International Journal of Research in Engineering and Science (IJRES)
ISSN (Online): 2320-9364, ISSN (Print): 2320-9356
www.ijres.org Volume 11 Issue 5 ǁ May 2023 ǁ PP. 350-353

Rice Grain Classification Using Multi Class Support Vector Machine (SVM)

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Abstract
Main purpose of this process is to present an image processing-based solution to classify different varieties of rice grains. In this paper the authors proposed an approach based on the combination of feature extraction and classification. The dataset consist of different kinds of rice grain varieties. As a first step, pre-processing of the input image is performed to remove any unwanted information and enhance the image. Feature extraction is carried out in the second stage to extract needed information related to the process. Finally, classification is performed by comparing the sample image with the database image and the category of the rice was classified. Hence, to carry out the process SVM classifier was used to detect the type of the rice grain. Based on the results, the classifier performance will be evaluated based on the accuracy, sensitivity and specificity.
Keywords: *Pre-processing, Feature Extraction, SVM Classifier.*

Date of Submission: 01-05-2023 Date of acceptance: 10-05-2023

I. Introduction

Rice is an essential staple food for half of the global population. Rice grains of hundreds of varieties are cultivated and traded in considerable amounts worldwide. Most facilities share the same equipment for handling various products. Rice grains of different varieties can be mixed during the cultivation, harvesting, transporting, and processing, reducing the purity, quality, and value of the subsequent products. Despite the neglect, the Introduction of impurities can also be intentional, in a dishonest manner. Hence, the demand for the nondestructive authentication of grain varieties is emerging. However, this process is time-consuming and subjective. This paper proposes identifying the rice Grains of 30 varieties through image analysis and sparse-representation-based classification techniques. Various genetic marker-based methods have been applied for identifying rice grain varieties. Steele et al. (2008) selected insertion and deletion markers to distinguish Basmati rice grains from some other fragrant rice varieties. Carrillo et al.applied random amplified polymorphic DNA (RAPD) approach to fingerprint rice grains of 13 Italian accessions. Becerra et al.determined the genetic variability of certain Chilean and foreign commercial rice cultivars using simple sequence repeat (SSR) markers. Another study reported using SSR markers to distinguish 36 varieties of rice grains from different countries. Although these genetic marker-based methods are accurate, they are often too time-consuming or costly to be suitable for online applications. Image-based approaches, by contrast, are nondestructive and rapid. They combine image analysis and machine learning techniques to achieve automatic inspection and evaluation. Image-based approaches have been applied for discriminating varieties of cereal grains using either one of the morphological, color and textural traits, or a combination. Camelo-Méndez et al. characterized the rice grains of 9 Mexican cultivators by performing principle component analysis (PCA) and hierarchical analysis. Kong et al.classified the rice seeds of 4 accessions using a near-infrared hyper spectral imaging system and various machine learning algorithms. Mebatsion et al. distinguished between barley, oats and rye using a least-squares classification approach. Another study applied multilayer perception and neuro-fuzzy classification networks for identifying 5 Iranian rice varieties. Although the results of these studies have been promising, they have included a relatively limited number of varieties for discrimination.

II. Literature Review

In 2015, Becerra, V., Paredes, et al [3], proposed an approach to determine the genetic variability of Chilean and foreign commercial rice varieties, and determine, identify, and certify the genetic relationships among varieties, using simple sequence repeat (SSR) markers. A total of 16 commercial varieties, some of them closely related, were included sin the study, which were genetically analyzed using 54 microsatellites. The 54 microsatellite loci allowed the discrimination among the 16 varieties.

In 2013, Kong, W., et al [8], proposed an approach for extracting Spectral data from hyperspectral images. Along with Partial Least Squares Discriminant Analysis (PLS-DA), Soft Independent Modeling of Class Analogy (SIMCA), K-Nearest Neighbor Algorithm (KNN) and Support Vector Machine (SVM), a novel machine learning algorithm called Random Forest (RF) was applied in their study.

In 2013, Mebatsion, H., et al [9], made an Automatic classification of non-touching cereal grains in digital images using limited morphological and color features the color classification model was defined using color indices of individual kernels, which were calculated from the RGB color values of their images. The classification accuracies of different models were evaluated and compared. The combined model defined by morphological and color features achieved a classification accuracy of 98.5% for barley, 99.97% for CWRS, 99.93% for oat, and 100% for rye and CWAD.

In 2013, Williams, K., et al [10], made a Comparison of digital image analysis using elliptic Fourier descriptors and major dimensions to phenotype seed shape in hexaploid wheat (Triticum aestivum L.) The methods of shape quantification based on these models are useful for an accurate description allowing to compare between genotypes or along developmental phases as well as to establish the level of variation in different sets of seeds.

In 2015, Xie, C., et al [12], made an Automatic classification for field crop insects via multiple-task sparse representation and multiple-kernel learning to improve the classification accuracy, the authors developed an insect recognition system using advanced multiple-task sparse representation and multiple-kernel learning (MKL) techniques. As different features of insect images contribute differently to the classification of insect species, the multiple-task sparse representation technique can combine multiple features of insect species to enhance the recognition performance.

III. Methodology

3.1 Input Image:

The first stage of any vision system is the image acquisition stage. Image acquisition is the digitization and storage of an image. After the image has been obtained, various methods of processing can be applied to the image to perform many different vision tasks required today. First they Captured the Input Image from source file by using uigetfile and imread function. However, if the image has not been acquired satisfactorily then the intended tasks may not be achievable, even with the aid of some form of image enhancement.

3.2 Preprocessing:

Gray conversion:

In photography and computing, a grayscale or grayscale digital image is an image in which the value of each pixel is a single sample, that is, it carries only intensity information. Images of this sort, also known as black-and-white, are composed exclusively of shades of gray, varying from black at the weakest intensity to white at the strongest.

Image Resize:

In computer graphics and digital imaging, scaling refers to the resizing of a digital image. In video technology, the magnification of digital material is known as up scaling or resolution enhancement. When scaling a vector graphic image, the graphic primitives which make up the image can be scaled using geometric transformations, without any loss of image quality. When scaling a raster graphics image, a new image with a higher or lower number of pixels must be generated. In the case of decreasing the pixel number (scaling down) this usually results in a visible quality loss. From the standpoint of digital signal processing, the scaling of raster graphics is a two-dimensional example of sample rate conversion, the conversion of a discrete signal from a sampling rate (in this case the local sampling rate) to another.

3.3 Feature Extraction

Feature extraction a type of dimensionality reduction that efficiently represents interesting parts of an image as a compact feature vector. This approach is useful when image sizes are large and a reduced feature representation is required to quickly complete tasks such as image matching and retrieval.

3.4 Classification:

In machine learning, support-vector machines are supervised learning models with associated learning algorithms that analyze data for classification and regression analysis. Given a set of training examples, each marked as belonging to one of two categories, an SVM training algorithm builds a model that assigns new examples to one category or the other, making it a non-probabilistic binary linear classifier. SVM maps training examples to points in space so as to maximise the width of the gap between the two categories. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall.

3.5 Estimations

Sensitivity and specificity are statistical measures of the performance of a binary classification test, also known in statistics as classification function: Sensitivity (also called the true positive rate, the recall, or probability of detection[1] in some fields) measures the proportion of positives that are correctly identified as such .Specificity (also called the true negative rate) measures the proportion of negatives that are correctly identified as such (e.g., the percentage of healthy people who are correctly identified as not having the condition).

IV. Result & Discussion

Ninety testing images are tested for each type of rice grain. Table 2 displays some of the results plotted by the truth table from each type of rice grain. The performance of the rice grain classification is also demonstrated. From the calculation of accuracy, it is observed that the study produced a good performance with 90% of accuracy for the basmati, and a high percentage of accuracy of 93.33% for both ponni and brown rice. The overall mean percentage of accuracy is found to produce a very good percentage of accuracy which is 92.22%.

Table: 1E RICE GRAIN CLASSIFICATION

No	Rice Grain Type	Multi-Class SVM Classification	Accuracy Result
1	Basmati rice	Basmati rice	TRUE
2	Ponni rice	Ponni rice	TRUE
3	Brown rice	Brown rice	TRUE

Table 2: Accuracy table

Accuracy	Sensitivity	Specificity
99.5%	99.4995%	99.9995%

V. Conclusion

In this paper the authors distinguished the rice grains of 30 varieties through image analysis and techniques. Morphological and color variation among the rice grains of different varieties were also observed. This prompted the use of image-based approaches for differentiating the rice grains. In the proposed approach, the authors acquired the rice grain images through microscopy at a resolution of approximately 95 pixels per millimeter. The high resolution enabled observations of fine details of the rice grains was also analyzed. The morphological, textural, and color traits of the grains were quantified, and an SRC classifier was then developed to predict the varieties of the grains using the traits as the inputs. The classifier achieved an overall accuracy of 89.1%.

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