Efficient Shape Classification using Zernike Moments and Geometrical Features on MPEG-7 Dataset

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***Abstract*—There is an urgent need and demand for manipulating images to extract useful information from them. In every field, whether it is biotechnology, botany, medical, robotics or machinery, the demand for extracting useful aspects of a specific targeted image is growing. Effective systems and applications have been introduced for this purpose: CBIR and MPEG-7 are most common applications. Shape extraction and recognition is used in image retrieval and matching. Complex objects can be identified and classified by extracting their shape. This paper proposes an efficient algorithm for shape classification. Analyses are made on MPEG-7 dataset using 1400 images belonging to 70 classes. Zernike Moments descriptor and geometrical features are used for classification purposes. Cross validation and percentage split are used to evaluate the proposed scheme. Experimental results proved the efficiency of the proposed approach with an accuracy of 92.45 percent on the challenging dataset.**

***Index Terms*—classification algorithms, feature extraction, image classification, shape.**

I. INTRODUCTION

There is a remarkable surge of multimedia information, for which the need of multimedia content description is becoming necessary by automatic searching. CBIR [1] and MPEG-7 [2] are two multimedia applications which have emanated to address the issue. Shape being a fundamental property of an object, its description plays a key role in CBIR and MPEG-7. Other than color and texture, shape feature is more efficient for extracting important content from an image [3]. Searching for targeted information from a huge collection of images and then its retrieval has given rise to CBIR systems [4]. Some of the important features for CBIR are shape context [5], spectral features, contours curves, shape signature [6] and shape histogram. Not only researchers, professionals and educators, but also general users share the goal to find similar images from large collections or from remotely distributed databases. For shape classification, Zernike Moments are considered to be the best and most powerful shape descriptor. It is a region-based method according to [7]. It is insensitive to noise (holes) and somewhat sensitive to occlusion and deformation [8]. From the previous researches it is studied that Zernike Moments are extracted from spectral domain [9].

Other than time-consuming techniques, which discuss the classification problem from a retrieval point of view, many classifiers have been used which give better results such as kernel extreme learning machine (k-ELM) classifier along with the RBF kernel [10], K-NN rule [11] and Support Vector Machine [12]. Most present techniques are good enough and provide satisfactory accuracy levels.

Earlier, many researchers have proposed different frameworks for shape classification. In work of [12], more discriminative representation of a shape is obtained by a combination of local and global features, where local corresponds to shape context descriptor [5] and global corresponds to blurred shape model [13] descriptor. In order to achieve better accuracy for MPEG-7 dataset, k-NN classifier is then used for classification. Shape contexts are clustered to describe shapes as bag of shape context that acts as vocabulary [14] and clustering leads to codebook. Aligned training images are fed to blurred shape model for k-NN classification. Latest work in [11] proposes 2D shape classification using bioinformatics approach. Classification is performed on MPEG-7 by contouring 2D shape encoded through the chain code process, and then biological sequences conversion is done using three encoding strategies. A Biological Sequence alignment tool is then used with k-NN classifier.

MPEG-7 along with 99 shapes dataset [15] and articulated test shapes [16] have been used by [11]. The method proposed is based on combination of three descriptors i.e. simplified shape signature, region skeleton descriptor and region area descriptor, which deals with the collection of landmarks from contours using k-ELM classifier.

Blurred shape model for binary and grey shape images is used by [13] for MPEG-7 along with clefs and accidental dataset, real symbols dataset and 17 class dataset of grey level symbols. The research gives better accuracy on the dataset using Error Correcting Output Code (ECOC) along Adaboost as the base classifier.

Co-transduction algorithm for shape retrieval is introduced by [17] which involves combination of two distance metrics along with multiclass classifier.

II. MATERIALS AND METHODS

The proposed approach is evaluated using MPEG-7 Core Experiment (CE)-Shape-1 Part B dataset [18]. MPEG-7 was standardized in ISO/IEC 15938 multimedia content description interface. The dataset consists of 1400 shape images belonging to 70 classes and each class contains 20 images [10] as shown in Table I.

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TABLE I. DETAILED DESCRIPTION OF THE DATASET USED IN THE PROPOSED RESEARCH WORK

SN	Attributes	Values
1.	Name	MPEG-7 CE-Shape-1 Part B
2.	No. of images	1400
3.	No. of classes	70
4.	Images per class	20
5.	Resolution	Variable
6.	Format	JPEG
7.	Type	Binary images
8.	File extension	.jpg

The shapes are defined by a binary mask outlining the objects. A sample set images is shown in Fig. 1. This public dataset has been used widely for shape matching.

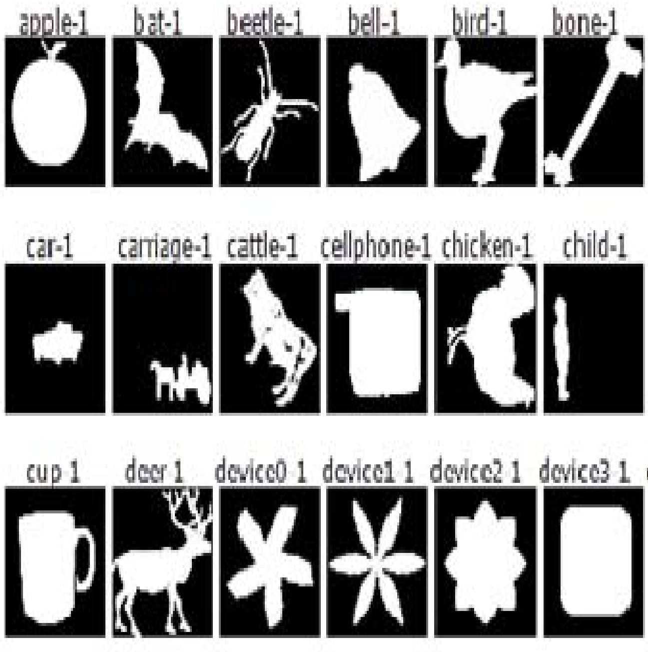


Figure 1. Sample images from MPEG-7 dataset

The proposed approach consists of three stages as shown in Fig. 2. First stage deals with the preprocessing on dataset images, second stage includes shape feature extraction and third and last stage is responsible for classification of the images.

During preprocessing, the input image is resized so that all images have same resolution (256x256). Two types of features are extracted form preprocessed images i.e. Zernike Moments and geometrical features. Classification accuracy is computed by using k-NN, K*, Bagging, RandomSubSpace and GaussianProcesses.

First types of features extracted from resized images are Zernike Moments [19] because they are invariant to rotation, scaling and translation but not invariant to affine transformations. Zernike Moments are selected because of their orthogonality property [20]. The matching complexity increases as the order of Zernike Moments increases [21]. Zernike Moments are derived from Zernike polynomials using Equation (1) and Equation (2).

$$V_{nm}(x,y)=V_{nm}(\rho\cos\theta,\rho\sin\theta)=R_{nm}(\rho)\exp(jm\theta) \quad (1)$$

where $R_{nm}(\rho)$ is the orthogonal radial polynomial.

$$R_{nm}(\rho)=\sum_{s=0}^{(n-|m|)/2}(-1)^s\frac{(n-s)!}{s!(\frac{n+|m|}{2}-s)!(\frac{n-|m|}{2}-s)!}\rho^{n-2s} \quad (2)$$

where n-|m| = even, |m|≤ n.

A complete set of complex valued function, orthogonal over the unit disk, i.e., $x^2 + y^2 \leq 1$ yield Zernike Moments. The order n complex Zernike Moments with repetition m are stated in Equation (3).

$$Z_{nm}=\frac{n+1}{\pi}\sum_x\sum_y f(x,y)V_{nm}^*(x,y), x^2+y^2\leq 1 \quad (3)$$

One of the drawbacks of moment descriptors is that it is difficult to relate high order moments with the shape. Zernike Moments are the most appropriate amongst many moment shape descriptors for the proposed shape description. Zernike Moments based shape description proves to give very encouraging results [22, 23].

The geometric features are used to categorize shapes with large dissimilarities among the images. In most of the previous works, they are usually combined with other shape descriptors in order to eliminate false hits, as they cannot be used as standalone shape descriptors [24]. In this research work, shape parameters used for extraction of geometric features are aspect ratio, convexity, rectangularity, circularity, circularity ratio, solidity and irregularity.

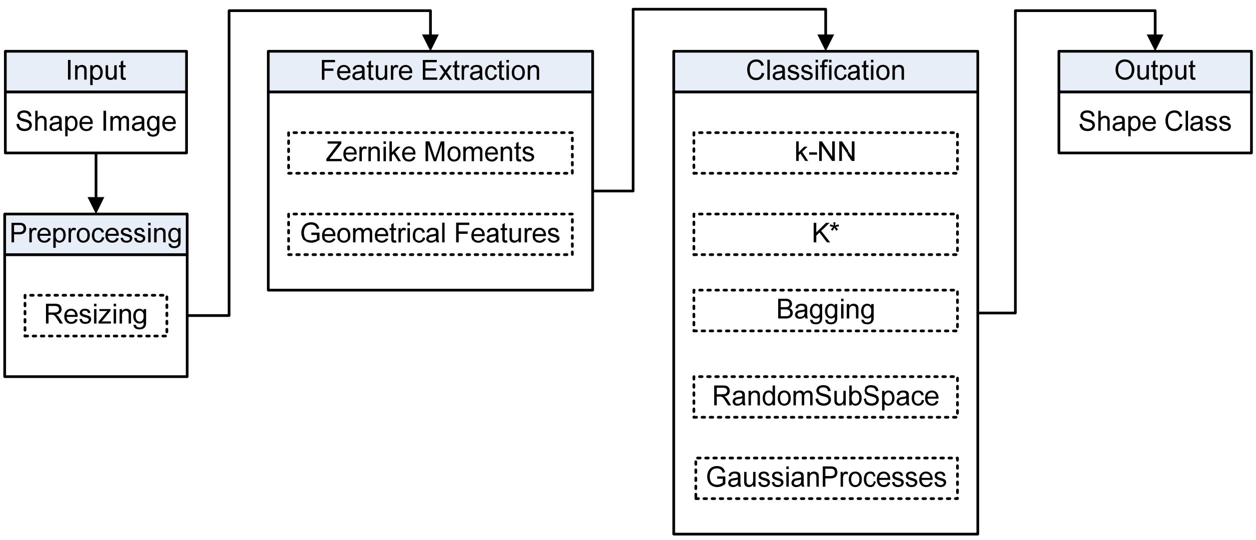


Figure 2. Flow chart of proposed approach

The closely fitted rectangular box that encloses a shape is known as bounding box. Height and width are significant parameters to characterize a shape. These parameters are made translation, rotation and resolution invariant by defining the bounding box with respect to principal axes of the shape. Principal axes are line segments intersecting each other orthogonally at the centroid of the shape. A principal component analysis (PCA) of the shape yields the directions of major and minor axis. Height is measured along the major axis and width along the minor axis. Aspect ratio is given as the ratio of length of major axes and length of minor axes of the shape in images. It is calculated by principal axis method using Equation (4).

$$AspectRatio = \frac{m_1}{m_2} \tag{4}$$

where m_1 is minor axes length and m_2 is major axes length of the shape as shown in the Fig. 3.

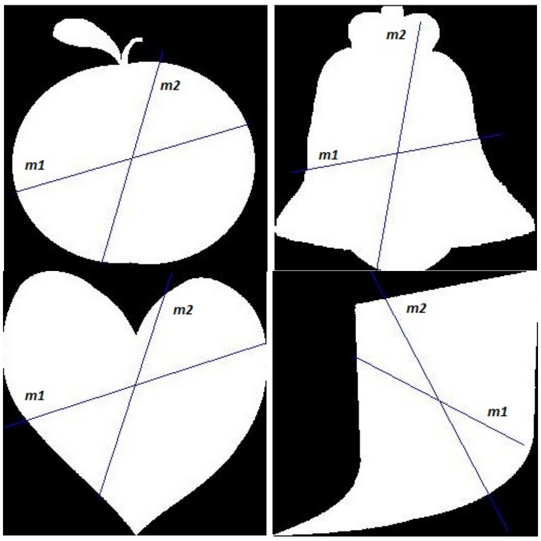


Figure 3. Illustration of aspect ratio for different shapes

A convex hull, i.e. minimal convex covering area of an object, is calculated for all shape images as shown in Fig. 4.

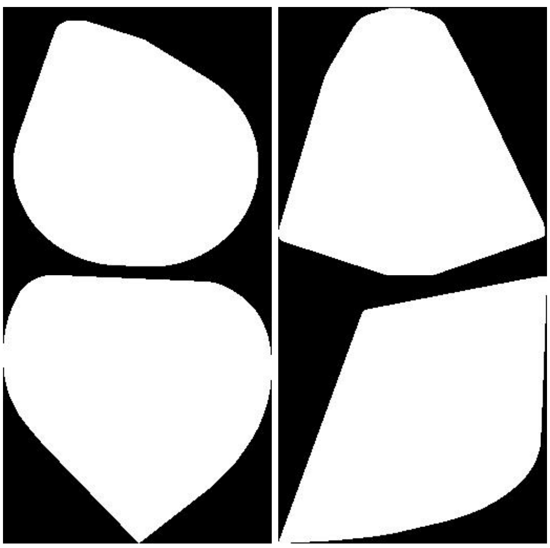


Figure 4. Illustration of convexity for different shape images

Shape covered by the minimal convex polygon yields the convex hull of the shape. Convex hull is constructed by traversing the shape contour in such a manner as to minimize the turn angle in each step. Convexity is thought of as elastic ribbon stretching across the boundaries of the object and is defined as the ratio of perimeter of the convex hull of the shape $\omega_{convexhull}$ (in pixels) and perimeter of the original shape ω (in pixels) using Equation (5).

$$Convexity = \frac{\omega_{convexhull}}{\omega} \tag{5}$$

Rectangularity, showing how much rectangular is a shape or how much it is in minimum bounding rectangle is calculated using Equation (6).

$$Rectangularity = \frac{A_s}{A_r} \tag{6}$$

where A_s is the shape area and A_r is the minimum bounding rectangle area.

Circularity, presenting how the shape is similar to circle, is calculated using Equation (7).

$$Circularity = \frac{A_s}{A_c} \tag{7}$$

where A_s is the shape area and A_c the area of the circle having the same perimeter as the shape.

Circularity ratio defined as the area of shape and shape's perimeter is calculated using Equation (8).

$$C_1 = \frac{A_s}{\vartheta^2} \tag{8}$$

Solidity defined as up to which extent the shape is convex or concave is calculated using Equation (9).

$$Solidity = \frac{A_s}{H} \tag{9}$$

where A_s is the area of the shape region and H is the area of the convex hull of the shape.

Irregularity, another feature of geometry, deals with the irregularity of the shape and is defined in Equation (10).

$$Irregularity = \frac{\max(\sqrt{(x_i - \bar{x})^2 + (y_i - \bar{y})^2})}{\min(\sqrt{(x_i - \bar{x})^2 + (y_i - \bar{y})^2})} \tag{10}$$

where $(\bar{x}, \bar{y})$ is the centroid of the shape, and (x_i, y_i) is the coordinate of a pixel in the shape boundary. Equation (10) provides ratio of radius of the maximum and minimum circle enclosing the region within the shape.

In addition to above defined major features, some minor features like narrow factor, perimeter ratio of diameter and form factor are also calculated [25]. Narrow factor is given as the diameter d and Minor axes length m_2 ratio: (d/m_2), whereas form factor is defined as the ratio between area A and perimeter p of the shape ($4\pi A/p^2$).

Five classifiers are used for classification in this research work including Lazy.KStar [26] also known as k*, Lazy.IBk [27] also known as k-NN, Meta.Bagging [28] also known as Bootstrap Aggregation, Meta.RandomSubSpace [29] also called feature bagging or attribute bagging and Functions.GaussianProcesses [30] also called kriging, using a publicly available free tool Weka [31].

k* is an instance based classifier. The class of a test instance is decided based on the class of those training instances similar to the test instance. Instance similarity is determined by some similarity function. k* is different from other instance based learners as it uses an entropy based distance function. K-NN classifier used with some suitable value of k is based on cross-validation and distance weighting. Bagging, a machine learning ensemble meta algorithm, is used to reduce variance and avoid overfitting. RandomSubSpace, also a machine learning ensemble meta algorithm is used to minimize the correlation between base classifiers by training them on random subsets of attributes. GaussianProcesses, belonging to supervised learning algorithms, is used to solve classification problem with the benefit that prediction interpolates the observations.

III. Results and Discussion

Two types of experiments were conducted. Experiment-I was performed using cross validation and Experiment-II using percentage split. Experiment-I was carried out using 10, 15 and 20 folds for cross validation. Cross validation divides the data in n parts (folds). The classification process is repeated n times, using n-1 folds for training and 1 fold for testing (each time a different fold is selected out of n folds). Experiment-II was conducted using percentage split of 50%, 66%, and 77%. In percentage split the data is split into two parts. The specified percentage of the data is used for training and the remaining for testing. Performance metrics used for evaluation of the proposed scheme were accuracy and root mean squared error (RMSE). Accuracy is the percentage of correctly classified instances and was calculated using Equation (11). RMSE is used to measure the difference between values predicted by the trained model and the actual values as defined in Equation (12). RMSE represents average errors taken on the features of a particular feature vector individually (Zernike moments, Geometrical, Zernike moments + Geometrical) used in the classification phase of the experiment. The results obtained are shown in Table II.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{11}$$

where TP, FN, FP and TN represent the number of true positives, false negatives, false positives and true negatives, respectively

$$RMSE = \sqrt{\frac{\sum_{i-1}^{n} (Predicted\_Value_i - Actual\_Value_i)^2}{n}} \tag{12}$$

Geometrical features (aspect ratio, convexity, rectangularity, circularity, circularity ratio, solidity, irregularity, narrow factor, perimeter ratio of diameter and form factor) and Zernike Moments were used as feature vector for this research work. Both experiments were conducted in three phases. In first phase, only Zernike Moments were used for classification. In second phase, geometrical features were used for classification. In third phase both types of features were combined (Zernike + Geometric) and classification was performed. It was observed that the combination of both descriptors produced better results on MPEG-7 CE-Shape-1 dataset. Best results achieved by using cross validation and percentage split were compared and presented in Table III.

The results obtained were improved when cross validation with 20 folds over combination of Zernike Moments and geometrical feature was used. An accuracy of 92.45% was achieved on the selected dataset. The accuracies using cross validation with 20 folds and 77% split were plotted graphically as shown in Fig. 5 (a)&(b), respectively.

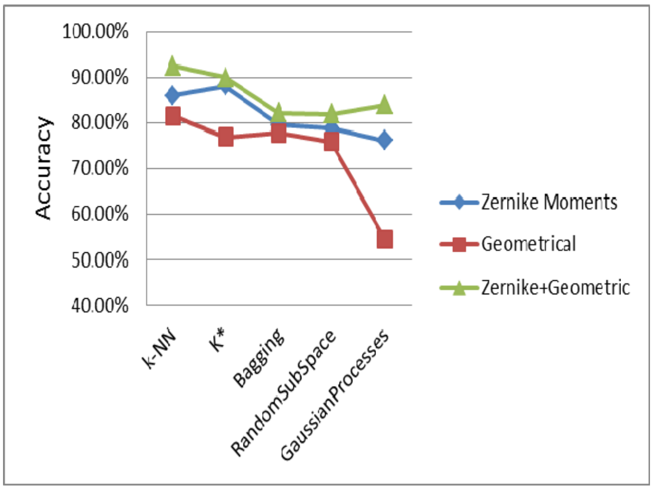
TABLE II. RESULTS OF CROSS VALIDATION AND PERCENTAGE SPLIT

Folds / Splits	Classifiers	Zernike Moments		Geometrical features		Zernike + Geometric	
		Accuracy	RMSE	Accuracy	RMSE	Accuracy	RMSE
Cross Validation with 10 Folds	k-NN	85.38	10.9977	81.03	12.4286	92.12	8.0757
	K*	87.64	9.9985	76.09	13.6452	89.79	9.1119
	Bagging	79.11	12.6642	76.3	13.276	82.07	11.9472
	RandomSubSpace	78.13	13.0708	75.37	13.6538	80.62	12.4797
	GaussianProcesses	75.92	13.4075	54.06	17.2428	83.72	11.3976
Cross Validation with 15 Folds	k-NN	86.25	10.6716	81.47	12.2878	92.32	7.972
	K*	88.05	9.8376	76.55	13.5243	89.97	9.0298
	Bagging	79.44	12.5445	76.65	13.1799	80.7	12.2575
	RandomSubSpace	77.66	13.1445	76.01	13.5852	81.37	12.3223
	GaussianProcesses	76.25	13.3344	54.56	17.1873	83.92	11.3262
Cross Validation with 20 Folds	k-NN	85.95	10.7782	81.47	12.2936	92.45	7.8965
	K*	88.13	9.805	76.85	13.4305	89.92	9.0571
	Bagging	79.51	12.5398	77.72	12.9933	82.08	11.8849
	RandomSubSpace	78.79	12.8805	75.93	13.5632	81.83	12.1778
	GaussianProcesses	76.13	13.3552	54.53	17.1844	83.86	11.3405
Percentage Split with 50% Split	k-NN	82.65	12.0736	74.71	14.4807	86.26	10.7573
	K*	81.1	12.4118	71.44	14.9807	85.11	11.1222
	Bagging	74.06	14.0264	64.7	15.662	75.96	13.7093
	RandomSubSpace	72.26	14.8462	61.97	16.1656	73.53	14.299
	GaussianProcesses	75.42	14.0551	50.49	17.8934	81.61	12.4223
Percentage Split with 60% Split	k-NN	83.03	12.094	72.82	15.1231	89.27	9.5503
	K*	86.8	10.3827	69.97	15.3922	85.41	11.0207
	Bagging	78.55	12.9272	70.96	14.5568	80.9	12.4138
	RandomSubSpace	76.66	13.6474	70.27	14.9192	78.86	13.2004
	GaussianProcesses	76.95	13.502	55.66	17.3467	83.24	11.7282
Percentage Split with 77% Split	k-NN	83.9	11.6924	72.58	15.2361	90.23	9.0879
	K*	88.84	9.4865	72.24	14.8736	87.25	10.1066
	Bagging	81.18	12.3551	73.05	13.9657	81.96	12.0208
	RandomSubSpace	78.99	12.9522	75.37	13.7419	80.17	12.6404
	GaussianProcesses	78.04	13.0421	57.41	17.0133	84.32	11.2634

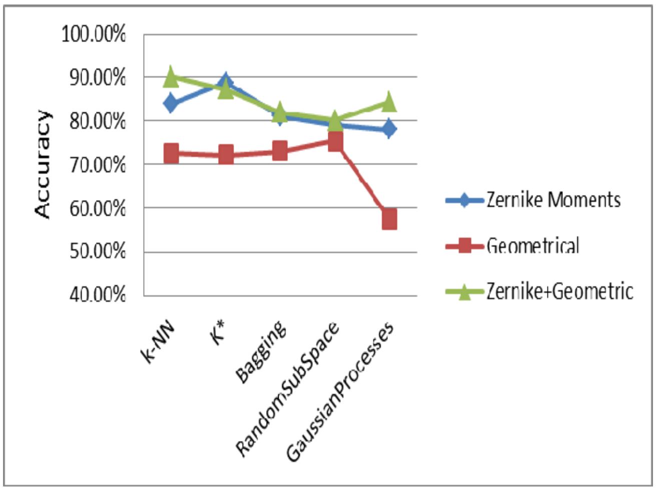
*Values are given in percentages

TABLE III. COMPARING BEST RESULTS OF CROSS VALIDATION AND PERCENTAGE SPLIT

Classifiers	Zernike Moments		Geometrical features		Zernike + Geometric	
	Cross validation (20 folds)	Percentage split (77%)	Cross validation (20 folds)	Percentage split (77%)	Cross validation (20 folds)	Percentage split (77%)
k-NN	85.95%	83.9%	81.47%	72.58%	92.45%	90.23%
K*	88.13%	88.84%	76.85%	72.24%	89.92%	87.25%
Bagging	79.51%	81.18%	77.72%	73.05%	82.08%	81.96%
RandomSubSpace	78.79%	78.99%	75.93%	75.37%	81.83%	80.17%
GaussianProcesses	76.13%	78.04%	54.53%	57.41%	83.86%	84.32%



(a)



(b)

Figure 5. Accuracy achieved (a) Using cross validation (20 folds), (b) Using percentage split (77%)

Geometrical features, when extracted on the dataset, produced an accuracy of 85.95%. In order to improve the results, it was necessary to combine geometrical features with any other descriptor. Zernike Moments, when used alone, produced an accuracy of 88.13% using k-NN classifier with of 20-fold cross validation and 88.8% with percentage split of 77%, whereas [22] reported an accuracy of 87.223% using Zernike Moments. Research work of [13] reported 80% accuracy using Zernike Moments.

The comparison showed that results of this research are outperforming when Zernike Moments are used. In work of [11] the accuracy reported on MPEG-7 dataset was 77.24% using a different feature set. An accuracy of 43.64% was obtained by [32] using Zernike Moments with k-NN classifier where k=3 and with Adaboost it resulted in 51.29% accuracy. Shape matching using shape context [14] resulted in an accuracy of 76.51%. An accuracy of 93.32% on MPEG-7 dataset using Diffusion process [33] was achieved. In the latest work of [10], accuracy of 91.43% was achieved by Region, Skeleton and Contour based descriptors on MPEG-7 dataset using k-ELM. Comparing it to the proposed approach, it was observed that Zernike Moments presented better results. Inverse of the original shape using Zernike Moments Extended form was used by [8] producing better accuracy but on a small data set whereas the dataset considered in this research was larger and presented excellent accuracy comparative to other researches.

IV. CONCLUSION

In this paper, we have proposed an approach for efficient shape classification using Zernike Moments and geometrical features. The paper addresses the problem of shape classification and retrieval, and has proposed a framework that combines Zernike Moments and geometric features. The described approach exploits the uniqueness of Zernike Moments and when combined with geometrical features yields better classification results. The images are classified using five classifiers but k-NN classifier has turned out to be the best for shape classification. The proposed approach has been analyzed on the challenging MPEG-7 CE Shape-1 dataset. The results concluded that the proposed approach is efficient and achieves high accuracy of 92.45% which outperforms the accuracies of existing state-of-the-art-methods.

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