Almonds classification using supervised learning methods

Delila Halac, Emir Sokic, Emir Turajlic
Faculty of Electrical Engineering Sarajevo
University of Sarajevo
Bosnia and Herzegovina
{dhalac1, esokic, eturajlic}@etf.unsa.ba

***Abstract*—Digital image processing techniques are commonly employed for food classification in an industrial environment. In this paper, we propose the use of supervised learning methods, namely multi-class support vector machines and artificial neural networks to perform classification of different type of almonds. In the process of defining the feature vectors, the proposed method has relied on the principal component analysis to identify the most significant shape and color parameters. The comparative analysis of considered classification algorithms has shown that the higher levels of accuracy in almond classification are attained when support vector machine are used as the basis for classification, rather than artificial neural networks. Moreover, the experimental results have demonstrated that the proposed method exhibits significant levels of robustness and computational efficiency to facilitate the use in the real-time applications. In addition, for the purpose of this paper, a dataset of almond images containing various classes of almonds is formed and made freely available to be used by other researchers in this field.**

***Index Terms*—Feature selection, image segmentation, feature extraction, classification, Neural networks, SVM, PCA, computer vision, machine learning**

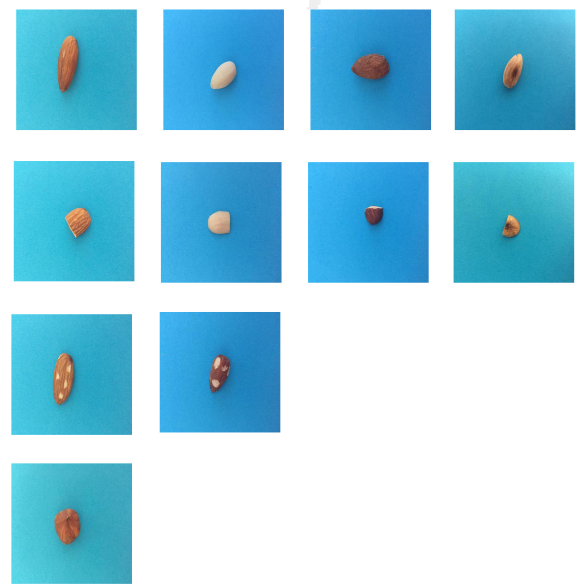

Fig. 1. Representative images of each type of almond - in first row are whole almonds, in second row are parted almonds, in third row are presented damaged almonds and in the last row is unknown class (hazelnuts).

I. Introduction

Despite the fact that the food industry includes a diverse set of businesses such as agriculture, food processing, marketing and sale, and that its value and importance in the increasingly globalized world is unsurpassed, it is surprising that the process of food quality evaluation is still mostly done manually by trained people. This approach is costly, inherently subjective and prone to error. Thus, there exists demand to increase the levels of objectivity, consistency, and efficiency in food quality evaluation. The digital image processing techniques and pattern recognition algorithms can be an important part of this endeavour.

Although visual food recognition may be considered a complex problem in computer vision and pattern recognition, applications of machine vision and image processing in the food industry have grown over years and are widely used for automatic inspection of food [1]. These algorithms enable relatively fast, easy and efficient way to assess food characteristics (such as type, weight, quality, etc.), detect possible defects, or to estimate some of the properties (such as size, shape, texture, color, etc.). Due to the diversity of the tasks which need to be solved, different approaches are possible, such as SVM, neural networks, K-NN, naive Bayes etc. [2], [3].

In addition to classification itself, the process of image processing-based food analysis consists of several steps. These steps include acquiring a high-quality image and extracting the most relevant features. The most recognizable features are color, shape and texture [4]. Apparently, color-based features are the first and most intuitive choice for food processing. For example, using simple color analysis one can tell if the food is fresh or rotten, or if the food is raw or roasted. Different types of color models may be used [5]. Color is used for many image-based food classification problems [5], [6]. Alongside color, shape is often a significant feature that can provide information. Based on shape one can tell if the food is damaged, irregular or not. Therefore, shape features are widely used as seen in [3], [7]. Other important and recognizable features which may provide important information about food samples are length, width, aspect ratio, area, perimeter, etc. [8]. In addition to these two features, texture is also important for image analysis. Texture a is very robust feature and it is widely used in image processing. Texture-based approaches are classified into two groups: spatial texture feature extraction and spectral texture feature extraction [4]. Although texture can be important, experiments have shown that in the context of the classification problem studied in this paper, namely almond classification, texture-based features do not improve the classification accuracy. Therefore, textural features are omitted, and only shape and color were used as features.

Image classification is the last step that follows image acquisition and feature extraction. By using extracted features on training images, classifiers may be trained and later used to classify unknown food (for example is the food fresh, rotten, damaged, etc.). In papers [1], [9]–[12] classifiers are used for different kinds of food such as rice, chestnuts, bananas etc. Different classification algorithms are used in combination with different features for food classification, but SVM and neural networks are most common choices. These algorithms exhibit very good performance and accuracy for food classification. Beside these two approaches, K-NN nearest neighbour is often used to support other methods (such as Discriminant analysis) and may provide excellent results by using separate color and morphological features [10].

In this paper, multi-class SVM and neural networks are considered in the design of the image-based classification system for differentiating various almond classes. Hybrid multi-level classifiers are proposed. Experimental results show that the developed classifiers have more than 90% classification accuracy and may operate in real-time. In addition, an Almond image database set was created (110 images divided in 11 classes), which is freely available for download.

The paper is organised as follows. A brief description of the Almond dataset is given in Section II. Image preprocessing and feature extraction steps are presented in Section III. Classification algorithms are described in Section IV, and experimental results are shown in Section V. Conclusion and guidelines for future work are presented in the last section.

II. Almonds database set

In order to be able to distinguish among different types of almonds, training sets/images for supervised learning methods needed to be generated. Therefore, various species of almonds are chosen, captured by a digital camera, sorted and labelled so that they may be easily identified. The base consists of a total 110 images sorted in five classes (raw, blanched, roasted, roasted blanched, unknown/hazelnuts) with three states (whole, parted and damaged). All images are captured under equal conditions (same digital camera, same position, same background).

The dataset structure is represented by Table I, while the representative images from the dataset are shown in Figure 1. The entire dataset may be downloaded from the following URL: people.etf.unsa.ba/˜esokic/AlmondDataset/AlmondDataset.zip.

TABLE I
Dataset structure - classes and states

Class / State	Whole	Parted	Damaged
Class 1 (raw almonds)	10	10	10
Class 2 (blanched almonds)	10	10	/
Class 3 (roasted almonds)	10	10	10
Class 4 (roasted blanched almonds)	10	10	/
Class 5 (unknown/hazelnuts)	10	/	/

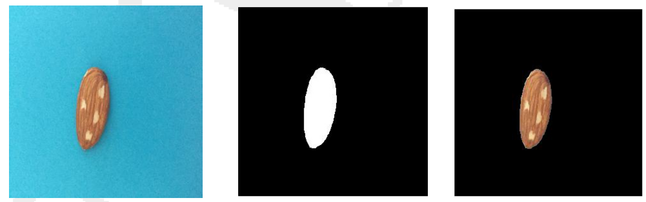

Fig. 2. Original image, segmented image and segmented almond, respectively

III. Image preprocessing and feature extraction

Prior to perform feature extraction, image segmentation needs to be conducted. Different methods of image segmentation may be applied, such as Thresholding methods, Region-based methods [3], Edge-based methods [13], Fuzzy Clustering, and one of the most popular methods being K-means clustering algorithm [14]. K-means clustering algorithm is an unsupervised algorithm that may be used to segment the area of interest from the background. The algorithm consists of two separate phases. In the first phase it computes k centroids randomly, where k is given in advance. In the second phase, it joins each point to the cluster which has the smallest distance from the centroid. The distance between points and centroid may be computed using different methods and most popular is Euclidean distance [14]. Since every image has one almond and a relatively homogeneous background, there are two clusters to classify. We used the faster implementation of K-means (using preallocation and parallel operations) to optimize algorithm time. The $L^*a^*b^*$ space color is used for segmentation, where a and b components are used to differentiate almond from the background. As the result of clustering, there are two images; one of them is the segmented almond and the other one is background. Figure 2 illustrate the process of segmentation using example of raw almond (first class).

A. Shape features

The shape is one of the most common object feature for food quality evaluation. Moreover, it is one of the most important attributes which the consumer evaluates when buying. Shape is a very typical parameter for almonds quality assessment due to the fact that they can be easily broken and damaged, and these defects are reflected through the change of their shape.

It is important to note that the result of the initial segmentation is a binary image. This image may contain numerous imperfections. In particular, the binary regions produced by simple thresholding are distorted by noise and texture. Morphological image processing aids in removing these imperfections by accounting for the form and structure of the image. Therefore, all connected components (objects) that have fewer than P pixels are removed from the binary image. After this process, the following shape features can be extracted:

- Eccentricity - Since almonds have shape similar to ellipse it is natural to extract their eccentricity feature. Eccentricity is the measure of the aspect ratio. It is the ratio of the length of the major axis to the length of the minor axis. It can be calculated by principal axes method or minimum bounding rectangle method.
- Circularity - ratio represents how a shape is similar to a circle and this feature can be very important for classification since the almonds have the elongated shape of a circle. Circularity ratio is the ratio of the area of a shape to the area of a circle having the same perimeter.

$$C = \frac{Area}{(Perimeter)^2} \tag{1}$$

  Circularity can help to distinguish almonds from unknown/hazelnuts class since hazelnuts have a shape similar to the circle. Circularity is computed using equation 1.

- Major Axis Length - the longest diameter of the ellipse. It is given by equation 2,

$$M = a + b, \tag{2}$$

  where a and b are the distances from each focus to any point on the ellipse.

- Radius is computed using equation 3.

$$Radius = \sqrt{\frac{Area}{\pi}} \tag{3}$$

- Roundness - a measure of how much a shape departs from being a perfect circle (equation 4).

$$Roundness = \frac{4\pi Area}{Perimeter^2} \tag{4}$$

  Roundness closer to 1 indicates that the object is approximately round.

- Other important features for shape inspection include: area, perimeter, width, height and the ratio of width and height [3], [13], that are computed for each image sample.

B. Color features

In image classification and image retrieval, color is the most important feature. It is also one of the most efficient and accurate feature, since it is independent and insensitive to changes in image rotation, translation or scaling. Color-based features have proven successful for objective measurement of many types of food products. This is also the case with almonds, since they possess unique color characteristics for every class. The most common method for extraction of color features is the color histogram [3]. It represents the distribution of the color in the image and can be obtained by examining every pixel within the object boundaries. This method does not exhibit satisfactory performance for most of the images in our dataset. In contrast, we adopted a simpler yet more effective approach. The mean values of each RGB component are computed on the segmented almond image, and used as color features. Other color spaces are also analysed (such as YCbCr, CMYK, HSV and $L^*a^*b^*$), however RGB color space provided the best results and therefore was used in our proposed classification method.

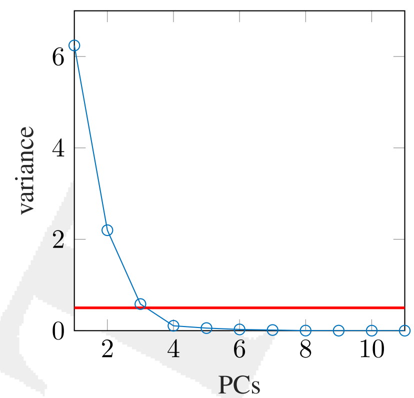

Fig. 3. Eigenvalue for each feature

C. Feature selection

Dimensionality reduction of a feature set is a common preprocessing step used for pattern recognition and classification applications. The most popular method for dimension reduction is Principal Component Analysis (PCA) and it can be shown to be optimal by using different optimality criteria [15]. PCA is used abundantly in all forms of analysis - from neuroscience to computer graphics. In this paper, PCA is used for determining which are the optimal features to use in the classifier to achieve best results. Prior to the usage of the PCA, all extracted features are normalized using *z-score* normalization. Thus, all features are treated equally important. All eleven types of almonds have been analyzed and most important features for differing one type from another have been identified.

For example, in order to distinguish whole blanched almonds from whole roasted almonds according to PCA, it is best to use color features. This is also the most intuitive solution, since bleached almonds are white and roasted are brown.

An additional remark is related to the number of components needed to be preserved. According to the Figure 3, it is evident that three principal components (PCs) were enough to explain the data and the remaining components were only less informative. As it can be seen 97.78% of the variance could be captured by the first three PCs and the rest of components can be ignored.

In Figure 4 the coordinates of the original data are presented in the new coordinate system defined by the principal components. It may be seen that blanched raw almonds (represented by red stars) are grouped together and roasted whole almonds

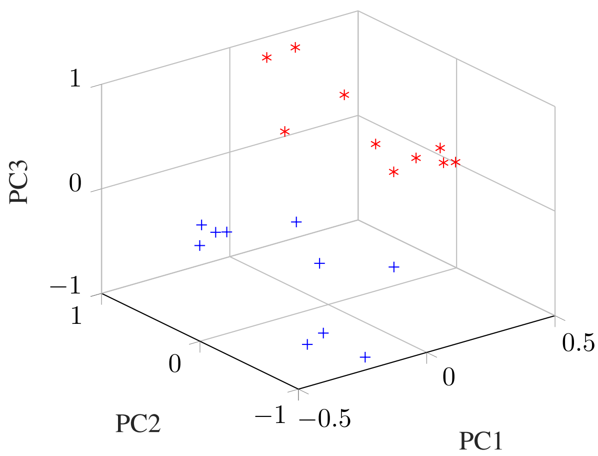

Fig. 4. Selected features of Blanched whole (red stars) and Roasted whole almonds (blue crosses)

(blue crosses) are grouped in the second group. This indicates that using first three PCs these two types of almond can be differentiated one from another.

Similar approach is used for choosing important features for differing different types of almonds.

IV. Classification algorithms

In order to develop a suitable image-based almond classifier this paper will focus on the following supervised machine learning methods: support vector machines (SVM) and neural networks (NN).

A. Support vector machines (SVM)

SVM represents one of the most popular and widely used classification algorithms. SVM may be used in different areas, from medicine (EEG and ECG classification) or web-mining, to food industry [4]. The unique characteristic of SVM is that it does not try to minimize the error of classification; instead the algorithm is trying to find the maximum margin between classes, and separate classes by hyperplane (therefore every data of training dataset should be classified correctly). This feature is also the downside of this method. It can require significant computational time for training and can be much more complex compared with other methods. Moreover, the dimensionality of margin can be higher than dimensionality of the dataset itself. To reduce this problem soft-margin SVMs are introduced [16]. Other very important issue is that algorithm is used only for binary problems (for problems which have only two classes). For multi-class problems (as the one presented in this work), other approaches must be used. These approaches use more than one SVM classifier [17], so this can increase computational time.

1) SVM One vs All: The first approach used in this is paper is the common *One vs All* strategy [17]. For every class an individual SVM was created, that can classify if the almond is in that class or not. At the end eleven (N=11) SVM classifiers were created. When an unknown sample has to be classified, its features are used as input in every classifier. The main problem of this approach is that the new sample may be classified in more than one class. This makes the algorithm much more unreliable, especially because training process is very unbalanced (ratio between classes is about 1:11 for every classifier). However, the number of classifiers is smaller and approach is faster than the other SVM based algorithms, and it can provide satisfying results if the features are distinguishable enough.

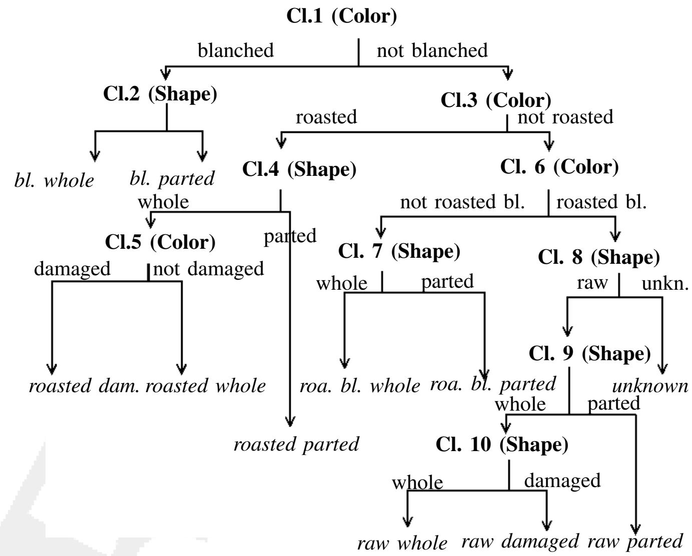

Fig. 5. Proposed scheme for SVM and NN based classification of various almond classes

2) SVM One vs One: The second approach that was used is *One vs One* strategy. For every combination of two classes a SVM-based classifier was created. This resulted in fifty-five $\left(\frac{N(N-1)}{2}\right)$ SVM classifiers. Process of determining the class of unknown almond is to classify almond with every classifier. Every time when an almond is classified in one of the classes, the counter for that class will increase by one. At the end, almond is classified as class that has the highest counter. This approach is much more complex, mostly because of the number of SVM classifiers, but it is much more balanced at the same time.

3) Hybrid SVM classifiers: This approach combines two aforementioned strategies and it is one of the contributions of this paper. The main idea of this strategy is similar to the decision-based tree, constructed on a priori knowledge of the almond classes. It is based on several binary SVM classifiers constructed by analysing the features of specific almond classes. The main idea is illustrated in Figure 5.

This approach requires ten SVM classifiers, less than the previous two approaches, while the training dataset is much more balanced compared with other strategies. To maximize the accuracy of the classifiers, different kernel functions are used for every classifier, and most relevant features were used. Kernel functions used for each SVM classifier, alongside with the used features are presented in Table II.

TABLE II
KERNEL FUNCTIONS AND FEATURES USED FOR HYBRID SVM-BASED CLASSIFICATION

Classifier / State	Kernel function	Features
blanched	polynomial (n=4)	R and G component (color)
blanched-whole	polynomial (n=3)	area and metric (shape)
roasted	polynomial (n=4)	G and B component (color)
roasted-parted	polynomial (n=4)	area and metric (shape)
roasted-whole	Gaussian	G and B component (color)
blanched-roasted	polynomial (n=5)	mean R and mean B component (color)
blanched-roasted-whole	Gaussian	area, metric and eccentricity (shape)
raw	polynomial ($n = 5$)	area and metric (shape)
raw-parted	Gaussian	area and metric (shape)
raw-whole	Gaussiann	R and B component (color)

TABLE III
PARAMETERS OF NEURAL NETWORKS

Class / State	Training function	Number of neurons
NN-blanched	RP (resilient propagation)	100
NN-blanched-whole	RP	100
NN-roasted	RP	100
NN-roasted-parted	RP	100
NN-roasted-whole	CGF	1500
NN-blanched-roasted	CGF	1000
NN-blanched-roasted-whole	RP	1000
SVM-raw	CGF	1000
SVM-raw-parted	RP	100
SVM-raw-whole	CGF	100

TABLE IV
RESULTS OF CLASSIFIERS WITH TRAIN AND TEST SAMPLES IN 50(%):50(%) RATIO

Classification method	Result (%)	Corr. img.	Avg. [ms]/img.
SVM Hybrid	92.7273	51	5.5
SVM One vs One	87.2727	48	22.8
Hybrid NN	85.4545	47	177.1
NN with N classes	72.7273	40	10.9
NN with M cl. P states	70.9091	39	10.9
SVM One vs All	43.6364	24	4.2

B. Neural networks

Neural networks (NN) are one of the most popular techniques used for classification, widely used in different areas such as speech recognition, medical diagnosis, statistics [18].

The process of training neural networks consists of minimizing output error (until the set goal or maximum number of iterations is reached). This is the main difference between neural networks and SVM classifiers. A significant advantage of neural networks is that they are directly applicable to solve multi-class problems, unlike SVM classifiers. In this work, two-layer neural networks were used. Most neural networks had 100 neurons per layer. For the first layer $tansig$ activation function was used and for the other layer $softmax$ activation function was used. Performance of the neural networks was measured using the sum of the squared error (sse) in every case. In most cases, neural networks were trained using resilient backpropagation algorithm.

1) Neural network with N classes: This approach focuses on direct determination of the almond class using neural network. Features of training dataset are used as inputs in neural network, and the target values are one of the classes. Therefore, every unknown almond will be directly classified. The biggest advantage of this algorithm is its simplicity and reduced complexity (as it uses only one neural network). However, using all the features will make the process of training much harder and classification is not reliable enough, especially if the features are not easy to differ.

2) Neural network with N classes and M states: For this approach, every almond is described with its class and its state. There are five classes (raw, blanched, roasted, blanched-roasted and unknown) and three states (whole, parted and damaged). Two neural networks are used; one for determining the class and the other for determining the state. This algorithm requires one extra neural network, but the process of training is less complex, as features are easier to distinguish. In this case, $tansig$ function was used as activation function for the second layer.

3) Hybrid neural network structure: The proposed approach is similar to the hybrid approach used with SVM classifiers, with the only difference being usage of neural networks as classifiers. The main disadvantage of this approach is the number of neural networks (algorithm requires ten neural networks) which need to be trained. However, the training process for each neural network is much shorter, and provides much more reliable separation of different classes because only the adequate features are used for each neural networks. Parameters of the used neural networks are given in Table III. It can be observed that for least distinguishable features more neurons were used in order to maximize performance. Moreover, in some cases different training function was used to increase accuracy.

V. EXPERIMENTAL RESULTS AND DISCUSSION

All eleven types of almonds were tested using classifier systems described in Section IV. Two image sets of 55 images are chosen randomly (5 almonds in every class). First group is used for training and second for testing. The achieved results of every classifier are shown in Table IV. As it can be seen from Table IV best results are achieved with the proposed SVM hybrid classifier, while SVM with *One vs One* strategy and hybrid neural networks just slightly underperformed. This was expected, since the hybrid SVM and hybrid neural networks were implemented with the goal to maximize accuracy. Another advantage of these approaches is that they can be trained using only relevant features obtained from PCA, unlike other approaches where relevant features in the most cases cannot be determined. As a consequence, other approaches exhibit lower performance. In addition to its best performance, Hybrid SVM needs only $5.5ms$ in average per image for classification, which is significantly less than SVM One vs One which uses 55 classifiers. In contrast, SVM One vs All require significantly less computation time but

TABLE V
RESULTS OF CLASSIFIERS WITH TRAIN AND TEST SAMPLES IN 80(%):20(%) RATIO

Classification method	Result (%)	Corr. img.	Avg. [ms]/img.
SVM Hybrid	90.9091	20	5.5
Hybrid NN	86.3636	19	177.1
NN with N classes	81.8182	18	10.9
NN - M classes, P states	81.8182	18	10.9
SVM One vs One	81.8182	18	22.8
SVM One vs All	50	11	4.2

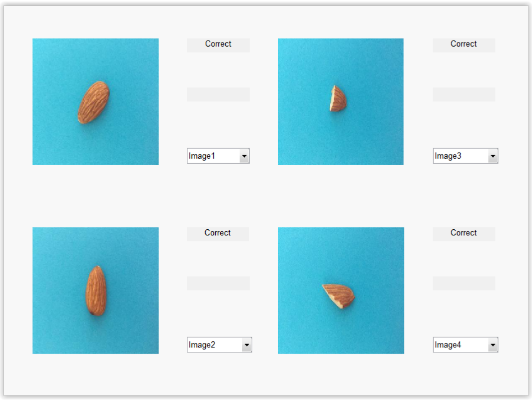

Fig. 6. MATLAB GUI for almonds classification using hybrid SVM and neural networks

their performance is unsatisfactory. Hybrid neural network needs increased amount of time for classification due to the fact that this approach use the largest number of neural networks. Despite the increased computation time hybrid NN outperforms other NN-based approaches.

When the ratio of training and testing images have changed (80% to 20%) similar results were obtained (Table V), however the accuracy of the classifiers has increased. The most precise algorithm again was the hybrid SVM classifier. However, the biggest difference is that accuracy of the neural networks is significantly greater than in the previous case, due to a larger training set. For both cases the accuracy of hybrid classifiers are similar, therefore it can be concluded that they are not much dependent on the ratio between training and test set. After classification, every test image is shown in a suitable graphic user interface, as in Figure 6. Every image is presented with its classified class and classification result.

VI. CONCLUSION AND GUIDELINES FOR FUTURE WORK

In this paper, a novel approach for classification of various almond classes is proposed. The proposed method entails a structure that is similar to the decision-based tree. It is designed to exploit the a priori knowledge of the almond classes, further improved by optimizing the feature set via the principal component analysis. Under the proposed framework, the paper considers the usage of two classifiers, namely support vector machines and artificial neural networks. The experimental results demonstrate that the proposed framework outperforms the traditional approaches for classification of almonds, in terms of classification accuracy levels. However, the increased levels of computational complexity, and the somewhat increased computational time is identified as the main drawback of the proposed framework.

This paper has demonstrated that SVM offer superior classification performance over the NN under the proposed framework. Thus, additional classification algorithms need to be tested as part of the future work. Moreover, the performance of the proposed classifiers should be studied in more detail in order to fine-tune the parameters and optimize the classification performance. The other direction is to investigate a broader set of features that could be used in the classification process.

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