Automatic Detection of Regular Geometrical Shapes in Photograph using Machine Learning Approach

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***Abstract*— We propose a model for automatic detection of regular geometrical shapes in a photograph. The proposed framework uses a machine learning approach to detect shapes based on geometrical features. The geometrical shapes are elements of compositions in a photograph. Usually, the regular shapes play a very important role in photo aesthetic analysis. They provide a good amount of aesthetic score to photographs. The developed model is a multi-class classifier using Random Forest based on 9 distinct geometrical features, which can detect and classify the regular shapes into 'Circle', 'Rectangle', 'Square', and 'Triangle'. We test our model on a ground truth dataset containing 250 images. The experimental result shows that the proposed model gives the accuracy up to 96%, which outperforms the current state-of-the-art. Its application to the problem of aesthetic score evaluation of photographs, and online guidance to amateur photographers to improve their photography skill.**

Keywords—Aesthetics, Decision Tree, Geometrical Shapes, Machine Learning, Photographs, Random Forest, SVM.

I. INTRODUCTION

In photography, shape is one of the classic elements of photographic composition. Shape is involved with two-dimensional feature of an object. Usually, in photographs, geometrical shapes convey a lot of information to the viewers. Squares and Circles convey a sense of symmetrical, and Triangle shape plays as the best composition in photography [15], [16]. If the subject is triangular, the viewer's eyes automatically draw the focus on that subject. Because of this, geometrical shapes play a very important role in photography to assess the aesthetic score of photographs. Also, for photographers, the use of shapes in the composition is very important to make a photograph attractive. Fig. 1 shows the different geometrical shapes in photographs. In this paper, we proposed an approach to detect geometrical shapes in photographs automatically and classify them into four categories, such as, "Circle", "Rectangle", "Square", "Triangle" using machine learning techniques. In our proposed approach, we use the Random Forest classifier for multiclass classification. Random Forest is a bag of decision trees; it is an ensemble learning method for classification and combines a set of decision trees into one, selecting the decision trees randomly. We developed a classification model using Random Forest based on 9 different geometrical features. These geometrical features are very unique to identify different geometrical shapes over existing literatures. Due to these distinct features, automatic shape detection process using machine learning technique is boosted. In the proposed approach, first select the salient object from the photograph, after selecting the object, extract set of geometrical features to detect shape. The classifier is-

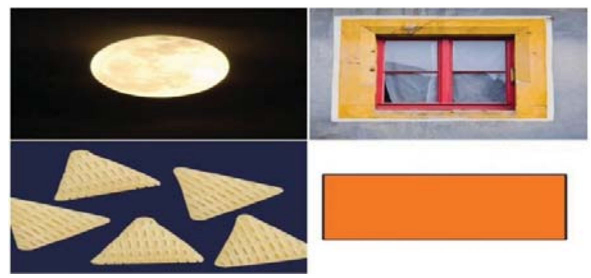

Fig. 1: The different geometrical shapes in photographs.

trained based on these geometrical features. The shapes are classified by Random Forest using the feature vector. The predictive accuracy of Random Forest is 96%, which outperforms the current state-of-the-art. Beside the Random Forest, we also implement Decision Tree and SVM-Multiclass model for shape classification. We notice the predictive accuracy of Decision Tree is 86%, and accuracy of the SVM-Multiclass model is 89%. As Random Forest performs better than other classifiers, we choose Random Forest multiclass classifier for our proposed approach to detect and classify the shapes.

II. RELATED WORK

A. Shape Detection

Moon et al. [1] proposed a 2-dimensional shape detection technique based on optimal edge of shapes. They first derived a one-dimensional optimal step edge operator, and minimized the noise power and mean squared error. They defined an operator to detect shape by extending the derivative of double exponential function with shape's boundary contour and performed edge detection at the pixel level of global contour detection. Their applications of shape detection were vehicle detection in aerial images, features detection from human faces, and track contour in video images. Abbadi et al. [2] proposed a method to detect and recognize different shapes in an image. First, they enhanced the contrast of image by using contrast-limited adaptive histogram equalization (CLAHE)

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technique on small region of an image. Then applied the Gaussian filter to reduce noise, and adjusted the image intensity. Converted the image into binary image, and trace the region boundaries. Labeled all regions of the image and determined all the connected components. They calculated the shape factor based on the area and the diameter of labeled region of the image. Then recognized the shape of connected components based on shape factors. Gomez et al. [3] recognized the regular 2-dimensional shapes using machine learning approach. They found the contour of the shapes and applied the Gaussian filter to remove noise. After that, they extracted a vector of 4 features, e.g. number of sides of the polygon, standard deviation of the sides divided by the perimeter, standard deviations of the magnitude of the angle, and the magnitude of the angle closest to 180 degrees. They used binary classification tree model to recognize the different shapes. Zakaria et al. [4] proposed a shape recognition using the intensity values of image, and then apply Otsu's method for thresholding to get binary image. Median filtering was used for noise reduction from images and applied Sobel filter to find the edges. Then thinning method was used to remove unnecessary edge pixels. Singh et al. [5] proposed an approach to detect shape from the tactile images. These images contain various real life objects. The four objects of geometrical shaped were used to detect shape. They segmented out the high pressure regions denoting surface edge via multilevel thresholding. They used Linear Support Vector Machine (SVM) classifier for classification of objects shape.

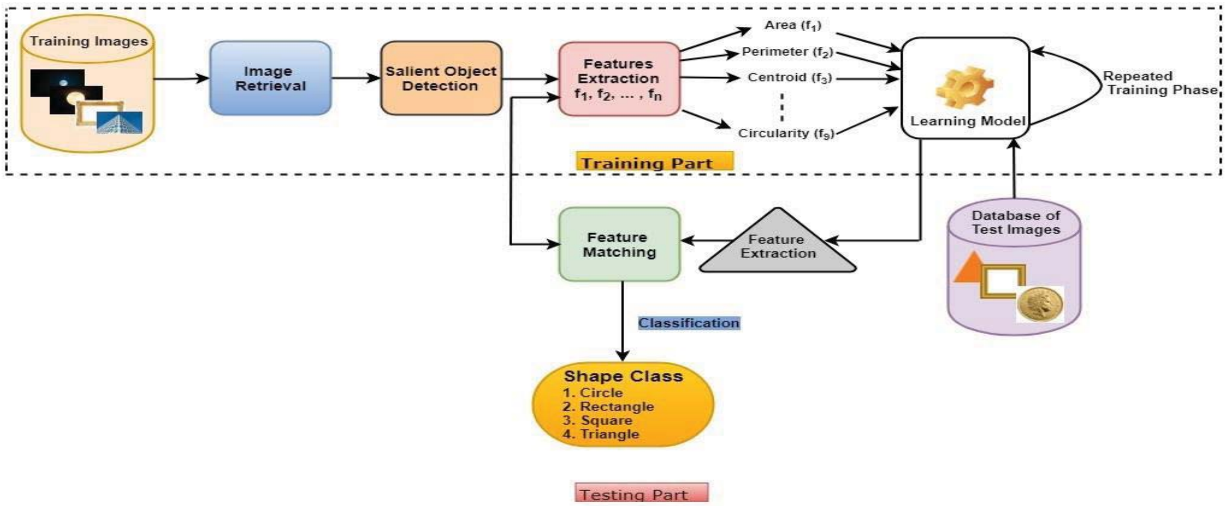

Fig. 2: The framework of the proposed shape detection model. In this model, first, we retrieve images from the scenic photo database. Detect salient object through CRF [10] technology from the images. Then extract a set of features f_1, f_2,…, f_n. Create a learning model using Random Forest Classifier, and perform the training phase repeatedly. In the testing part, again extract the same features from test data set of images and perform the feature matching procedure with extracted features from the training set of images. Finally, perform the classification of shapes into "Circle", "Rectangle", "Square", and "Triangle" based on the extracted features.

B. Salient Object Detection

To detect shape from images, it is also very important to detect salient object's region or boundary. The properties of the object's region can say about the shape structure. Jalled et al. [6] proposed a method to detect object using image processing techniques. They used Haar cascade algorithm to detect object and face for Unmanned Ariel Vehicle (UAV). The UAVs are used to detect and attack the infiltrated ground targets. It is also used for surveillance using Viola-jones algorithm to detect and track human beings. Angelova et al. [7] proposed a detection and segmentation algorithm for fine-grained recognition purpose from image. In their proposed method, first, they localized the object, and normalized the object for scale. They proposed a region-guided detection and segmentation of the object. Their proposed method used Laplacian propagation to reduce the run time for segmentation. At last, they used Linear SVM to classify the flowers from its background region to detect the object. In [8] Gould et al. proposed a region-based segmentation and object detection technique. Their model combines the scene structure and semantics in coherent probabilistic model, creates a hierarchical model. They decomposed the scene into a number of regions, and analyze pixel by pixel in coherent energy function. Their model learns a linear SVM over feature vectors, computing by Histogram of gradient orientations. Borja et al. [9] proposed a method to detect object using Principal Component Analysis (PCA). They used PCA reconstruction combining with SVM classifier to enhance the performance of system. They tried to detect pedestrian in a cluttered gray scale image rather than any other object in the image. Their system detected the frontal, rear, and side view of a pedestrian. In [10] Liu et al. proposed a supervised approach to detect a salient object in an image using a set of local, global, and regional features of salient object. The model used the salient object detection using a condition random field (CRF). The CRF learning can combine the group of salient features. Segmentation method was incorporated with the CRF for salient object detection of different size and shape.

III. Proposed Approach

This paper proposed an approach of automatic detection of geometrical shapes in photograph using machine learning techniques. Shapes are very important feature in the area of computer vision, and image processing tasks. Shape detection has various real-time applications in the problem of vehicle detection in aerial images, contour tracking in videos, and human face detection. Shapes play a very important role in photo aesthetic analysis task also. Usually, the regular shapes in a photograph add a good amount of aesthetic score to photograph. Because this regular shapes transmit a sense of geographical order. Specially, among regular shapes “Circle” draws an attention of viewers. In the proposed approach, we first detect the salient object using the salient object detection technique [10], then from the salient object; we extract the shape features to learn a classifier for shape classification.

The following sections describe the proposed approach we employed to detect and classify the regular geometrical shapes in an image, as shown in Fig. 2, and the experimental result we obtained which outperforms the other traditional shape detection techniques in image processing.

A. Salient Object Detection

The proposed approach first investigates the problem of salient object detection to detect shapes from photographs. Our approach uses the salient object detection method of Liu et al. [10]. We detect salient object through CRF learning, segment the object region and combine this segmented area with CRF to detect object of different shape and size. Consider the salient object as a binary mask S={a_x}, for each pixel x, it has to check that image pixels belongs to salient object or not. In CRF frame work [11], the probability of a label S={a_x}, the observation image I , modeled as conditional distribution

$$P(S|I) = \frac{1}{Z}\exp\left(-E(S|I)\right) \quad (1)$$

where Z is a partition function. E(S|I) is the energy, which is a linear mixture of static salient features. We define the energy function as :

$$E(S|I) = \sum_x \sum_{k=1}^{k} \lambda_k F_k(a_x, I) + \sum_{x,x'} S(a_x, a_{x'}, I) \quad (2)$$

where K is the number of unary features, indicated by $F_k(a_x, I)$ and a pairwise features $S(a_x, a_{x'}, I)$. λ_k is the weight of k^{th} feature, and x, x′ are two adjacent pixels.

B. Extraction of Features to Detect Shape

Features are very important to detect regular shapes because every shape has very different feature values. The selection of features is also very crucial because based on these features a learning model is trained. The learning model can detect and classify the different shapes based on training feature vector. In this paper, we select and extract a set of shape features after salient object detection. Here, we extract 9 different shape features for each photograph. We denote our feature set as F= {f_i | 1≤ i ≤ 9}, which are explained as follows. ..

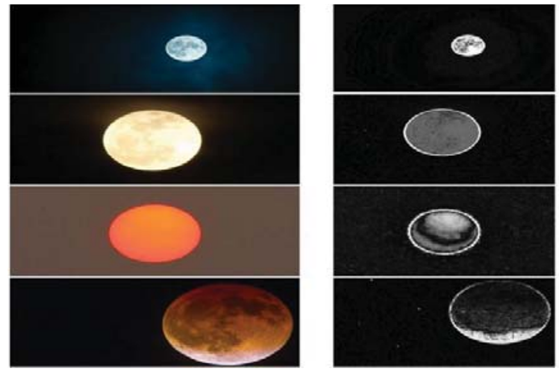

Fig. 3: The salient object detects through CRF learning [10].

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1. **Perimeter**, it indicates a path that surrounds the two-dimensional shape. This is a length of the outline of the shape.
2. **Area**, it indicates a quantity which expresses the extent of the two-dimensional shapes or Fig..
3. **Filled Area,** it is an extent of area to be filled.
4. **Solidity,** it is a measure describing the affinity of the Shape's area with its convex area.
5. **Centroid,** it indicates a geometrical center of a shape.
6. **Bounding Box,** it is a boundary area of a shape.
7. **Extent,** it is ratio of pixels in the region to pixels in the total bounding box.
8. **Eccentricity,** it indicates the distance between foci of ellipse and its major axis length in a shape region.
9. **Circularity,** it is concerned with the roundness of the shape.

D. Learning Model (Classification Framework)

After the extraction of features, we build up a learning model Random Forest classifier. We generate a bagged of 50 classification trees, called Random Forest to classify the regular shapes into 4 categories, like “Circle”, “Rectangle”, “Square”, “Triangle”. Random Forest is an ensemble learning method for classification, this bagged decision tree reduce the effect of overfitting and improve the generalization. The training algorithm for Random Forest [12, 13] applies bootstrap aggregating or bagging. Assume a training dataset X=x_1, x_2,…, x_n and corresponding label Y=y_1, y_2, … ,y_n bagging repeatedly, say N times, then train a classification tree f_n on X_n and Y_n, by:

For n= 1, 2, … , N

$$f' = \frac{1}{N}\sum_{n=1}^{N} f_n(x') \tag{3}$$

And the standard deviation of predictions from all individual classification trees is:

$$\sigma = \sqrt{\frac{\sum_{n=1}^{N}(f_n(x') - f')^2}{N-1}} \tag{4}$$

Here σ represents the standard deviation of predictions and N is a free parameter, which indicates number of samples or trees.

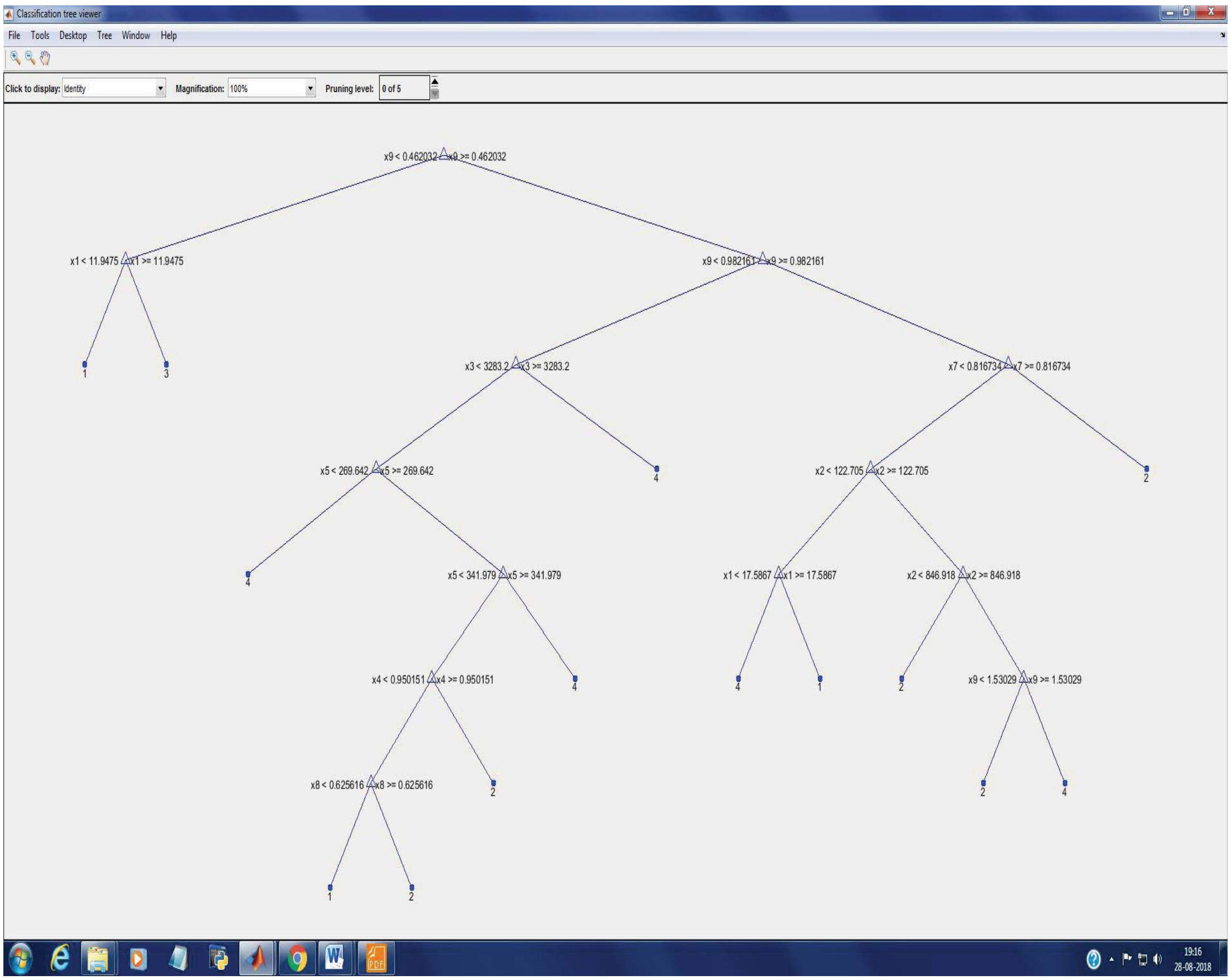

Fig. 4: Decision tree obtained on shape classification using 9 features.

IV. Experiment

For the experiment we use our own created ground truth dataset of 250 images contain regular geometrical shapes. We divide the dataset randomly to choose the training dataset and test dataset. Our training dataset contains 150 images and test dataset contains 100 images of different shapes. We implement our method in MATLAB environment. In the proposed experiment, initially, we detect the salient object from images, and then extract the set of features from the detected object. Using these features a learning model is build up. The proposed learning model is a multiclass Random Forest classifier, which trained on extracted features, and can detect the shapes. Multiclass Random Forest classifier classifies the images into 4 categories of shapes. The observed weight in Random Forest model is 0.0116, and the predictive accuracy is 96%. For comparison purpose, we then implement

Decision tree [14] with gdi (Gini Diversity Index) split criteria and weight is adjusted to 0.0116. The maximum splitting of nodes is 250, and the minimum number of parent is 10. In decision tree, decision nodes are denoted by triangle and the leaf nodes are expressed by circle. Fig. 4 shows the generated Decision tree on shape classification, and the predictive accuracy of Decision tree is 86%.We then use a multiclass model for

Support Vector Machine (SVM) using ClassificationECOC. ECOC is an error-correcting output codes classifier for multiclass learning by reduction to multiple binary classifiers like SVM. The learner weights are adjusted to [0.5698; 0.4884; 0.56980; 0.4302; 0.5116; 0.4302]. Binary loss is quadratic. The predictive accuracy of SVM-Multiclass classifier is 89%. Fig. 9 shows the ROC curve for Classification tree, Random Forest and SVM-Multiclass Model. Hence, we can notice that the Random Forest classifier gives better predictive accuracy than Decision tree multiclass classifier, and SVM-Multiclass model. We choose the Random Forest as our proposed classification model for shape classification.

V. COMPARISON WITH TRADITIONAL APPROACHES

For detection of regular geometrical shapes, we proposed a machine learning approach with Random Forest multiclass classifier. Our proposed approach outperforms the current state-of-the-art in shape detection. In this section, we compare our proposed approach with traditional shape detection approaches. Some failure cases of traditional shape detection approach are shown below.

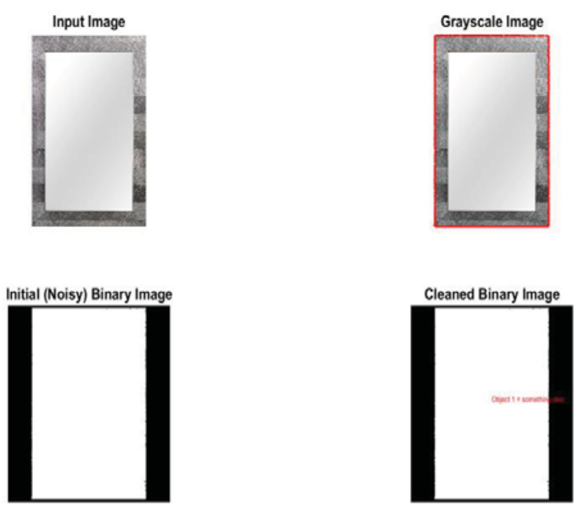

Fig. 5: A failure case to detect rectangle shape using traditional shape detection approach.

Fig. 6: Traditional approach fails to detect circle shape.

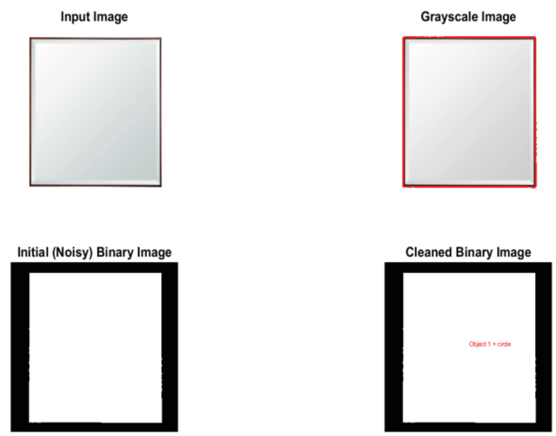

Fig. 7: The failure case of square shape detection by traditional image processing approach.

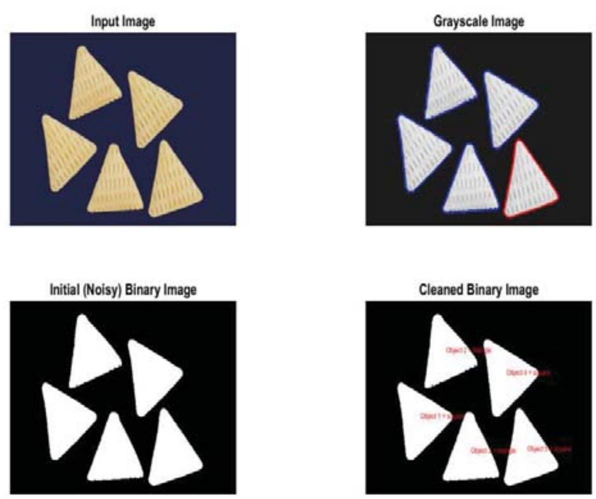

Fig. 8: Traditional approach fails to detect triangle shape.

TABLE I. ACCURACY COMPARISON BETWEEN 5 BASELINES AND OUR PROPOSED APPROACH

Shape Features	Accuracy (%)
Gomez et. al [3]	90.02
Moon et. al [1]	89
Abbadi et. al [2]	87
Zakaria et. al [4]	85
Singh et. al [5]	92.6
Proposed Approach	**96**

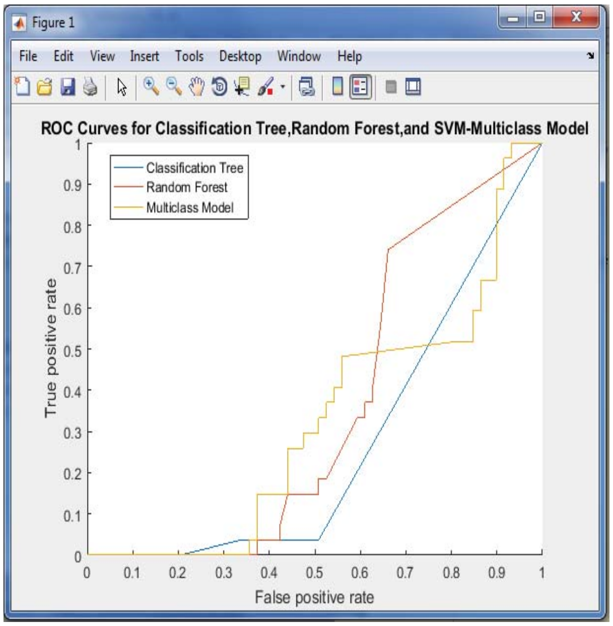

Fig. 9: Accuracy comparison among implemented Classification Tree, Random Forest, and SVM-Multiclass Model.

VI. Conclusion and Future Work

This paper proposed an approach for automatic detection of regular geometrical shapes in photographs using machine learning technique. The proposed approach used a Random Forest multiclass classifier for shape classification. At first, it investigates the problem of salient object detection in images. We employ CRF technique to detect salient object, after detection of salient object, we extract a set of geometrical features for training of classification model. Based on this features, classifier can detect and classify the shapes into four different categories, such as, “Circle”, “Rectangle”, “Square”, and “Triangle”. The proposed approach gives a satisfactory result on shape detection and classification as compared to other traditional approaches. The future applications of this approach are to the problem of aesthetic score assessment of photographs and the on-site guidance to the amateur photographers to improve their photography skills.

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