

Machine Learning has a wide range of application in food industry. Image processing has been used for feature extraction in different fields of agriculture. As India grows variety of rice grains, the challenge of identification its type is also tough. The human inspection method for grain classification is tedious and laborious. It totally depends on the knowledge of the expert. As this is subjective, the need for automatic machine-vision based solution is increasing day-by-day. In this novel work, four types of similar looking Indian rice samples are considered. The challenge increases as these are similar variety. Image processing methods are used is used to extract texture, color and wavelet features. The efficient Machine Learning models like Multi-class Support Vector Machine (SVM) and Convolution Neural Network (CNN) are used to compare the performance of the classification. The results obtained shows that CNN is better compared to SVM. An accuracy of 97% for testing set and 88% for validation accuracy is achieved using CNN model.

KEYWORDS:SVM, CNN, similar looking, Indian Rice and Image processing

1. INTRODUCTION

In India many crops are grown which includes wheat, rice, spices and some non-food crops as well [1]. Rice is one of the staple crops of most parts of the world. India is a highest exporter of rice since 2011 as it is grown in more than 43 million hectares [2]. There are around 82,700 varieties of rice grown in India including notified and hybrid types [3]. As one of the primary centers of origin of Oryza sativa (commonly known as Asian Rice), India has rich and diverse genetic wealth of rice.

As India grows rich varieties of rice, analysing the quality becomes a major challenge. The quality of grain is affected by several factors which includes, growing practices, time and type of harvesting, postharvest handling, storage management and transportation practices [4]. Identifying the correct quality of rice is a laborious and time consuming. Measurement of grain quality on the commodity crops such as rice, wheat, barley, corn, maize is a wide research area. Grain quality generally refers to its physical characteristics like shape, color, size, hardness and presence of foreign materials. The premium quality of grain is the one which is free from adulterants and does not cause any health hazards [5].

It is tedious and the same time is very to measure individual kernel to analyse the quality of grain. Currently this is carried out by human inspection method which is subjective, time consuming and less accurate. To address this issue, there is a need of machine based automated method to provide consistent results. Recent research in the field of computer vision and machine learning has opened up a wide scope in the field of grain quality analysis [7].

Through image processing, the captured images are pre-processed and various features such as texture, shape, color and fracture rate are extracted based on which Rice is priced in the commercial market [8]. Accessing the quality of morphologically similar rice varieties is a challenge for both food industry and the consumers. Most of the times the producer and seller quote higher prices for the similar low quality rice in the market. Hence, this work objects to address this issue by using Image processing and Machine learning based solution to classify morphologically similar varieties of rice. After acquiring digital images of the rice kernels, Support Vector Machine (SVM) and Convolution Neural Network (CNN) is used to determine the variety of rice.

2. LITERATURE SURVEY

In last decades many research work is carried on classification rice quality using features extracted from digital images. Most of the work is present on morphologically dis-similar type of rice. As the features vary widely, identification is comparatively easy. The details of the work carried so far on the rice variety classification using various machine learning algorithms are listed in the table 1.

Table - 1: Summary of Literature

Sl. no.	No. of Class	Classification algm.	Dataset size	Results	References, Year
1	5	ANN, DNN and CNN	75,000	99.87% for ANN, 99.95% for DNN and 100% for CNN	[9], 2021
2	2	LR	3810	93.02%	[10], 2019
3	15	SVM	75 (each with 40 to 60 grains)	93%	[11], 2019
4	3	DCNN	7399	95.50%	[12], 2018
5	3	PNN	-	98%	[13], 2014

The above literature shows that very less work is carried on Indian variety of rice. The study carried out by Harini et. al., provides the detailed review on the methods used for food grain quality analysis [14]. A work from the same author on analysis of rice quality based on Degree of milling also shows the benefits of using Machine learning in the field of agriculture [15]. The research on Classification of Indian rice variety has considered morphologically different variety of rice. In this novel work, classifying morphologically similar Indian rice varieties is carried out using SVM and CNN. The methodology and results obtained are discussed in the further section of the paper.

3. METHODOLOGY

In this work specific variety of rice grains were considered, the first step was to collect the sample and capture the images to create the dataset. The complete process followed for this study is given in the figure 1 below.

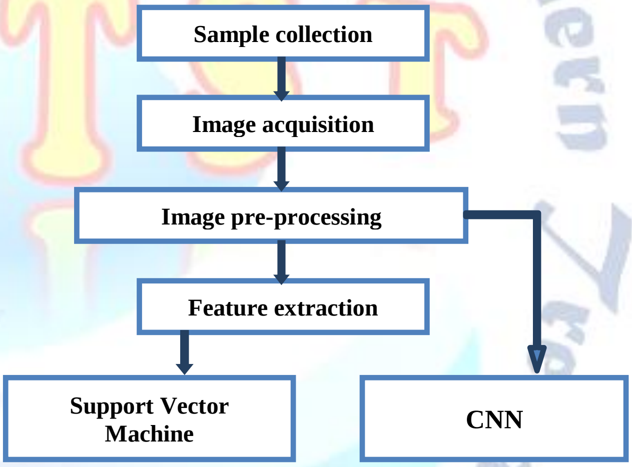
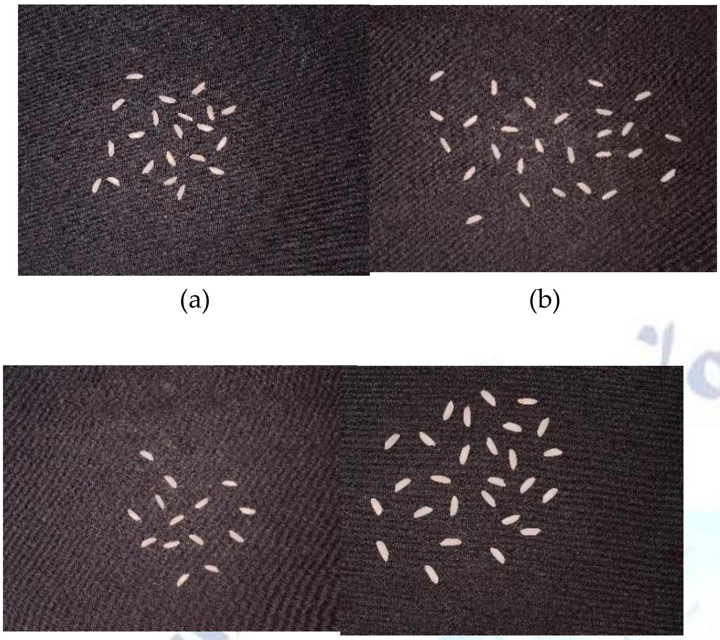


Fig- 1: System architecture

Four variety of rice samples are collected for quality analysis from commercial market and as examined at ShriBhagyalakshmi agro food pvt.ltd. These varieties belong to medium sized rice, similar to Sonamasoori and are commercially named as:

- B.R.T Daiwan (Rawh)
- Grine world (Rawl)
- Royal Sona (Steamh)
- DaiwanSona (Steaml)

The four varieties include two raw rice and two steam rice category. As these varieties have similar features, the challenge lies in correct identification of the type which affects the market value of the product. The sample images of these four varieties are shown in figure 2.



(a) (b)

(c) (d)

Fig - 2: Sample images of (a)B.R.T Daiwan (Rawh) ,(b)Grine world (Rawl) (c)Royal Sona (Steamh) and (d)DaiwanSona (Steaml)

A total of 4180 images for four similar looking rice kernels are considered. The images are captured using a standard image acquisition model. Each image is of 4080X3060 dimensions which is captured using Mobile camera with flash light.

The colour, texture and wavelet features are extracted from the images captured. The texture features extracted using Grey Level Co-occurrence Matrix (GLCM) method are Width, Height, Aspect Ratio, Contrast, Dissimilarity, Homogeneity, Energy and Correlation. The colour features are extracted from both RGB and HSV colour space. The features extracted from colour space are Mean, Standard deviation, Skewness, Kurtosis and Wavelet decomposition. A total of fifty six features are extracted for the classification of rice types.

The entire dataset is been split into train-set and test-set. 80% of the images are considered for training and 20% are used for testing. The analysis and identification of different rice types is performed using SVM and customized CNN model.

Multi-class SVM is nothing but multiple binary SVM's. The two approaches to combine multiple binary SVMs are One-v/s-One and One-v/s-Rest. SVM is an efficient classification model which finds the optimized hyperplane to separate the given instances. SVM uses three types of kernel trick, namely, Linear, Polynomial and RBF. Based on the available dataset, each of these kernel functions work differently. A through experiment is carried out in each of these kernel functions using the features extracted in the previous step [16].

CNN is a deep learning method which is often used for Image classification [17]. CNN can extract features from the data which are given as input and with these features, it can learn and classify. There are five main layers in CNN model:

- Convolution layer
- Pooling layer
- Activation layer
- Fully connected layer
- Softmax layer.

In the first layer i.e, convolution layer, various filters are applied step by step in the regions on the image to extract image features from each region. Operations are performed to reduce the large number of data coming from the convolution layer and reduce complexity in pooling layer. Activation layer is added after pooling layer and is followed by fully connected layer. At the end we will have softmax layer as this is a multi-class problem [18].

In this work, the customized CNN network is built and used for training. The model includes three Convolutional layers followed by max-pooling layer. The images are resized to 224x224 and are fed as input to the first layer. The Dropout layer is added after the third layer which is flattened and is followed by Softmax activation function which has 4 neurons to parse four different similar looking rice varieties. The figure 3 below shows the CNN model used in this work.

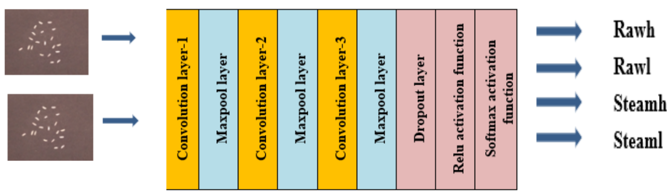


Fig - 3: Customized CNN model used for classification of rice types

4. RESULTS AND DISCUSSION

SVM model with different kernel function are trained using each of these features separately and a comparative study is made to choose the best feature set and the model to classify morphologically similar variety of rice. The results obtained in this study are tabulated in table 2.

Table - 2: Testing accuracy obtained from SVM, KNN and DT models on different set of features

Feature Set	SVM_ linear	SVM_ Polynomial	SVM_RBF
GLCM	56.33%	58.85%	58.9% (gamma=0.8)
RGB (Color and Wavelet)	54.06%	72.24%	68.66% (gamma=0.8)
HSV (Color and Wavelet)	56.93%	69.13%	67.22% (gamma=0.8)
ALL	68.18%	72.48%	68.99%

From the table 4.1 it is been observed that the good testing accuracy is achieved for color and wavelet features along with textural features. It has been observed that the highest accuracy of 72.48% is achieved by SVM with Polynomial kernel function by considering all 56 feature set.

The acquired 280 images are divided into train set (80%) and test set (20%).The images are resized to 224X224 dimensions before feeding to the CNN model, a sample image is as shown in the figure 4.

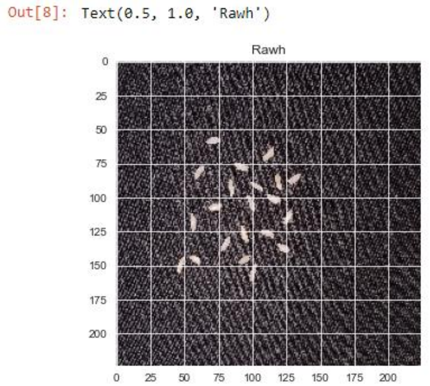


Fig - 4: Resized image of Rawh variety

We have developed the CNN model with three convolution layers. Initially the experiments are conducted with 32 filters each 3X3, in all three layers all the layers. The work is continued the same architecture and for varied number of iterations (epochs). The results of this experiment are shown in the table 3.

Table -3: Train and validation accuracy for 32 filters in all three layers against different number of epochs

Filter size	Epochs	Train accuracy	Validation accuracy
All three layers with 32 filters, each (3x3).	Epoch=100	45%	50%
	Epoch=200	72.9%	67.5%
	Epoch=300	89%	80%
	Epoch=400	91.95%	82.5%
	Epoch=500	94.25%	87.5%

The table 4.2 shows that for this model with 32 filters in all three layers, a highest training accuracy of 94% and test accuracy of 88% is achieved with epoch=500.

Table- 4: Train and validation accuracy for 32 filters in first two layers and 64 filters in third layer against different number of epochs

Filter size	Epochs	Train accuracy	Validation accuracy
Layer one and two with 32 filters and layer three with 64 filters each (3x3).	Epoch=100	50.7%	50%
	Epoch=200	73.08%	70%
	Epoch=300	81%	73%
	Epoch=400	80.7%	73%
	Epoch=500	90.7%	73%

From the table 4, we can infer that the training accuracy increases with number of epochs (i.e., 91% at epoch=500) but the validation accuracy remains is constant i.e., 73%.

Table 5: Train and validation accuracy for 32 first layer and 64 filters in second, third layer against different number of epochs

Filter size	Epochs	Train accuracy	Validation accuracy
Layer one with 32 filters and two, three with 64 filters each (3x3).	Epoch=100	69.5%	57.5%
	Epoch=200	85.6%	80%
	Epoch=300	89.08%	80%
	Epoch=400	94.8%	80%
	Epoch=500	97.13%	87.5%

The table 5 shows that the train accuracy and test accuracy is highest i.e., 97.13% and 87.5% respectively for epochs=500.

The testing and validation accuracy and loss curve obtained from our CNN model CNN model with 32 filters in layer1 and 64 filters (each 3X3) in layer2 and layer3 for classifying the rice varieties is shown in the graph Figure 4 below. We can observe that the loss reduces as the number of iterations increases and accuracy increases with the increase in iterations.

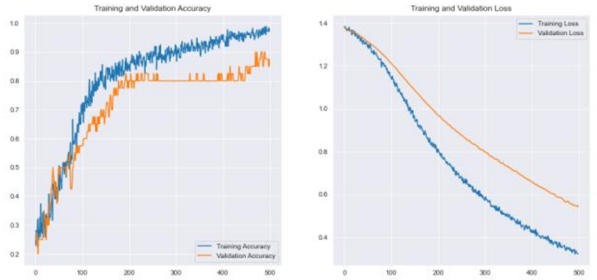


Fig 4: Testing and validation accuracy/loss curve for CNN model with 32 filters in layer1 and 64 filters (each 3X3) in layer2 and layer3

The overall precision, recall, accuracy and F1-score for the novel work of classification of morphologically similar rice varieties using CNN model with 32 filters in layer1 and 64 filters (each 3X3) in layer2 and layer3 is shown in the table 6.

Table 6: Precision, recall and F1-score for the CNN model with 32 filters in Layer1, 64 filters in layer2 and layer3 at epoch=500

Variety	Precision	Recall	F1-score
B.R.T Daiwan (Rawh)	86%	60%	71%
Grine world (Rawl)	100%	100%	100%
Royal Sona (Steamh)	69%	90%	78%
DaiwanSona (Steaml)	100%	100%	100%
Average	**89%**	**88%**	**87%**

5. CONCLUSIONS

An attempt is been made to analyze quality of rice based on the morphologically similar types of rice. For this novel work, the samples of four different medium sized rice (similar to Sonamasoori rice) varieties are collected from commercial market and as examined at ShriBhagyalakshmi agro food pvt.ltd. The whole dataset is divided into 80% for training and 20% are used for testing. Color, texture and wavelet features are extracted and SVM model is used for analysis. The results are compared with CNN model for which the images are fed as input. The following are the observations made for SVM and CNN:

- Using only textural features extracted by GLCM method yields a highest accuracy of 58.9% for SVM with RBF kernel function.
- The RGB color and wavelet feature sets have improved the accuracy to 72.24% and with HSV color and wavelet feature sets have obtained the accuracy to 69.13% for SVM with Polynomial kernel function.
- When the overall feature set is considered which includes all 56 features, the accuracy achieved is 72.48%.
- For the CNN model with 32 filters in all three layers, a highest training accuracy of 94% and test accuracy of 88% is achieved with epoch=500.
- For the CNN model with 32 filters in first two layers and 64 filters in third layer, the training accuracy increases with number of epochs (i.e., 91% at epoch=500) but the validation accuracy remains is constant i.e., 73%.
- For the CNN model with 32 filters in first layer and 64 filters with second and third layer, a highest testing accuracy of 97% and validation accuracy of 88% is obtained for epoch=500.
- The results obtained shows that it is quite challenging to classify morphologically similar rice grains and using CNN model the highest accuracy of 88% is achieved.

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Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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