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Gender classification from face images by mixing the classifier outcome of prime, distinct descriptors

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Abstract

Since the last decade, the area of recognizing gender of a person from an image of his/her face has been playing an important role in the research field. A automatic gender recognition is an important concept, essential for many fields like forensic science and automatic payment system. However, it is very onerous due to high variability factors such as illumination, expression, pose, age, scales, camera quality and occlusion. Humans can easily recognize the difference between genders, but it is a critical task for computer. To overcome this issue, many experimental results have been explained in the existing literature as per the advancement of machine vision. But, still definite optimal solution could not be found. For practical usage, a novel full approach to gender classification which is mainly based on image intensity variation, shape and texture features is proposed in this work. These multi-attribute features are mixed at different spatial scales or levels. The proposed novel system uses two datasets such as Facial ExpressIon Set (FEI) dataset and self-built dataset with various facial expressions. In this research, eight local directional pattern algorithms are used for extracting facial edge feature. Local binary pattern is also used for extracting texture feature, whereas intensity as a added feature. Finally, spatial histograms computed from the above features are concatenated to build a gender descriptor. The proposed descriptor efficiently extracts discriminating information from three different levels, including regional, global and directional level. After the extraction of a gender descriptor, effective linear kernel-based support vector machine superior to other classifiers is used to classify the face image as either male or female. The experimental results show that the classification accuracy obtained with the mixture of outcome of multi-scale, multi-block, distinct and prime feature classification is better than having a single-scaled image. It is worth mentioning that the proposed approach is implemented in MATLAB which achieves an accuracy of 99% on the FEI face dataset (200 faces) and 94% on self-built dataset (200 faces).

Keywords Gender classification · ELDP · Local binary pattern · Kirsch compass mask · Support vector machine

1 Introduction

Gender classification is an important research area that can be widely used in computer vision system, biometric systems, credit card verification system, visual surveillance system, age estimation and for security system. In recent years, this motivating area of research has impacts in development machine learning, image processing and human interaction domains. It is more difficult in practical implementation due to lighting, pose, expression, etc.

In the study of gender classification, representation of descriptor of face appearance is a critical issue during classification. The common steps carried out in image processing are object or target recognition, preprocessing, feature extraction and then finally classification. In gender

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classification analysis, the external features such as hair, mole, neck region and other parts may be included. The performance ability of computer vision system is affected since a person has several facial expressions. Hence it is very tedious to categorize the image as either male or female.

Numerous algorithms have been designed for describing the facial gender recognition. They are principle component analysis, linear discriminant analysis, independent analysis, artificial neural networks, Gabor wavelets and so on. In object recognition, the human face region is identified and after that it is cropped from whole image. The cropped image must be involved in preprocessing steps. Some of the processes are geometric alignment, resizing or histogram equalization. In the next step, the important discriminative features of preprocessed image are extracted.

Texture feature is an inherent or innate property of entities and commonly has attributes of image brightness variation, shape or structure, color, size scale and so on. Its main objective is to interpret and understand real internal visual pattern of an subjected image. Hence, several intensive approaches have to be developed for texture feature extraction. Some intensive approaches are local binary pattern (LBP), histogram of oriented gradients (HOG) feature, local phase quantization (LPQ), BSIF and relevant approaches. Gender classification is one of the binary issues, an effective classifier (SVM) that can be used for categorization. In this research, an empirical mixture technique that integrates various kinds of features likes shape, texture and intensity which are obtained at multi-scale with both overlapping and non-overlapping blocks has been focused.

2 Literature review

Face is the most important part of the human body because it has peculiar feature that permit us for certain applications. Human beings can distinguish between male and female with ease. By looking at the image, they can approximately estimate age, state of mind, emotions and discover either person is familiar or not. Generally, human has same parts with some spatial aspects related to position of other parts. Nowadays, the analysis of automatic gender classification through images or videos is an interesting area of research to most of the scrutinizers. Several advanced algorithms are developed to categorize the gender, having a potential ability in many commercial applications. In fact, unique features like gender age, race and identity are crucial for real-world sophisticated analysis. These could be really helpful in users identification and related data of user in market field analysis.

In today's world most of the automatic systematic frameworks are designed to classify the gender category. Ng et al. (2012) had surveyed a computer vision system for gender classification which utilizes information from both face and whole body. The input images are taken from either still images or gait sequences. They highlighted the challenges faced and surveyed the representative methods of their approaches to achieve better classification accuracy for the datasets captured under controlled environments. Gilani and Mian (2014) showed that the ratio of 3D Euclidean and geodesic distances extracted between biologically significant facial anatomical landmarks as proposed features which are robust to ethnicity and classified gender with high accuracy.

Wang et al. (2018) had proposed a complete review of facial feature extraction. In their research, they collected information from 300 articles regarding feature extraction which were mainly focused on filtering, encoding, spatial pooling and holistic representation and analyzed individual with multiple levels. They used deep learning methods to effectively extract the crucial factors. Ballihi et al. (2012) combined tools from Riemannian geometry of shape analysis and the well-known AdaBoost algorithm for selecting feature to obtain the most discriminating curves for facial recognition and gender classification. Li et al. (2012) had proposed a novel gender classification framework, which utilizes not only facial features, but also external information, i.e., hair and clothing. They considered five facial components: forehead, eyes, nose, mouth and chin instead of using the whole face. They had investigated and proved that clothing information has discriminate ability and design feature representations for hair and clothing information that is discarded in most existing work due to high variability. Moreover, classifier combination mechanisms are used to integrate various features to successfully boost the gender classification performance.

Han et al. (2013) had compared a study on illumination preprocessing presented by many scrutinizers investigation about landmark localization, face normalization and matching in a recognition system. This comparison will be useful for designing a better illumination preprocessing method. Kim et al. (2013) had proposed an illumination invariant, a robust face recognition system which is having input of local directional pattern information as LDP has an advantage to degrade the illumination effects and 2D-PCA is also used for getting more robust features against illumination variation.

Suhr et al. (2012) had reported recognizability assessment of occluded facial images which is used in automatic teller machine. Their proposed system achieved the robustness against facial postures and acceptable partial occlusions using a component-based approach and insensitivity toward illumination conditions via the gray scale image-based methods. Its feasibility in both non-intrusive and intrusive scenarios was proven with a large-scale facial occlusion database. Bekios-Calfa et al. (2014) had identified the problem of gender recognition from a multi-attribute perspective like pose variations and age. They suggested that the appearance-based dependencies among gender, age and pose will be exploited to remove the intra-class variability and also for improving the recognition performance. Therefore, gender recognition in laboratory conditions (e.g., the Color FERET database) provides good performances well above 90% compared to be tested in a real setting. They had found that this is caused by the existence of dependencies among facial attributes that have not been considered when building the classifier.

Lu et al. (2015) proposed automatic gender classification for unconstrained sequences that depend on collaborative representation. In this experiment, they took AR database and self-built database and images are resized as 165×120, 55×40, 33×24 and 11×8 pixels where recognition rate is estimated by fivefold cross-validation. To enhance the classification accuracy with affordable complexity Eigen face features and collaborative representation classifier were embedded to the gender classifier. Faraji and Qi (2014) had suggested an illumination invariant face recognition method called adaptive homomorphic eight local directional patterns, which uses Kirsch compass mask algorithm. It achieves an accuracy rate of 99.45% for the CMU-PIE face images, 96.67% for the Yale B face images and 84.42% for the Extended Yale B dataset. Carcagni (2015) had proposed a comprehensive study of facial expression recognition using histograms of oriented gradients (HOG) descriptor (Li and Lin 2018) which could be efficiently exploited facial expression recognition. The proposed result indicates it is also well suited for video sequences in real-world application contexts.

Ramirez Rivera et al. (2013) had recommended an empirical face descriptor called local directional number pattern (LDN) which encodes both structural information and intensity variations of the face's textures by dividing the face into several regions. The concatenated features into a feature vector are used as a face descriptor. Satpathy et al. (2014) had proposed a Discriminative Robust Local Binary Pattern (DRL_{BP}) and Ternary Pattern (DRL_{TP}), which use edge and texture information for object recognition. Furthermore, the proposed features retain contrast information necessary for proper presentation of object contours that LBP, LTP and RLBP discard. Guo et al. (2012) presented a three-layered generalized learning model for discriminative feature extraction, integrated with existing LBP variants such as conventional LBP, rotation invariant patterns, local patterns with anisotropic structure, completed local binary pattern (CLBP) and local ternary pattern (LTP) to derive new image features for texture classification. It considers robustness, discriminating power and representation capability.

Juha Ylioinas et al. (2012) had investigated dense sampling encoding strategy for extracting more stable and discriminative texture patterns in local regions. They proved that their proposed dense sampling carried out richer information compared to the conventional "sparse" sampling scheme commonly used in basic LBP and also it is less prone to noise. This dense sampling scheme can be easily integrated with many existing LBP variants. Kotsia and Pitas (2007) adopted support vector machine (SVM) for the recognition of facial expression and achieved a facial expression recognition accuracy of 99.7%. The achieved accuracy of facial expression recognition using multi-class SVM is better than any other reported in the literature so far. Results showed that SVM classifier performs best (Huerta et al. 2015). This paper presented a simple, effective approach which fuses and exploits texture- and local appearance-based descriptors to achieve faster and more accurate results. A series of local descriptors and their combinations have been evaluated under a diversity of settings.

Azzopardi et al. (2016) had proposed a fusion method that includes domain specific and trained features for gender recognition. Their proposed approach has taken two datasets such as FERET (Face Recognition Technology) and LFW (Labeled Face in the Wild) which are evaluated based on state-of-the-art recognition rate. In their work, they have used COSFIRE filters that use the Gabor technique to differentiate different features from an input image. The local prototype patterns are created from trained face images that are used by the COSFIRE filter to extract multi-attribute features and classifying it. Tapia and Perez (2013) had proposed a novel fusion method which uses image features selected from mutual information such as intensity, histogram of LBP and shape for gender classification. In this work, the extracted feature was compared with multi-level algorithms that are related to image mutual information. Their experimental results proved that the classification accuracy was greater by fusing features from different scales, even when using a single scale.

3 Problem statement

Many technical researchers have experimented on gender classification in order to increase the accuracy in certain applications. The important multi-factors are position, pose, background, illumination, camera quality, expression, age and occlusion. These are used to resolve gender classification problem. The collected database contains different set of images, and these images are captured at several emotional conditions. The precise value experimental parameters are widely used in many practical applications such as forensic science, surveillance and automatic payment system. The analysis of gender classification can be applied in unbounded scenarios. During gender classification analysis, external features such as hair, ear and neck region are discarded, since the human face has several expression variations that may affect the performance of computer vision system.

Figure 1 shows sample-extracted images of both male and female. The key difference between them is only variation in image contrast. The left side image indicates extracted region of male, while right side image indicates female image.

Generally, two methods of feature extraction have been followed—one is geometric based and another one is appearance based.

3.1 Geometric-based feature extraction

In geometric-based method, local features are extracted that uses face shape, nose and eyes information to illustrate face geometry. However, this information does not give sufficient information to classify the gender since some crucial data are lost.

3.2 Appearance-based feature extraction

It is different from geometric-based method, since it deals with full face or particular region. Commonly, Gabor wavelet transform or local binary pattern (LBP) is used for this purpose. This technique is well suited for constrained environment and unfit for dynamic changing environment. However, it is difficult to represent the extracted features and texture features practically.

4 Proposed implementation

Face recognition is considered as the backbone approach for gender classification in digital image processing. However, it is one of the most challenging assignments against several biometric factors. The various biometric factors are illumination, pose, age, expressions and occlusions. In this paper, a real-time novel system that is mainly considering crucial biometric factors such as intensity variation, shape and texture features is proposed. These factors are given as an input to the proposed system. Here, two set of databases such as FEI (Facial ExpressIon Set) and self-built dataset with smile under normal illumination condition are taken.

(a) (b)

Fig. 1 Sample extracted images of male (**a**) and female (**b**)

In this proposed approach, the first step involves preprocessing which consists of two modules such as gray scale convertor and image resize. The face images are considered at different image size as 20×20, 36×36 and 128×128. Integration of multiple subregions produces best accurate results than the whole face region. In the second step, ELDP descriptor is used to extract more edge information by utilizing all eight directional edge images, whereas LBP descriptor extracts texture information. The main intent of third category is to estimate gender classification with the help of mixing of highly effective extracted features result from multi-scale face image. An empirical SVM is used for gender classification that uses mixed feature of intensity, shape and texture characteristics. Figure 2 shows the block diagram of the proposed methodology in detail.

Figure 2 shows the overall implementation process of the proposed scheme which used SVM classifier in two stages in order to classify the gender. The symbol differentiation between male and female is clearly given in the figure. The symbol ♀ denotes female category, whereas ♂ denotes male category.

4.1 Face detection and preprocessing

Gender classification has three crucial processes: preprocessing, feature extraction and classification. The additional processes used are gray scaling, detecting landmarks on faces, cropping the required region and finally resizing images assigned to it in uniform grid. In the proposed method, the images are considered at different image size as 20×20, 36×36 and 128×128. As the captured images suffer from illumination, pose and inaccuracies, after the face detection, the preprocessing is carried out. In preprocessing, face alignment has been considered as a prime task to achieve a high accuracy rate. Normalization of brightness, removing the unwanted region, face alignment, resizing an image and gray scale conversion are the other fundamental steps involved in preprocessing. Resizing of an image is essential for analyzing precision performance in gender recognition. Integration of multiple subregions produces best accurate results than the whole face region.

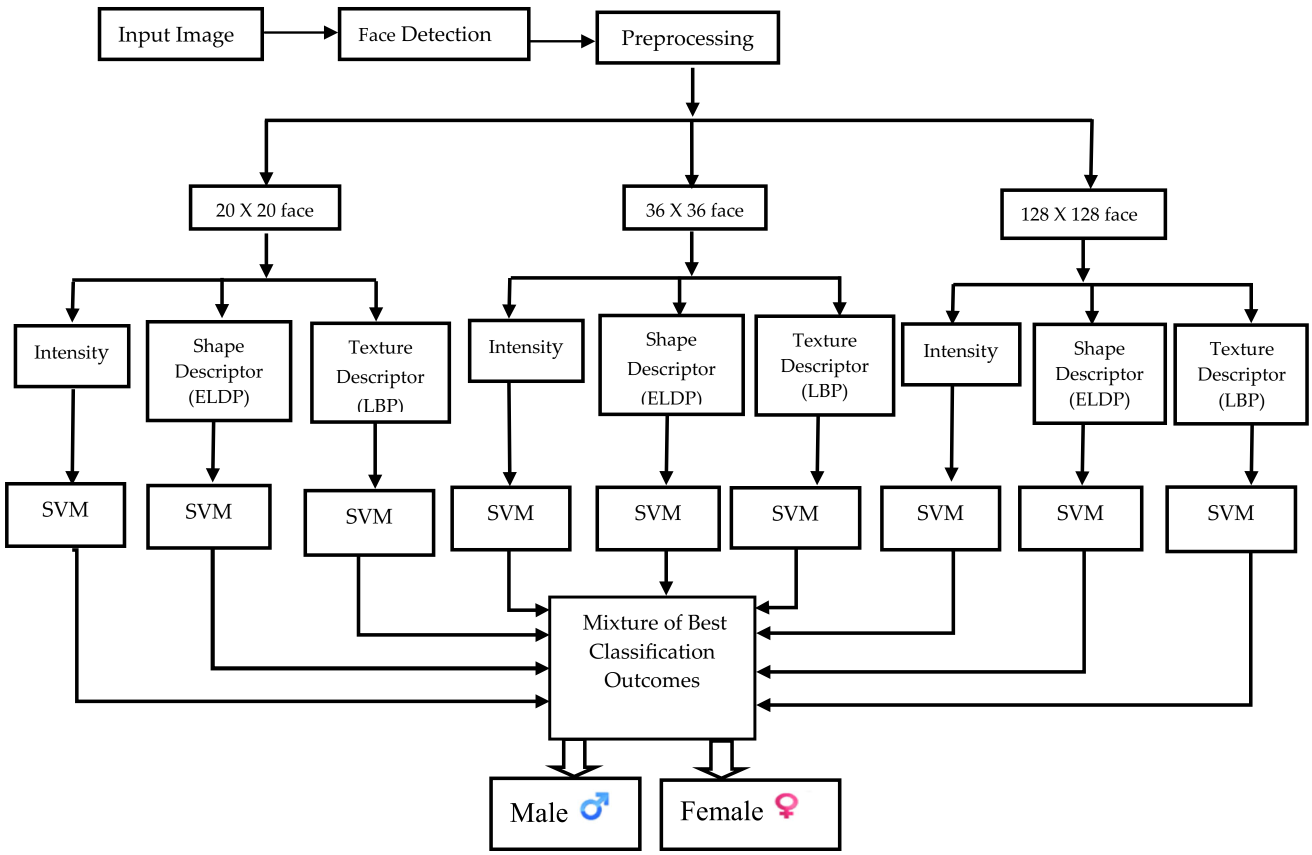


Fig. 2 Block diagram of proposed methodology

4.2 Image feature extraction

Conventionally, the gender classification is determined by multi-factors such as shape, texture, intensity level and characteristics of facial structure. After completion of preprocessing, it is necessary to extract important facial features.

In the proposed system, each image-discriminating feature is extracted using an effective descriptor. A robust face descriptor is followed in the proposed scheme called eight local directional patterns (ELDP) that analyze the edge features of an input image, which encodes information related to structural features of the face. The ELDP technique is the most suited one, which permits the intensity variation from bright to darkness and vice versa. Since it is also a compact one, it holds just 6-bit code to describe edge information. The method ELDP has an advantage compared to existing schemes like local directional number pattern (LDP) and local ternary pattern (LTP). The eight directional number patterns are derived from prominent Kirsch compass mask algorithm since it requires edge response of the image.

4.2.1 Shape features

Traditionally, shape features are extracted using histograms of edge direction, but in this approach, the input images are gray scale and no normalization to histograms is performed.

4.2.1.1 Eight local directional patterns (ELDP) ELDP is an eight-bit binary code that is assigned to every pixel in an input image. This code describes the shape and edge details of the image and transition of the intensity variations. In the existing schemes, major drawback is as the lighting condition changes, edge magnitudes are also changed. Since the edge responses are taken into account, compass mask algorithm was used. ELDP coding system is represented in Fig. 3. Relevant positive and negative information yields valuable data of neighboring pixels. ELDP code has been developed for each instance, and transitions occur frequently in the face.

4.2.1.2 Kirsch compass mask (KCM) algorithm In ELDP coding scheme, edge response is evaluated of all masks from M0, M1, M2, M3, M4, M5, M6 and M7 that describe respective directions and each directional number. ELDP code can be defined in mathematical equation as

$$\text{KCM:} \quad I_i = I_i * M_i \quad \text{where} \quad i = 0, 1, 2, \ldots, 7 \tag{1}$$

M_i = KCM mask; I = image blocks

$$\text{ELDP:} \quad B_i(x, y) = \begin{cases} 1 & I_i(x, y) > 0 \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

$$\text{ELDP}(x, y) = \sum_{n=0}^{7} B_i(x, y) * (2^n) \tag{3}$$

The Kirsch compass mask is used to derive edge response, and it is calculated from M_0, M_1… M_7. It is mainly operated in a gradient domain that gives actual structure of the face. Figure 4 shows eight-dimensional Kirsch compass mask and each rotated equally at 45°. Angle of rotation that differs between two adjacent pixels is 45° and is represented as 0°, 45°, 90°, 135°, 180°, 255°, 270°, 315° with respect to the next rotation. Figure 4 shows the set of matrix represents Kirsch masks that describe respective directions.

4.2.2 Texture features

Local binary pattern is one of the popularized methods to extract texture features that have been used in certain applications. For computational effectiveness, it is specifically used to incorporate monotonic gray-level variation and this makes LBP descriptor in demand compared to other descriptors. LBP operator assigns 8-bit binary number to each pixel, with respect to the center pixel value. Based on the intensity level at each pixel and its eight neighbors, the binary pattern was derived. This pattern can be viewed as a transformation of input image into the LBP operator.

To create a LBP pattern, the center pixel is compared with neighborhood pixel. If the center pixel value is greater than neighborhood, assign "0" to the neighboring pixel, if not assign "1." A center pixel with its q neighborhood evenly spaced pixel structure is shown in Fig. 5. Starting with $x_{0,0}$, patterns were calculated by comparing with their q neighborhood pixels.

From Fig. 5, local binary pattern is calculated as

$$\text{LBP} = \sum_{n=0}^{p-1} s(X_p - X_c) 2^n \tag{4}$$

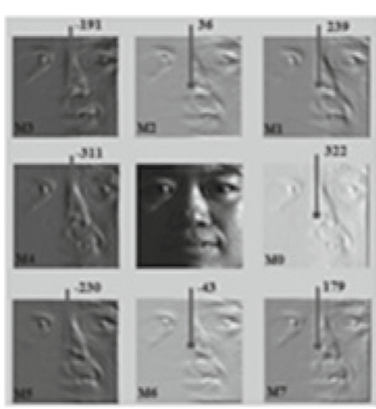
$$s(x) = \begin{cases} 1 & x \geq 0 \\ 0 & x < 0 \end{cases} \tag{5}$$

Figure 6 shows the overall process of local binary pattern to extract the image features. The following steps are used to create local binary pattern feature vector to help the descriptor for categorization. The steps are as follows:

- Dividing an image into cells (example 20 × 20 pixels of each cell)
- Each cell pixel value is compared with its neighboring pixels.
- It is true that center of pixel has higher value than each of its neighboring pixels. If it is high, write output as "0" else write "1." This binary output provides 8-bit binary code. For convenience, it may be transformed into decimal form. The basic LBP operator response is shown in Fig. 5.
- Next, calculate the histogram for over all cells depending on number of occurrences of output.
- After computation, normalization is made in each cell, and finally, the histograms from each block are concatenated to generate the feature vector.

4.3 Classification

After extracting crucial facial features, the final step is classification in which face is categorized as either male or female. In face analysis, several classifiers have been used, namely *k*-nearest neighbor, neural network and support vector machine. In this approach, SVM with the linear kernel method has been used for this binary classification.



-191 2	36 1	239 8
-311 3		322 7
-230 4	-43 5	179 6

ELDP:
10000111 = **135**

Fig. 3 ELDP code generation

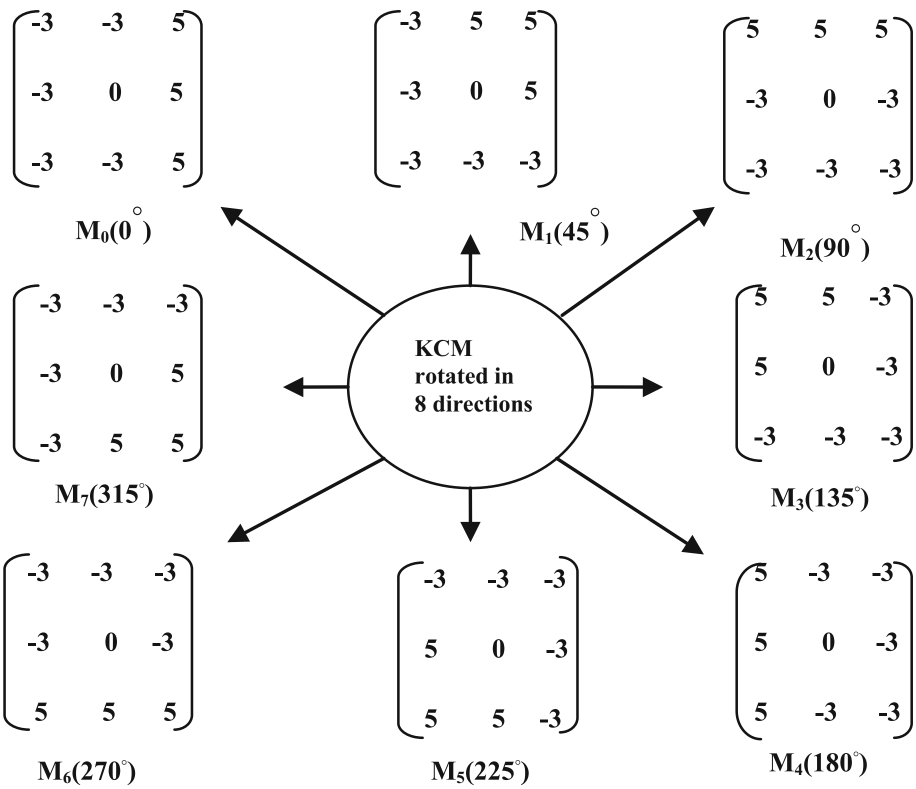


Fig. 4 Kirsch compass mask (KCM) algorithm

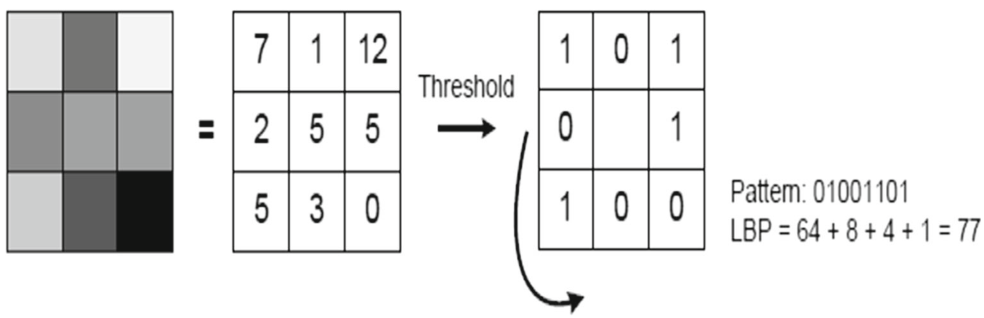


Fig. 5 Basic LBP operator

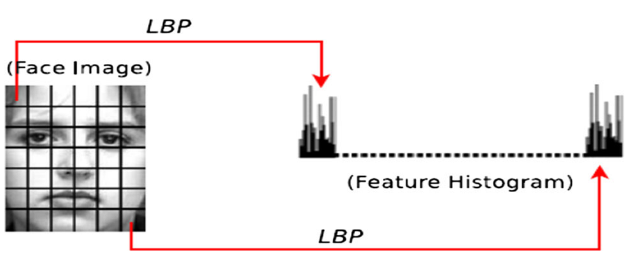


Fig. 6 Process of LBP feature vector extraction

A set of training examples is given, each marked for belonging to one of two categories; an SVM training algorithm builds a model that assigns new examples into one category or the other, making it a non-probabilistic binary linear classifier.

In this approach, in the first step, gender recognition performance has been evaluated by using the intensity pixels directly using SVM. In the next step, the gender recognition performance of shape and texture features has been evaluated using SVM.

5 Experimental results

5.1 A new dataset

In this approach, a dataset called FEI is used to prove the effectiveness of the proposed algorithm. A new self-built dataset is created and used. A self-built dataset is taken with the smile under normal illumination condition.

This dataset has the following characteristics: It has a total of 200 images; training set contains 50 images of each gender; test set contains 50 female and 50 male images. No person has two images in the dataset: This prevents the

Table 1 Number of images used in experimental datasets and their sizes

Dataset	Image size	Total number	Train		Test	
			Male	Female	Male	Female
FEI	100 × 100	200	50	50	50	50
Self-built dataset	100 × 100	200	50	50	50	50

Table 2 Classification accuracy based on intensity values

Image size	Classification accuracy	
	FEI dataset (%)	Self-built dataset (%)
20 × 20	94	67
36 × 36	95	77
128 × 128	89	79

classifiers from learning to recognize persons instead of gender. Images in the test set are more difficult than in the training set. There are more images captured in a normal illumination and with smile expression than in the training set, thus making the test set more challenging than the training set.

The experiments were performed with one public available dataset FEI and a self-built dataset with the expression. All the tables show the classification accuracy which was obtained for the test sets. Details of these datasets are in Table 1.

5.2 Intensity values

The principal set of results assesses the gender classification execution utilizing the intensity pixels specifically. The classifier gets each face image as a solitary vector with a size equivalent to the quantity of pixels in the image. The classification accuracy obtained is exhibited in Table 2.

With respect to FEI dataset classification results, the best recognition rate (95%) is acquired utilizing 36 × 36 image sizes. Results for the 20 × 20 image size are near to the above one (94%).

For the self-built dataset, the circumstance is turned around: The best outcomes are acquired with the 128 × 128 image size (79%), while the other two image sizes accomplish the lesser outcome than greater size image. These outcomes affirm the thought that the self-built dataset presents a more troublesome issue than the FEI dataset since the best outcomes acquired are 15% worse than the ones got in the FEI dataset.

5.3 Shape features

The classification accuracy of shape features is displayed in Table 3. The best outcomes were acquired for both datasets, utilizing images of 128 × 128 and block size of 32 × 32 with overlapping. The best outcome for each dataset in various image sizes is in bold face.

The shape and texture feature extraction was not done on the full image, but rather on small blocks with and without overlapping. Contingent upon the image size, diverse block sizes were also tried. A variation is the utilization of overlapping blocks, and for this situation, the blocks have half-overlap both vertically and horizontally. Figure 7 demonstrates a comparison chart of classification accuracy dependent on shape features.

Table 3 Classification accuracy based on shape features

Image size	Block size	Classification accuracy	
		FEI gray (%)	Self-built expression (%)
20 × 20	5 × 5	90	78
	10 × 10	84	75
	10 × 10 overlap	86	77
36 × 36	6 × 6	94	70
	9 × 9	94	72
	9 × 9 overlap	95	78
	18 × 18	86	77
	18 × 18 overlap	88	80
128 × 128	16 × 16	95	91
	32 × 32	96	85
	32 × 32 overlap	97	92
	64 × 64	95	87
	64 × 64 overlap	92	85

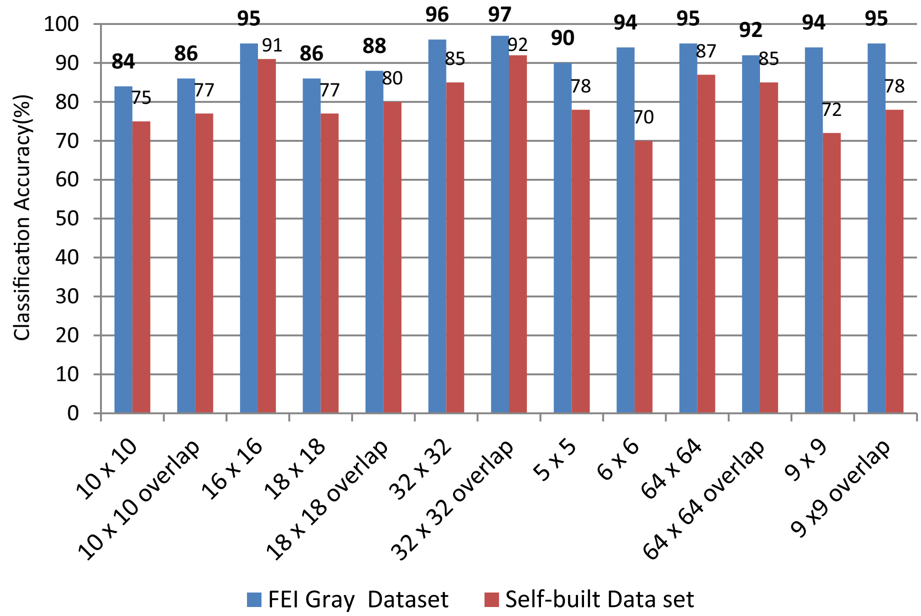


Fig. 7 Classification accuracy based on shape features

Table 4 Classification accuracy based on texture features

Image size	Block size	Classification accuracy (%)	
		FEI gray	Self-built expression
20 × 20	5 × 5	86	70
	10 × 10	84	78
	10 × 10 overlap	83	79
36 × 36	6 × 6	91	78
	9 × 9	95	75
	9 × 9 overlap	92	77
	18 × 18	81	76
	18 × 18 overlap	75	78
128 × 128	16 × 16	98	86
	32 × 32	98	84
	32 × 32 overlap	95	81
	64 × 64	96	83
	64 × 64 overlap	90	78

5.4 Texture features

Next, the gender classification execution utilizing the LBP features was assessed. For the FEI dataset, the non-overlapped block classification was dependably as great or superior to the overlapped for all the image sizes. In the self-built data collection, this occurred in three out of five cases. In Table 4, classification accuracy with texture feature is shown in percentage.

The best outcome for the FEI dataset acquired with the texture feature is 98% with 128 × 128 image size and 16 × 16 block size. For the self-built dataset, the shape features completed a superior job. The best outcome utilizing texture features with 128 × 128 image size and 16 × 16 block size was 86% versus the 91% acquired by the shape features. Figure 8 demonstrates a comparison chart of classification accuracy dependent on texture features.

5.5 Mixture of classifier outcome

In this section, a mixture of crosswise over image sizes and block sizes is introduced. The best outcome of the SVM classifier for each dataset in various image sizes and block sizes which are marked in bold face is added columnwise. Next, the classification is performed on rowwise by counting the maximum number of gender classes in each row. Suppose if the count of both classes will be the same, then it is assigned to classify as male. From this, it is known that data from various scales, regardless of whether just from a single-scale feature could really better compare to having data from various distinct features at a single scale. Table 5 indicates classification accuracy by combining the best outcome of SVM got from the past three methods.

The final classification accuracy was acquired by mixing the outcome of SVM classifier, and it is very much seen that the proposed methodology got the best outcomes for both datasets. In any case, there is still opportunity to get better given that there were six images wrongly classified out of the 100 test images (94% accuracy). Figure 9 displays the comparison chart of classification accuracy dependent on mixed outcome of various scales, distinct and prime descriptors.

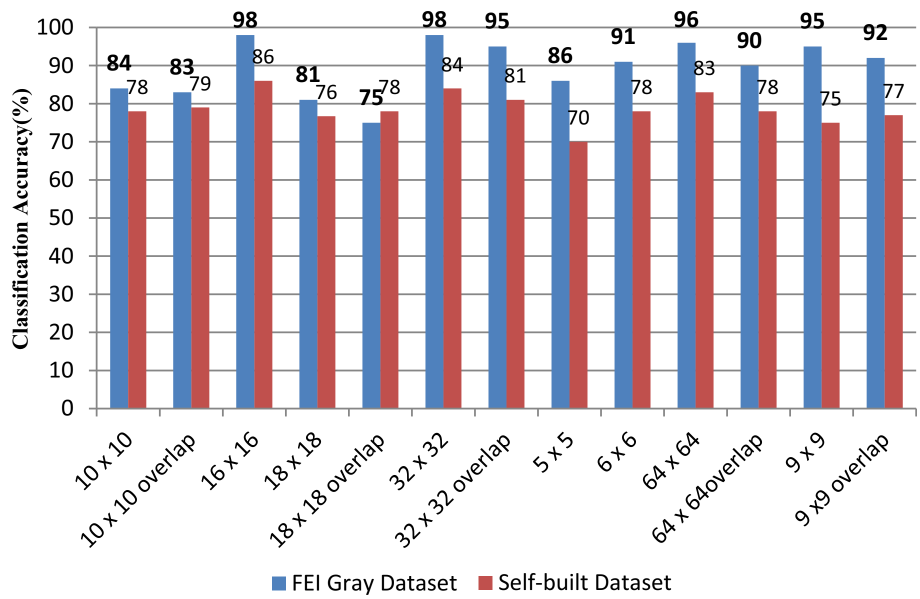


Fig. 8 Classification accuracy based on texture features

Table 5 Classification accuracy after fusion of intensity, shape and texture features

Dataset	Classification accuracy					
	FEI gray			Self-built expression		
Gender	Male	Female	Overall (%)	Male	Female	Overall (%)
Intensity, shape and texture results of multi-scale	50	49	99	49	45	94

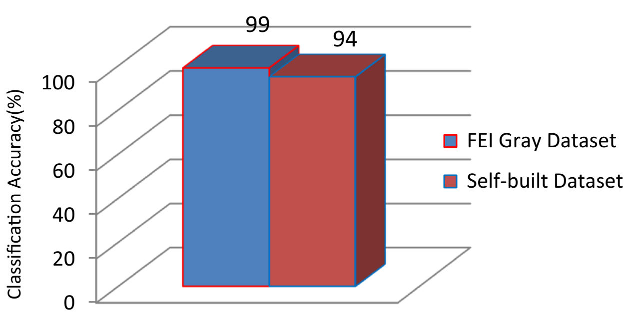


Fig. 9 Classification accuracy after fusion of intensity, shape and texture features result from multi-scale

6 Conclusion

This paper discussed an exploratory examination on gender classification of face images that demonstrate the impact of various features combination approaches depending on the outcome of various features from numerous scales that can enhance gender recognition precision. An assessment was done on three diverse image sizes, eight block sizes with and without overlap and three distinct feature types and on two different datasets (FEI dataset with 200 face images and a self-built dataset with 200 face images). The gender classification accuracy with mixed outcomes of various scales and distinct descriptors obtained for the FEI dataset is 99% and for self-built dataset is 94%. Future work incorporates the utilization of this technique to other non-cooperative environment factors such as occlusion, low illumination and pose variation and extended to enhance the accuracy by minimizing the false recognition rate.

Compliance with ethical standards

Conflict of interest The authors of the paper declare that they have no conflict of interest.

Ethical approval There is no human/animal involved in this research work. We agree that we have used our own data.

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