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DESIGNING OF NEW PATTERN CLASSIFIER BASED ON MORPHOLOGICAL PARAMETER

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Abstract- Face and text recognition system should be able to automatically detect a face and text in any sample video or images. This involves extraction and analysis of its features. Pattern Classifier system recognizes face and text, regardless of lighting, ageing, occlusion, expression, illumination and pose. Morphological feature based on thresholding of image and gray level components analysis are used for linear discriminant analysis. These are than tested and compared for the template of face and text recognition of facial and textual images database. Present paper discusses designing of new pattern classifier based on morphological parameter. Present research used standard face 95 database, local database, and text databases. The performance of new pattern classifier based on morphological parameter is found to be 100%.Although performance of this classifier is highly dependent on the selection of parameters for thresholding and evaluation.

Keywords: *Morphological parameters, Pattern Classifier, thresholding, Object recognition Pattern matching.*

I. INTRODUCTION

Pattern recognition is the science of making inferences from perceptual data, using tools from statistics, probability, computational geometry, machine learning, signal processing, and algorithm. design. Thus, it is of central importance to artificial intelligence and computer vision, and has far reaching applications in engineering, science, medicine, and business. From automated speech recognition, fingerprint identification, optical character recognition, DNA. Sequence identification, and much more, it is clear that reliable, accurate pattern recognition by machine can be immensely useful. For some problems, such as speech and visual recognition, design efforts may in fact be influenced by knowledge of how these are solved in nature, both in the algorithms employed and in the design of special-purpose hardware. Pattern classification is the organization of patterns into groups of patterns sharing the same set of properties.

II. PROPOSED APPROACH

The problem of pattern recognition is to associate classes wi , i = 1, . . . ,Nc with measured data.

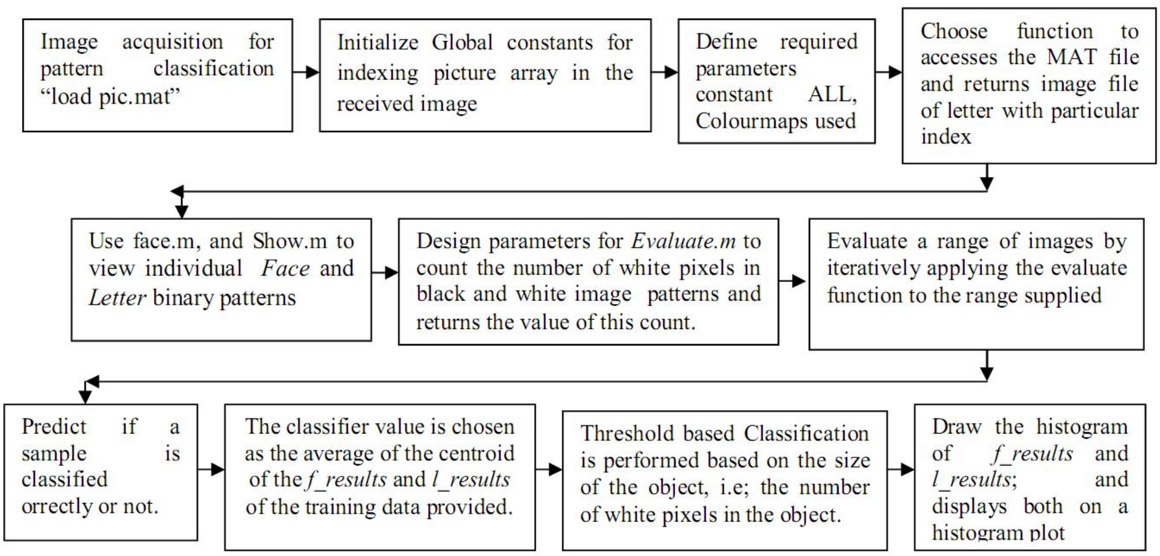

Figure 1: Flowchart of designed Pattern Classifier Based On Morphological Parameter

Statistical methods allow two distinct approaches Calculate the probability that a given feature vector, x, is associated with a given class wi .i.e; this is the conditional probability P(wi |x). Repeat for all possible classes and choose that which gives the highest probability. Calculate the error associated with choosing a particular class, for all classes and then pick the class which minimises it.

Statistical methods are necessary because in general, many different measurement vectors will correspond to noisy or distorted versions of the same basic pattern or template and thus require assignment to the same class. It is assumed throughout that training data is available i.e. a sequence of measurement vectors x(k), k = 1, . . ,Nt are known, together with the correct class for each vector wi (k). This allows the construction of the conditional probability density function p(x|wi) which specifies the probability that a measurement vector x can arise from a class wi. Suppose that there is a single distinguishing feature x and that there exist p.d.f.s p(x|w1) and p(x|w2), then the basic decision rule is choose w1 if (w1|x) > P(w2|x) otherwise choose w2 The decision boundary is a single number α, fixed by the condition, p(α|w1) = p(α|w2)

III. IMPLEMENTATION

In brief, the problem of pattern recognition is to associate classes wi , i = 1, . . . ,Nc with measured data. Statistical methods allow two distinct approaches.

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In MATLAB Command Window, >> *show (face(4))* This function helps to view individual *Face* and *Letter* binary patterns as grayscale images in the range [0,255] by plotting the scaled binary matrix.
Evaluaion helps to count the number of white pixels in individual *Face* and *Letter* black and white image patterns and returns the value of this count. Variable *b* stores the *rgb to gray* mapped image matrix values. Conversion is performed. Variable *c* stores the binary value matrix of the gray scale image, *b*. Classification evaluates a range of images by iteratively applying the evaluate function to the range supplied and predicts if a sample is classified correctly or not.

Classification of range will be used for both faces AND letters. It should evaluate and return two matrices containing the results (*f_results* and *l_results).* It should also evaluate if the pattern has been correctly classified or if it has been misclassified.
Classification is performed based on the size of the object, i.e; the number of white pixels in the object. The classifier value is chosen as the average of the centroid of the *f_results* and *l_results* of the training data provided.

This program performs thresholding operation for a given image. This program produces 3 jpeg images, thresholded to different levels, as a result. *alpha* is the thresholding parameter and is required to be less than 1/3. *I_max* and *I_min* calculate the maximum and minimum pixel intensities of the given image. *level1*, *level2* and *level3* are 1x1x3 matrices storing the threshold values by which the image is to be gray scale transformed by. *level11*, *level21* and *level31* are mxnx3 matrix replicas of *level1*, *level2* and *level3* matrices. *thx1*, *thx2* and *thx3* are image matrices storing image values after thresholding operation is performed. The 3 images after thresholding operation has been performed, are stored as *Result1.jpg*, *Result2.jpg* and *Result3.jpg*

IV. FIGURES AND RESULTS OBTAINED

By changing the thresholding factor *alpha*, we can achieve more black or more white images or the particular object. In Figure 3, Threshold 3*alpha, when *evaluate.m* function is run, the number of black pixels help predict the size of the object. This function can be used in applications where classification is required, based on size of the object. Figure 4 shows images with e different *alpha* value.

4.1 Thresholding results

In all the images the gray levels of pixels belonging to the object are quite different from the gray levels of the pixels belonging to the background. Thresholding becomes then a simple but effective tool to separate objects from the background. The output of the thresholding operation is a binary image whose gray level of 0 (black) will indicate a pixel belonging to a print, legend, drawing, or target and a gray level of 1 (white) will indicate the background. The main difficulties associated with thresholding occur when the associated noise process is non-stationary, correlated and non-Gaussian. Other factors complicating thresholding operation are ambient illumination, variance of gray levels within the object and the background, inadequate contrast, object shape and size non-commensurate with the scene. Finally the lack of objective measures to assess the performance of thresholding algorithms is another handicap. In fact most authors limit themselves to the visual inspection of a few test cases.

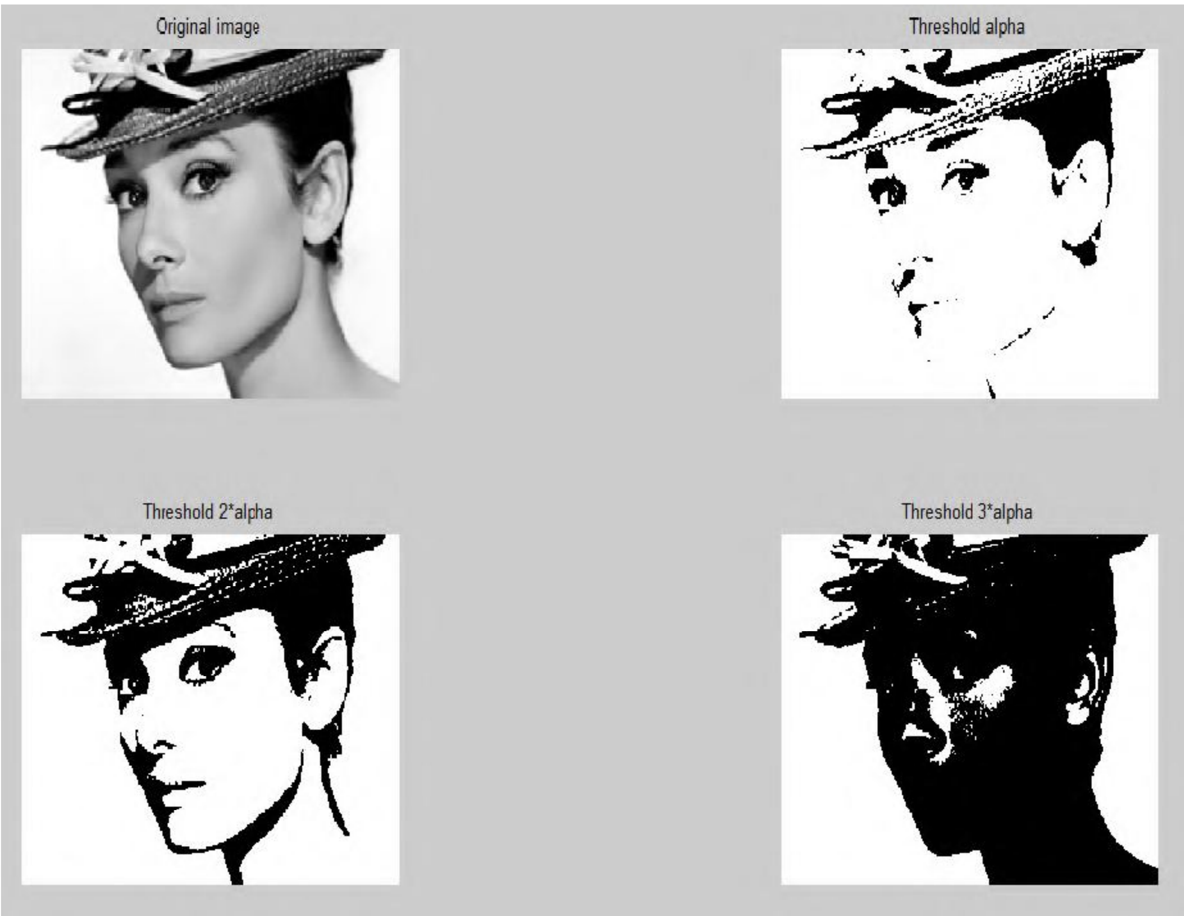

Figure 3 Thresholding alpha = 0.27

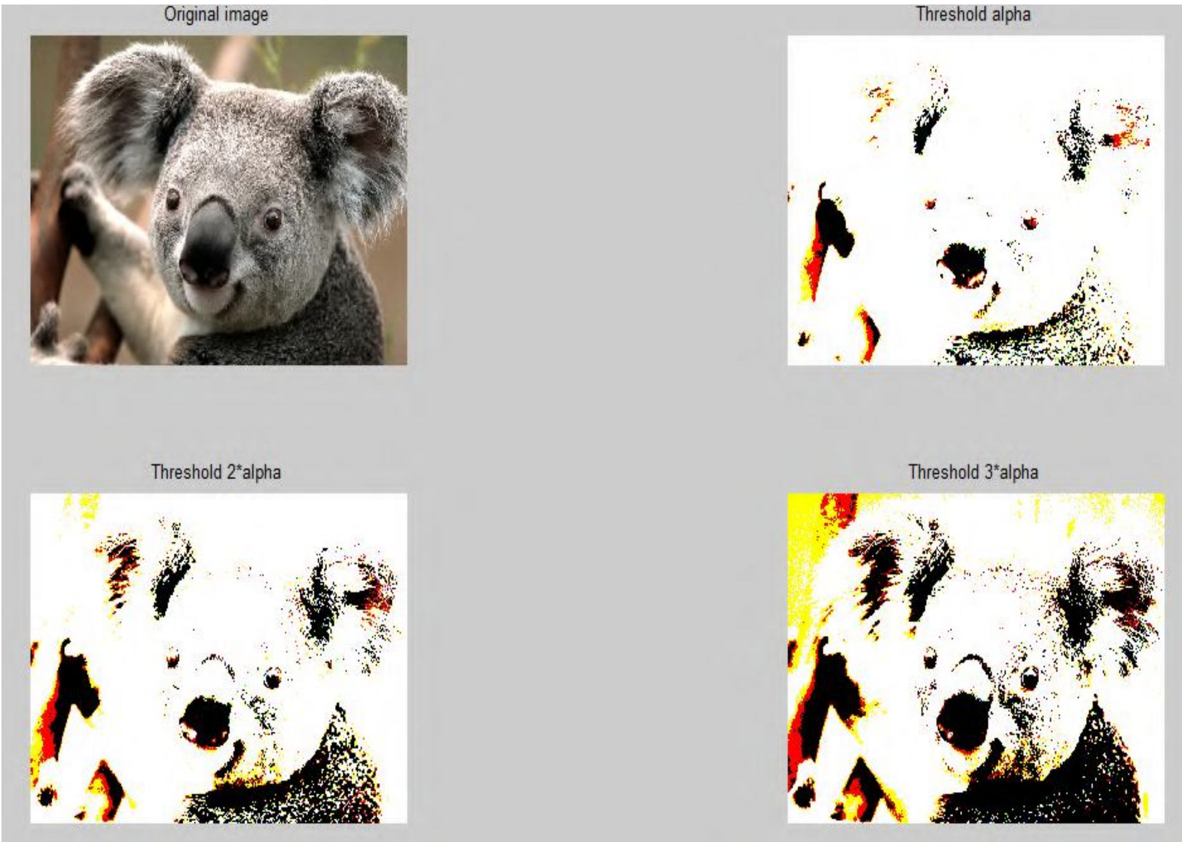

Figure 4 Thresholding aplha = 0.1

4.2 Evaluation results

The *evaluate.m* function returns the number of white pixels in an image after thresholding is performed and image is converted to a binary image.

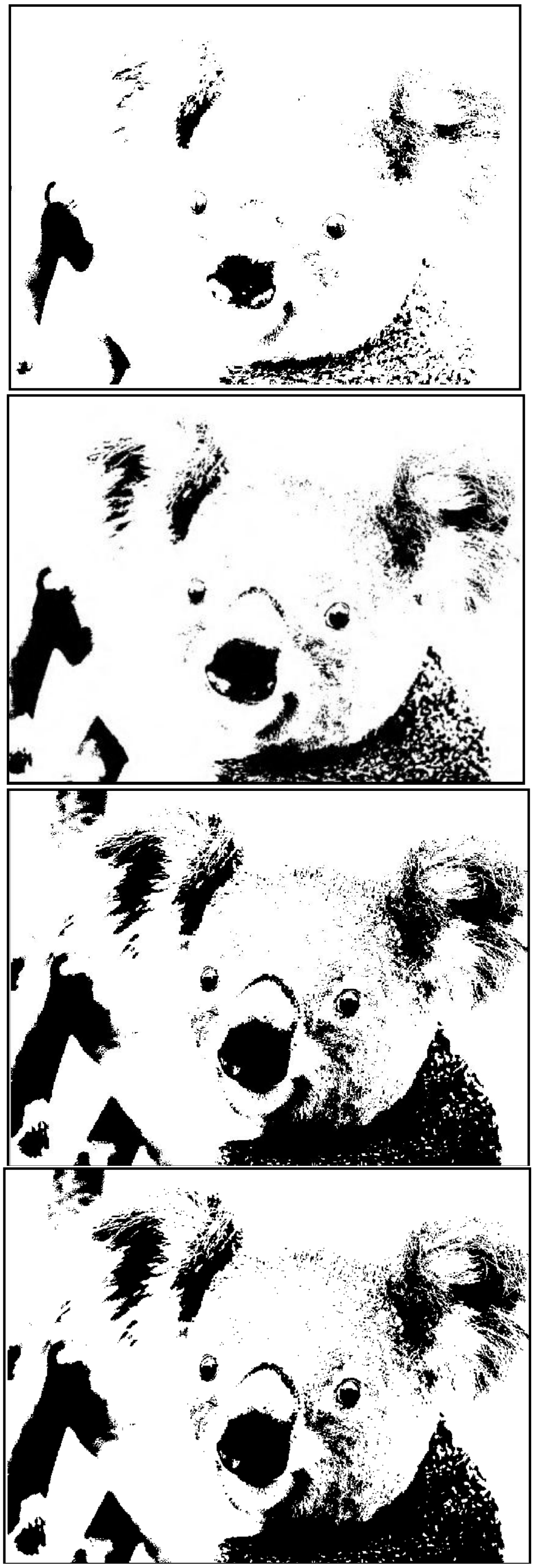

Figure 5 Evaluate and generate binary images of threshold 'Koala.jpg as a. Result1.jpg; b. Result2.jpg and c.Result3.jpg d.Results4.jpg

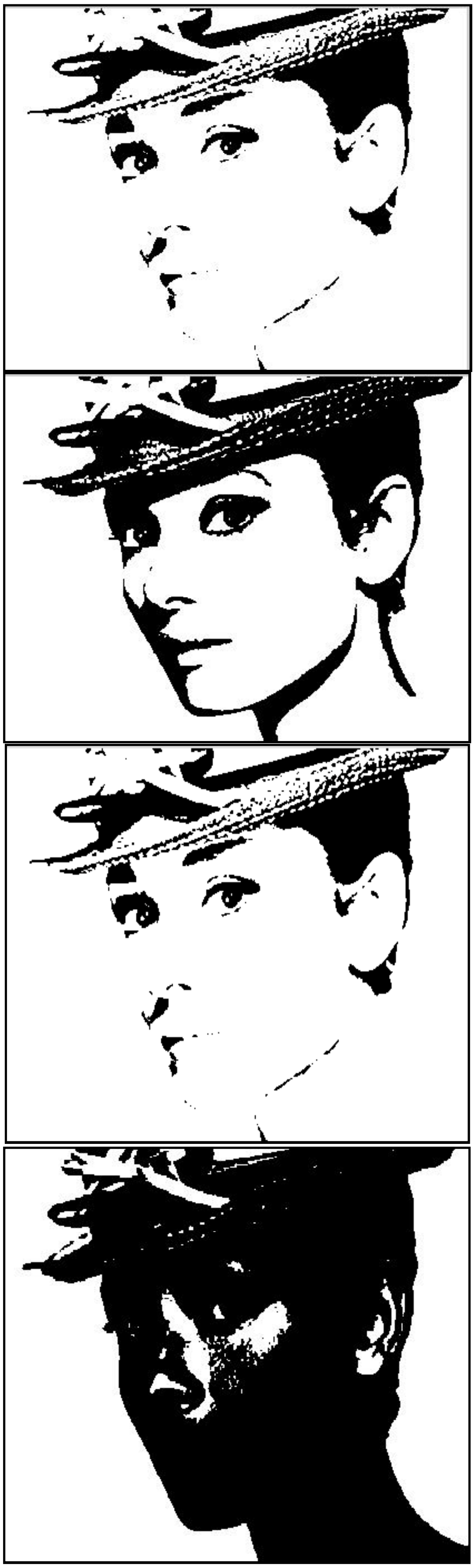

Figure 6 Evaluate and generate binary images of thresholded 'Img8.

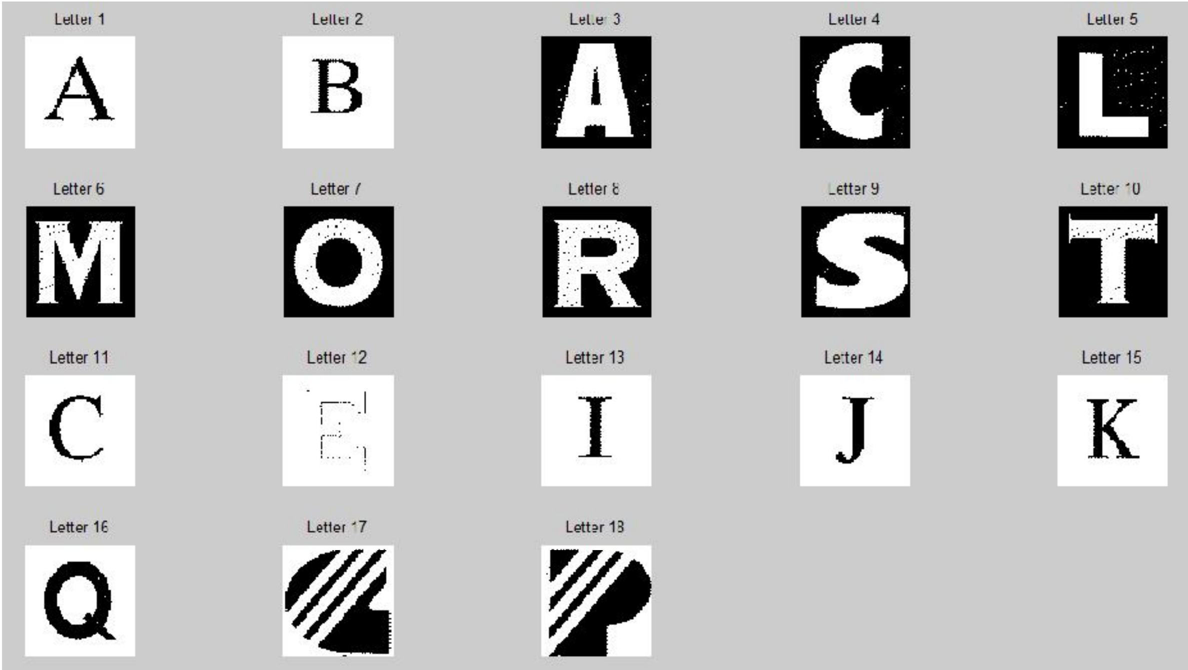

Figure 7 Image database for *LETTERS*.

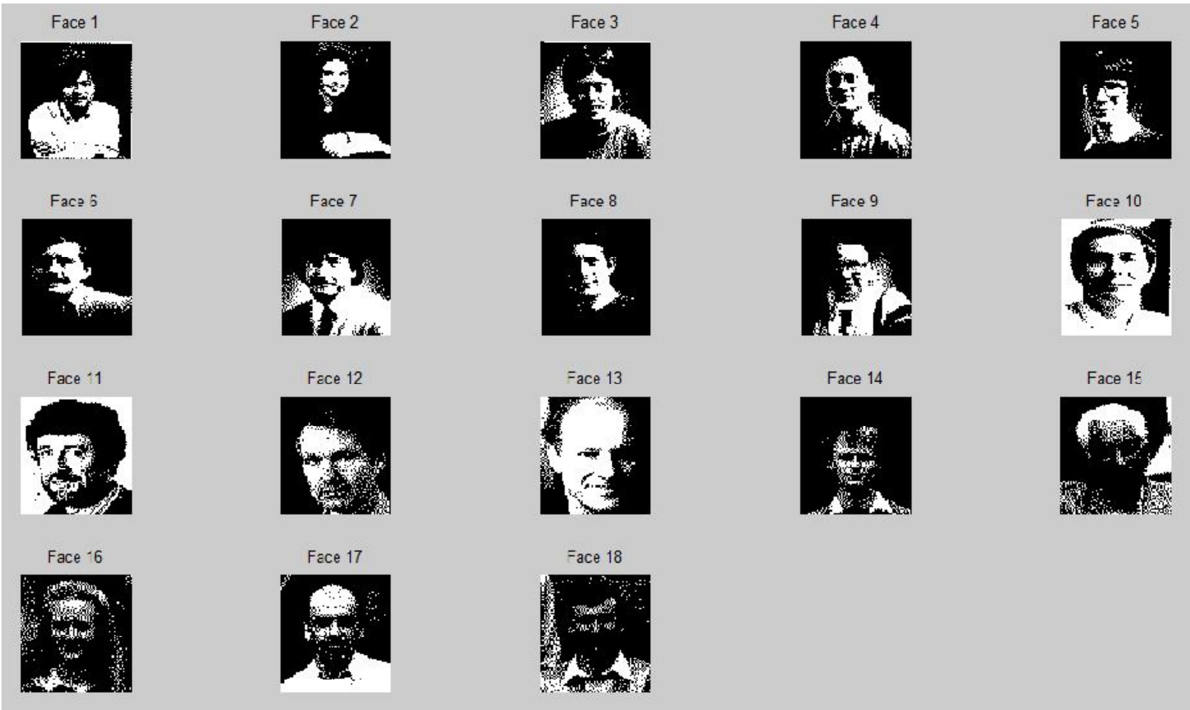

Figure 8 Image database for *FACES*.

4.3 Results for Show.m

Evaluate('Koala.Jpg') = 322969
Evaluate('Img8.Jpg') = 104020
Evaluate('Tripty.Jpg') = 569650
Evaluate('Result3.Jpg') = 592514
Evaluate('Result1.Jpg') = 722712
Evaluate('Result1.Jpg') = 117551
Evaluate('Result1.Jpg') = 653447
Evaluate('Result2.Jpg') = 101777
Evaluate('Result1.Jpg') = 569650
Evaluate('Result4.Jpg') = 759251
Evaluate('Result1.Jpg') = 437823
Evaluate('Result5.Jpg') = 1645932
Evaluate('Result1.Jpg') = 85623
Evaluate('Result6.Jpg') = 1758498
Evaluate('Result1.Jpg') = 456895
Evaluate('Result7.Jpg') = 8965791
Evaluate('Result1.Jpg') = 596321
Evaluate('Result8.Jpg') = 1324845
Evaluate('Result1.Jpg') = 785424
Evaluate('Result9.Jpg') = 8162562
Evaluate('Result1.Jpg') = 496328
Evaluate('Result10.Jpg') = 4589632

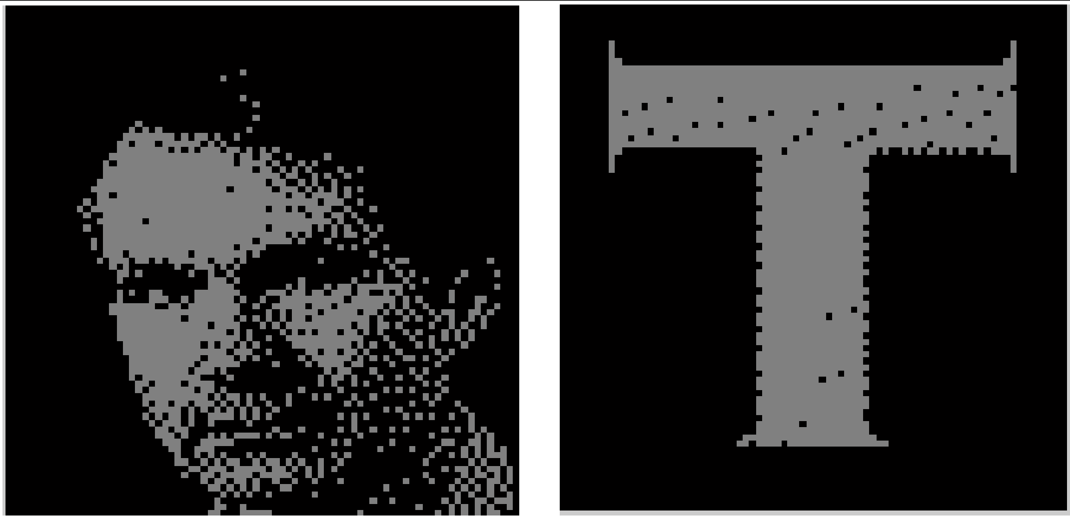

Figure 9 Individual *FACE* and *LETTER* images.

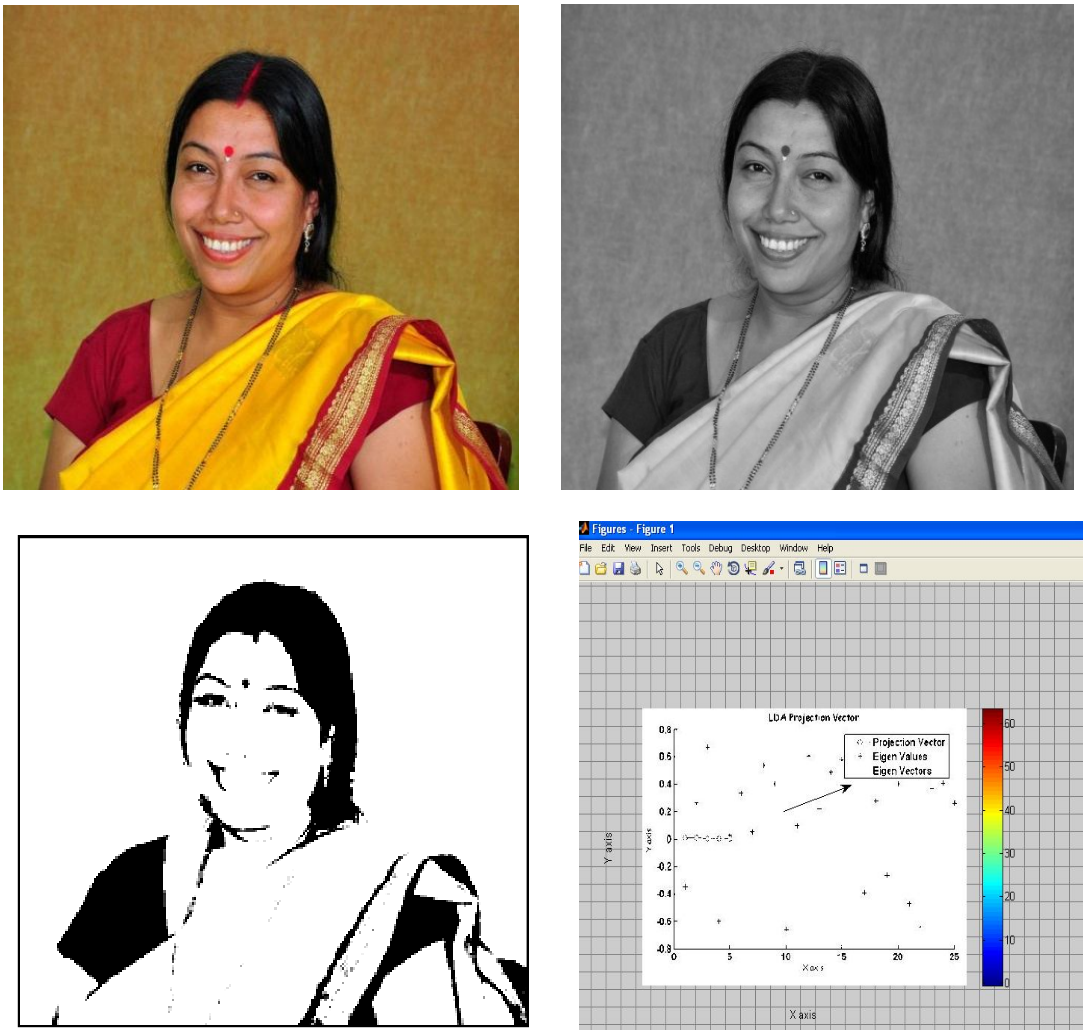

Figure 10. Result Obtained after Thresholding Tripty.jpg

Experiments were conducted standard face and text database. The face database contains number of individuals 72. The background consists of a red curtain. Background variation is caused by shadows as subject moves forward. Large head scale and some expression variation. The position of face in image is some translation. All images have same size and the extension of these images jpeg. The designed pattern classifier was also tested on Tripty.jpg so as to test the validity o system whether it classifies tripty.jpg correctly or not. Snap Shots Of Implementation are shown in figure 11 and 12.

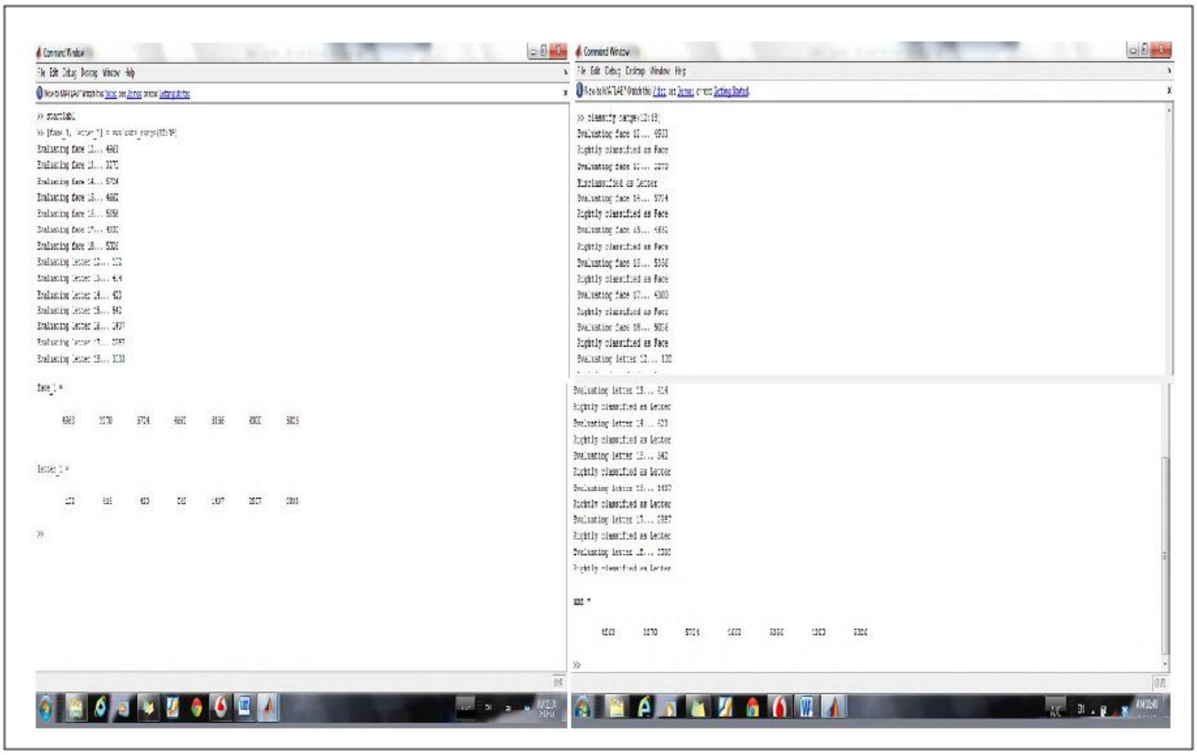

Figure 11. Snapshot of evaluate_range.m. Evaluate function of images in the range 12 to 18.

V. CONCLUSION

The given pattern classifier classifies object based on size (number of white or black pixels). It classifies objects into 2 classes based on a single feature vector - size. The thresholding_img.m program file produces images thresholded at 3 levels.

The evaluate_range.m and classify_range.m evaluates the number of white pixels and classifies the image as a face or a letter.

This classifier finds its application in assembly line production industries where products of 2 or more different sizes are to be classified when all products move on same conveyor belt. Like all systems, errors arise in this system, for example when a. images of different sizes are provided as input, b. the threshold computed for training data might not classify test data accurately, One feature vector isn't sufficient to classify objects.

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