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Comparison of Support Vector Machines and ShuffleNet for Detection of Rice Species

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Abstract – The objective of the current investigation is to identify the optimal approach for the automated identification of rice species based on images. Two types of datasets have been utilized. The initial dataset comprises a total of 75,000 images, including five different rice species, namely Arborio, Basmati, Ipsala, Jasmine, and Karacadag. The dataset is a balanced set comprising 15,000 images for each type. During this dataset's analysis phase, ShuffleNet, one of the pre-trained architectures in Convolutional Neural Networks (CNNs), was used. The second dataset was created by extracting features from the same rice images. 106 distinct features were acquired, which include morphological, shape, and color features as the main features. The previously extracted features have been analyzed for the classification of rice species using Support Vector Machines (SVM), which have a quadratic kernel function. Moreover, the two datasets have been obtained from the URL https://www.muratkoklu.com/datasets/. Additionally, 5-fold cross-validation has been applied for both ShuffleNet and SVM to avoid overfitting. Based on the empirical findings, ShuffleNet has achieved an accuracy rate of 99.8%, while SVM has acquired an accuracy rate of 99.9%. While the results exhibit minimal differences, the optimal algorithm choice may be contingent upon the researcher's level of proficiency in the field.

Keywords – Deep Learning, Classification, Convolutional Neural Networks, Hyperparameters, Machine Learning.

I. INTRODUCTION

Rice, a staple food from grain products, is grown and consumed worldwide [1]. Multiple factor parameters determine rice prices. Using digital images of the products, many machine learning algorithms determine these parameters which include texture, shape, color, and fracture rate, and classify them [1, 2]. Machine learning algorithms efficiently and reliably analyze large amounts of data [1]. Rice production methods are crucial for improving product quality and food safety through an automated, cost-effective, proficient, and non-invasive approach [1, 3-5]. Therefore, this study aims to determine rice species from images using machine learning algorithm and deep learning approach, effectively.

In currents, machine learning algorithms and deep learning approaches are used in agricultural field to improve quality and save time [6-9].

When the literature is investigated, both the classification of various diseases and a determination of the type of agricultural products are seen as follows:

Prajapati, et al. [10] classified three rice plant diseases using SVM. They obtained accuracies of 93.33% on the training dataset, 73.33% on the test dataset, 83.80%, and 88.57% based on 5 and 10-fold cross-validation, respectively. Koklu, et al. [1] classified rice images based on artificial neural networks (ANN), deep neural networks (DNN) and CNN with accuracies of 99.87%, 99.95% and 100%, respectively. Cinar and Koklu [11] also classified rice species and achieved an accuracy of 93.02% utilizing logistic regression. Phadikar, et al. [12] examined rice leaf diseases and detected these classes based on naïve bayes and SVM with accuracies of 79.5% and 68.1%, respectively.

Furthermore, it can be added numerous studies in this field [13-16].

This study presents a fair comparison of two algorithms: ShuffleNet [17] and SVM [18] to detect rice species. The contributions of this study are: (i) Rice grains dataset consisting of 75,000 images was utilized. (ii) These images were classified ShuffleNet using 5-fold cross-validation. (iii) 106 features obtained from these images including morphological, shape, and color main features were employed for SVM. (iv) it was tasked to class these features based on quadratic kernel function and in this phase of the study, 5-fold cross validation was performed again. (v) Empirical results show that these algorithms were quite successful in the dataset suitable for them. However, if features are obtained from images, SVM can be preferable for practical usage.

The rest of this study is as follows: Section II mentioned the datasets, ShuffleNet, SVM, and performance metrics, briefly. Following this section, classification results are presented and interpreted. In Section IV and V, this study is discussed and concluded.

II. Materials and Method

In this study, two datasets including rice images and features of these images were analyzed by using ShuffleNet and SVM. This is also comparison with CNNs and machine learning algorithm based on diverse performance metrics. In this section, the datasets, ShuffleNet, SVM and performance metrics are introduced, briefly.

A. *Datasets*

The datasets were acquired from https://www.muratkoklu.com/datasets/. The first dataset consists of 75,000 images of rice grains and was created by Cinar and Koklu [11] in 2019. This dataset comprises 15,000 images representing each of different species, namely Arborio, Basmati, Ipsala, Jasmine, and Karacadag. The images in this dataset are represented in the RGB (red, green, blue) color model [1]. Each image has a resolution of 250 pixels in width and 250 pixels in height. Within each image, the grains of rice are visible. Additionally, there exists a secondary dataset comprising 106 features in total, encompassing 12 morphological, 4 shape, and 90 color features extracted from each rice grain utilizing the images[1, 11, 13, 19]. Rice species are shown in Fig. 1

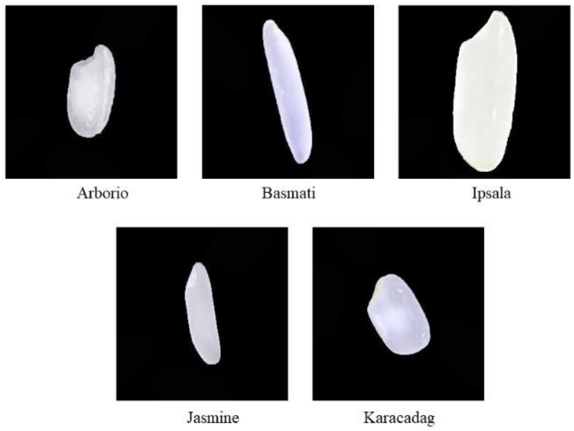

Fig. 1. Species of rice grain images.

B. *ShuffleNet*

ShuffleNet [17] is a CNN architecture renowned for its exceptional efficiency in the context of mobile devices [20]. In this study, shufflenetv1 which is a variant of the pre-trained ShuffleNet model was employed to optimize accuracy while minimizing computational expenses [20]. The model being proposed exhibits a greater depth compared to a standard CNN, consisting of 50 layers that are capable of being learned [20]. Specifically, this includes 1 layer for convolution and 48 layers for group convolution, which are subsequently followed by a fully connected (FC) layer. The architecture comprises a grand total of 172 layers, encompassing 1 layer for maximum pooling, 49 layers for batch normalization (BN), 33 layers for rectified linear unit (ReLU) activation, 4 layers for average pooling, 1 layer for softmax activation, and 1 layer for classification. The framework utilizes a total of four pooling layers in order to reduce the overall computational complexity. The input layer of ShuffleNet is the first layer, and it accepts 224×224 input images for processing. To generate the feature map, the initial convolution layer extracts the feature from the input image of size 224×224. This is achieved by applying 24 kernels (filters) of size 3×3 with a stride of 2×2.

The ShuffleNet unit, which has a shift (stride) of 2×2, is provided with the output feature map from the initial convolutional layer. The ShuffleNet unit is composed of three convolutional operations, specifically two 1×1 pointwise group convolutions and 3×3 depthwise convolutions. The initial pointwise group convolution is subsequently accompanied by BN, ReLU activation function, and channel shuffle operation. The utilization of this activation function is favored due to its computational efficiency and simplicity [20]. ShuffleNet units are shown in Fig.2 [17]. In Fig. 2, (a) indicates a bottleneck unit with depthwise convolution, (b) shows pointwise group convolution and channel shuffle, and (c) indicates a Shuffle unit with a stride of 2 [17].

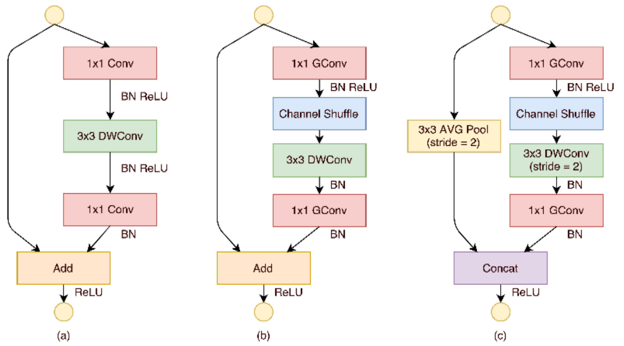

Fig.2. ShuffleNet Units [17].

In this study, the selection of ShuffleNet was based on its architectural no more complexity. This architecture was used to class rice images dataset. Its hyperparameters were selected as follows: adam optimization algorithm, 0.0001 learning rate, 8 minibatch sizes, 10 maximum epochs, ReLU activation function.

C. *Support Vector Machines (SVM)*

In numerous real-world instances, Support Vector Machines (SVM) have demonstrated their remarkable prowess, particularly in the realm of classification tasks. The fundamental design thinking of this system is to optimize the classification boundaries, while its primary objective is to maximize the hyperplane. In practical scenarios, a significant number of problems exhibit non-linear separability. Therefore, in the case of a non-linearly separable problem, it becomes necessary to transform it into a linearly separable problem. In order to decrease the time and space complexity of the SVM, numerous enhanced algorithms have been successfully implemented [21]. SVM algorithm was introduced by Cortes and Vapnik [18] in 1995 specifically for binary classification tasks. The algorithm has been further developed and expanded to handle multiclass and nonlinear datasets [22].

In this study, SVM was implemented to detect rice species from 106 features extracted from images. This study used hyperparameters for SVM: Quadratic kernel function because of non-linearity features, automatic kernel scale, 5 box constraint levels, and one-vs-one multiclass method.

D. *Performance Metrics*

This study aims to determine the optimal algorithm by evaluating its performance using various metrics. These metrics include accuracy (Acc), sensitivity (Sens), specificity (Spe), precision (Pre), and F1-Score. The equations for these metrics are provided below [22-24]:

$$Acc = \frac{(TP+TN)}{(TP+TN+FP+FN)} \quad (1)$$

$$Sens = \frac{TP}{(TP+FN)} \quad (2)$$

$$Spe = \frac{TN}{(TN+FP)} \quad (3)$$

$$Pr\,e = \frac{TP}{(TP+FP)} \quad (4)$$

$$F1 = \frac{(2\times TP)}{(2\times TP+FP+FN)} \quad (5)$$

where TP, FP, TN, and FN in Eq. 1-5 stand for True Positive, False Positive, True Negative, and False Negative, respectively.

III. RESULTS

Empirical results for this study were acquired using the Matlab (2022b) environment on a personal computer (pc). This study aimed to class rice species using ShuffleNet and SVM, respectively, from images and extracted 106 features. The total of images is 75,000 and each rice species is including 15,000 images. 5-fold cross validation was applied in both analyses. The data set is separated into 5 folds for cross validation. 1-1/5 datasets are trained, and up to 1/5 datasets are set aside for testing or validation on each fold. This procedure is repeated 5 times until all of the data set's components have been tested. Average results are shown in Table 1, Table 2, and Table 3.

Table 1. ShuffleNet classifier results for each rice species.

Class	Acc	Sens	Spe	Pre	F1
Arborio	0.9977	0.9977	0.9989	0.9956	0.9967
Basmati	0.9965	0.9965	0.9999	0.9997	0.9981
Ipsala	0.9997	0.9997	0.9999	0.9999	0.9998
Jasmine	0.9988	0.9988	0.9985	0.9943	0.9965
Karacadag	0.9966	0.9966	0.9999	0.9997	0.9982

Table 2. SVM classifier results for each rice species.

Class	Acc	Sens	Spe	Pre	F1
Arborio	0.9983	0.9983	0.9995	0.9979	0.9981
Basmati	0.9992	0.9992	1	0.9999	0.9995
Ipsala	0.9996	0.9996	1	1	0.9998
Jasmine	0.9989	0.9989	0.9995	0.9978	0.9984
Karacadag	0.9993	0.9993	0.9999	0.9997	0.9995

Table 3. Classifiers overall results.

Algorithm	Acc	Sens	Spe	Pre	F1
SVM	0.9991	0.9991	0.9998	0.9991	0.9991
ShuffleNet	0.9979	0.9979	0.9995	0.9979	0.9979

The findings from ShuffleNet revealed very good performance for each class, as seen in Table 1. Although there are many images, the achievement of such high performance is quite promising. The accuracy rates were 0.9977, 0.9965, 0.9997, 0.9988, and 0.9966, respectively, for the classes Arborio, Basmati, Ipsala, Jasmine, and Karacadag.

As was mentioned previously, 106 features extracted from images were classified using an SVM with a quadratic kernel function. All classes showed extremely good performance in this analysis. The accuracy ratings for the classes Arborio, Basmati, Ipsala, Jasmine, and Karacadag were 0.9983, 0.9992, 0.9996, 0.9989, and 0.9993, respectively.

Table 3 provides a comprehensive overview of the results obtained for all classes as a whole, including both the SVM and ShuffleNet algorithms. Upon careful examination of Table 3, it can be stated that the performances of the two classifiers exhibit a high degree of nearby. The SVM demonstrated superior performance compared to Shufflenet, attaining an accuracy of 0.9991, surpassing Shufflenet's accuracy of 0.9979 by a small margin. Fig.3 and Fig.4 exhibit confusion matrices of ShuffleNet and SVM.

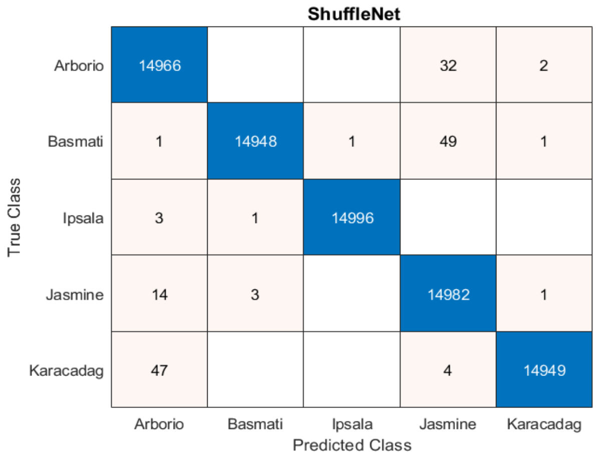

Fig.3. ShuffleNet Confusion matrix using 5-fold cross validation.

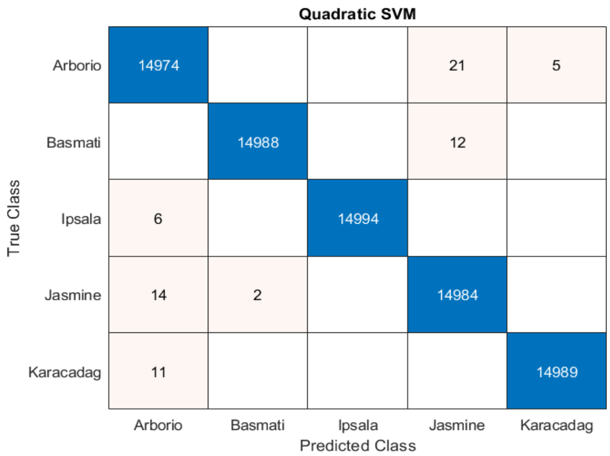

Fig.4. SVM Confusion matrix using 5-fold cross validation.

IV. DISCUSSION

This study presents an analysis from two distinct perspectives for the automated detection of rice grains. The initial perspective states that in the scenario where the researcher has solely images of these species, the utilization of CNNs for the purpose of classification is feasible. The alternative perspective states that if the researcher has the capability to extract specific features from images, or if these features have already been extracted, they can derive advantages from the utilization of machine learning algorithms. Tables 1, 2, and 3 exhibit that upon individual evaluation of the first and second scenarios, significant levels of performance can be attained from both standpoints. However, when considering these scenarios together, specifically when the user has both images and features, this study has demonstrated that the machine learning algorithm can yield more efficient outcomes within less time.

V. CONCLUSION

The automated identification of seed grains holds significant importance within the field of agriculture. One of the grains in issue, which may present challenges in visual discrimination, is rice. The objective of this study is to achieve the automatic detection of five distinct rice types by utilizing ShuffleNet and SVM. In this study, two different datasets were employed for the identical class of rice grains. The initial dataset comprised images, while the following dataset comprised the different features extracted from these images. A classification accuracy of 0.9971 was attained in the classification of rice images utilizing ShuffleNet, a mobile device-oriented algorithm. A classification accuracy of 0.9991 was achieved by employing Support Vector Machines (SVM) on a dataset consisting of 106 features extracted from rice images, including morphological, shape, and color main features. Based on the results obtained from both studies, it can be concluded that the Support Vector Machine (SVM) algorithm exhibits superior performance with accuracy rates approaching 100%. ShuffleNet employs an automatic process to extract features from images. It subsequently uses the entropy approach for classification. Despite the lower parameter count in ShuffleNet compared to various other pre-trained architectures, its utilization is a highly computational and time-consuming process. In this scenario, if the researcher or user encounters difficulties in extracting features from the images, it would be beneficial to employ architectures such as this and other similar ones. If the existence of extracted features from images is ensured, the utilization of machine learning algorithms becomes easier. Indeed, the process of manually extracting features from an image is a considerable challenge. Based on the findings of this study, it is clear that the selection of an algorithm should be contingent upon the type of the dataset.

In planned investigations, the objective is to enhance the existing work, gather a new dataset comprising both images and the related extracted features, and examine it using similar scenarios.

DATASET AVAILABLE

The dataset was acquired from the specified URL, https://www.muratkoklu.com/datasets/, in July (2023).

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