ACCURATE AGE RANGE PREDICTION SYSTEM OF INDIVIDUALS FROM FACIAL IMAGES

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Abstract: Age prediction is an active study field that can substantially affect on many computer vision problems like object recognition. In this paper, an accurate system with extensive experiments is proposed in order to provide an efficient and accurate approach for age range prediction of people from their facial images. Histogram Equalization technique used to reduce the illumination effects on all facial images taken from FG-NET and UTD aging databases, and image resizing used to unify all image's size. Moreover, Histogram of Oriented Gradient (HOG) and Local Binary Pattern (LBP) are used to extract the features of these images. Then, Support Vector Machine (SVM) and k-Nearest Neighbor (k-NN) are used for the classification processes. To evaluate the performance of proposed system, both Leave-One-Out (LOO) and Confusion Matrix (CM) are used. The extensive and intensified experiments improved the age range predicting performance up to 98.6%.

Keywords: Facial Images, Local Binary Pattern (LBP), Histogram of Oriented Gradient (HOG), SVM, kNN.

INTRODUCTION

Human faces are rich in details, such as age, gender, ethnic, emotions, skin color, etc. Whereas, these abilities that human being have aren't available in machines. Therefore, researchers have been trying to design and develop accurate systems to make the machine meet these challenging tasks. The age prediction of people is one of these tasks; and it is an interesting field of research and has been given increased attention in recent years.

Predicting a person's age from his/her face image isn't easy because of the large variation of face appearances, like variety of human race, poses, and facial expressions. However, age prediction has been recognized as an important module for many computer vision applications such as demographic profiling, forensic art, age-specific human-computer interfaces, security control, age-oriented advertisement systems, and electronic customer relationship management (ECRM).

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In general, age prediction approaches are divided into two different groups that are: Age Group Classification and Actual Age Estimation (cumulative years lived). In Age Group Classification, the age range is divided into classes, each class has a range of years (e.g., from 10 to 20 years). On the other hand, in the Actual Age Estimation, we need to determine the specific and correct age of the people, which is usually based on regression methods or a hybrid of classifications and regressions to give an exact number of the age. This study focuses on Age Group Classification approach by dividing the age ranges into 11 classes.

RELATED WORKS

There are many applications and studies trying to predict the age of individuals from facial images. A study related to age prediction based on the use of Anthropometric Models (AM) for age classification was introduced in 1994 by Kwon and Lobo (Ramanathan *et al*, 2009). It is aimed to find the primary features of the face such as eyes, mouth, nose, and chin. Furthermore, an Appearance Model (APM) (Hayashi *et al*, 2002) is also used to determine the density of wrinkles in each face using the snake-lets (Kass *et al*, 1988). They create a facial database for their study, which contains 47 faces, and then divided the images into three age groups; babies, young adults, and senior adults. As a result, 77% successes are obtained. (Lanitis *et al*, 2004) used the Active Appearance Model (AAM) (Cootes *et al*, 2001) for age prediction. They extracted facial features of 500 images from 0 to 35 years old people by using PCA. To estimate the age, they adopted the Neural Network for classification of data, and reported 94.42% age prediction performance. (Guo *et al*, 2008) similarly used the AAM to estimate the age of 500 facial images from FG-NET (Panis *et al*, 2016) database between 0 to 69 years old people. Images features have been extracted by using a Locally Adjusted Robust Regresses (LARR). Then, SVM and Support Vector Regression (SVR) methods are investigated to classify the age. The results of their experiments showed 94.93% success estimation rate. (Kanno *et al*, 2001) used an APM to determine the density of wrinkles and extract the information of the faces. Consequently, accuracy of 80% has been achieved when Artificial Neural Networks (ANN) has been employed to classify four age groups of 110 facial images that were selected from FG-NET aging database. (Bauckhage *et al*, 2010) offered an accurate and efficient approach for age prediction from facial images. They combined HOG and Compute histograms of range filter. They trained their system on UTD database and the FG-Net database. As a result, in a first experiment, they verified whether the algorithm correctly ordered the two images and they measured an accuracy of 77%. In a second experiment, they fixed the candidate images to strictly frontal pose of faces. As a result, the classification accuracy has been improved up to 85%.

(Iga *et al*, 2003) used graph matching with Gabor Wavelet Transformation (GWT) to extract image's information such as, skin color, moustache, hair, etc. All these information were classified by applying SVM on 300 facial images divided into 6 age groups from 15 to 64 years old and taken from Softopia Japan HOIP database. Consequently, they achieved to 67.4% age estimation rate. Yang and Ai (2007) employed LBP feature extractor to know the Chi square distance between the extracted LBPH and a reference histogram. Moreover, real Adaboost algorithm was used as a strong classifier, which learns a sequence of best local features. By using 696 images from PIE (Sim *et al*, 2002) database, accuracy of 92.12% age prediction has been achieved. Shirkey and Gupta (2013) developed an age recognition algorithm based on rectangle features method that are used to describe sub-regions of a human face, and hence component wise data can be transformed from pixel-wise data. A ratio of 85% for age classification was achived. Fazl-Ersi *et al* (2014) compared three methods, that are LBP, Color Histogram (CH) and Scale-Invariant Feature Transform (SIFT) to predict the age range. Moreover, they used SVM classifier to classify the features that are extracted from images obtained from Gallagher facial images database (Gallagher & Chen, 2009). As a result, they obtained the best accuracy by combining LBP, CH, and SIFT features, which is reported 63.01% age estimation. Eidinger *et al*, (2014) used LBP and the related Four Patch LBP codes (FPLBP) to learn and extract the most important properties of images features. These images have been selected from Gallagher database. By combining LBP and FPLBP features and SVM, they achieved an accuracy of 80.7% of age estimation.

MATERIALS AND METHODS

The core and methodology of the proposed system mainly rely on four phases: pre-processing phase; feature extraction phase, classification phase, and evaluation phase (Fig. 1).

Pre-processing Phase

Solving age prediction problem requires overcoming some main difficulties, such as differing image dimensions and qualities, varying levels of luminosity, choosing appropriate database for each problem, and employing sufficient number of images in each experiment. Therefore, FG-NET and University of Texas at Dallas (UTD) Database have been employed, and Histogram Equalization (HE) technique and dimensions alignment (image re-sizing) have been used to help solving age prediction problem.

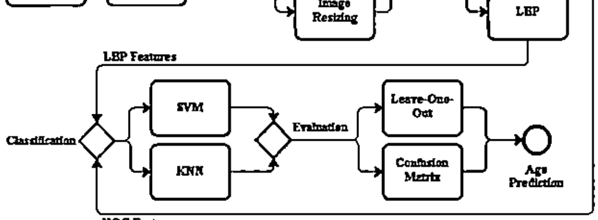

Fig. 1. General Methodology of Age Prediction System

Databases

Two aging databases that are FG-NET database (Panis *et al*, 2016) and UTD Database were used. A non-commercial FG-NET aging database (Fig. 2) was released in 2004 for understanding the changes in facial appearance caused by the age and other disciplines such as age progression, age estimation, age-invariant face recognition, or any other academic research-related activities. The FG-NET database contains 1,002 facial images from 82 different individuals that age ranging from 0 to 69 years old. Another database named UTD (Fig. 3) were provided for age prediction. It contains 580 facial images of people from 18 to 99 years old, where 352 of these images are female and 228 images are male. Furthermore, UTD can be used also for emotional recognition because all images in the database are detailed with face expressions such as happy, angry, annoyed, disgusted, grumpy, sad, and surprised.

However, in this study we combined both FG-NET (1,002 images) and UTD (580 images) databases to obtain huge database, including 1,582 facial images. All images distributed on 11 main classes; each class has a period of ages between 0 and 99 (Table 1).

Illumination Normalization

To normalize the illumination of the facial images, Histogram Equalization (HE) technique was applied. HE helps to reduce the effect of light and unify luminosity of all images in the databases, and this positively affects the accuracy and performance of the system.

Histogram Equalization (HE) (Dey *et al*, 2013) is a fast, simple and effective image illumination enhancing technique, which can effectively confirms the details of the density in any region.

Dimensions Alignment (Image Re-sizing)

Each image within selected databases has a different resolution dimensions (more than 400×400). Therefore, image re-sizing was applied to decrease the size of images, and make all image's size equal (all images = 192×128 size). This has advantages of helping the feature extractor algorithm to extract same number of features from all images. Moreover, it helps to decrease the processing time, and hence increases the system performance.

Feature Extraction Phase

Two different feature extraction algorithms are used. The details of these algorithms are given below.

Histograms of Oriented Gradients (HOG)

HOG was introduced by Dalal and Triggs (2005), which became later one of the excellent local feature descriptors that has largely been used in computer vision and image processing. It has given promising performance in variety of computer vision problems related to object detection and recognition as an appearance based feature extraction method. In addition, HOG has many advantages such as the easy to use with discriminate classifiers. Due to its ability to capture shape of an object from edges (gradients), HOG gives good results to identify object from cluttered background without using any segmentation algorithm.

HOG algorithm follows some substantial steps to describe objects in the images; first, it divides

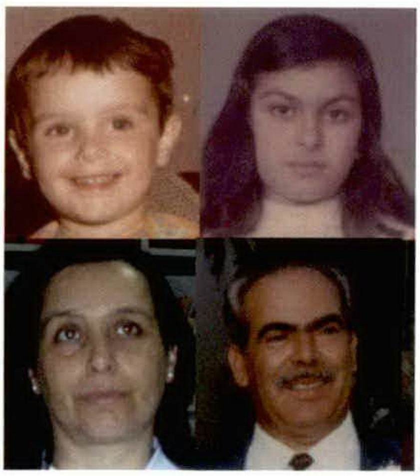

Fig. 2. Examples from FG-NET Database

Fig. 3. Examples from UTD Database

Table 1. The Number of Images in Aging Database (FG-NET & UTD)

Databases	The Age Classes											Total
	0 to 15	16 to 20	21 to 25	26 to 30	31 to 35	36 to 40	41 to 45	46 to 50	51 to 55	56 to 60	+60	
FG-NET	575	155	81	61	39	31	26	13	12	1	8	1,002
UTD	0	53	132	42	23	19	19	16	16	8	252	580
Total	575	208	213	103	62	50	45	29	28	9	260	1,582

the input image into blocks, and divides each block into smaller connected cells. Then it computes a histogram of gradient directions for all the pixels within the cell. According to these gradient orientations, each pixel reshaped into angular bins and then participated gradient to its parallel bin. Then it normalizes the group of cells (block) histograms, which represent a one-dimensional array of histograms called the descriptor (Mary *et al*, 2013).

LBP Features

The LBP, which was presented by Ojala *et al* (2002), is an efficient and powerful texture descriptor that is widely used in image processing and computer vision areas as a feature and histogram representation. LBP algorithm has the ability to capture the shape of body in the image by looking to each pixel's neighbors. The main LBP mechanism is that the input image is divided into local regions composed of a '3×3' neighborhood of pixels. Then, type of binary pattern assigned a label to each pixel according to its intensity value, where the distribution of these binary patterns in each block represents the results with an 8-bits integer, where the calculation of these patterns are represented as a one-dimensional array of patterns used as a feature representation (Ojala *et al*, 1996).

Classification Phase

k-Nearest Neighbour (k-NN) and Support Vector Machine (SVM) are used in the presented work as a classifers. The details of the classifiers are given below.

k-NN

k-NN is one of the simplest classifiers for predicting the class of a test sample used in machine learning, which is based on training samples that are very close to each other in the features scope (Wu *et al*, 2008). The main idea of the k-NN classifier mechanism is based on calculating and computing the distances between all training objects to test object, then finding and gathering a collection of k objects in the training set that are nearest to the test object, and finally calculating the average of them (see Fig. 4). Although the k-NN classifier performance is highly sensitive to the number of k value and the results are affected by any changes in it, k-NN classifier is widely used and very easy to implement in many classification problems. However, determining k value is very complex step because it is affected by the parameters like the type of feature extractor algorithm, and number of samples that is available in training set (Sudha & Bhavani, 2012).

Fig. 4 shows the mechanism of k-NN classifier. It is based on the value of k, which is used to compute the distances between training objects (circular shapes) and test object (star shape). For instance, in case of considering k value = 3, k-NN classify the closest 3 training objects to the test object, and then calculates the average of them. In this case, the star as purple-circle. Similarly, in case of considering k value = 6, k-NN classify the closest 6 training objects to the test object, and then calculates the average of them. In this case, the star classified as yellow circle.

SVM

SVM was developed by Cortes and Vapnik (1995) and has extensively been used as a powerful classification algorithm for pattern recognition applications. In addition, it gives promising and excellent performance on the range of machine learning by applying it to different classification problems, data separation, regression, and density estimation (Begg *et al*, 2005).

SVM classifier has many advantages, which make it one of the accurate and robust algorithms, such as:

- Gives promising performance even with small number of images in training set.
- Not sensitive to the number of dimensions,

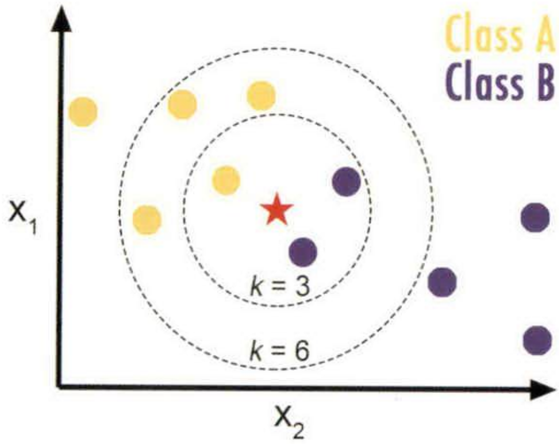

Fig. 4. Basic Concept of k-NN

which gives it promising performance with any images size.

- Ability to minimize empirical and structural risk, which leads to better generalization for data classification.

The main task of SVM is based on searching for the OSH "Optimal Separating Hyper-plane", which is the closest point between two classes (positive and negative samples) of data in the training set. By increasing the margin between these classes, SVM can modify the input data into a high-dimensional feature space where a hyper-plane may be found. Furthermore, it can reduce the structural risk; hence reducing the number of predictable errors (Sudha & Bhavani, 2012). However, the nearest OSH data to the border of each class are called the "Support Vectors" (Fig. 5).

Fig. 5 shows how SVM classifier can distinguish between two classes, where the Class 1 (star shapes) contains the positive features; and Class 2 (circular shapes) contains the negative features. SVM starts increasing the margin between the two classes bit by bit to find the OSH, which are the closest points between these classes. The OSH features in each class (orange color) are known as "Support Vectors" and used by SVM in classification process.

Evaluation Phase

Leave-One-Out Cross-Validation (LOO) technique

Leave-One-Out Cross-Validation (LOO) mechanism is simple; the dataset is split into N subsets, where N is the number of samples in the dataset. Then, the classification process is repeated N times, in each time, N-1 of subsets are used to train the classifier, and only one subset is selected for evaluation. In this study, Leave-One-Out technique have been applied on FG-NET and UTD databases in order to evaluate the performance of SVM and k-NN classifiers.

Confusion Matrix

The confusion matrix, which is also called an error matrix or a contingency table, provides a simple detail and visualization about predicted and actual classes that are accomplished by a classifier. The systems performance is generally evaluated by using the details mentioned in this matrix. Fig. 6 shows the confusion matrix layout of a two classification classes.

Each column in the above table shows the number of actual and correct class samples, whereas each row shows the number of predicted class samples. In more details, "True Positive" is the number of true or correct predictions that an example is positive. "False Negative" is the number of false or incorrect predictions that an example is negative. "False Positive" is the number of false or incorrect predictions that an example is positive. "True Negative" is the number of true or correct predictions that an example is negative.

EXPERIMENTAL CLASSIFICATION RESULTS AND ANALYSIS

As mentioned previously, FG-NET aging database contains 1,002 facial images, whereas UTD database contains 580 facial images. Therefore, both databases are combined in one bigger database containing 1,582 facial images, and then separated these images into 11 classes depending on their ages. We review all experiments done in order to predict the age range of people in the following sub-sections.

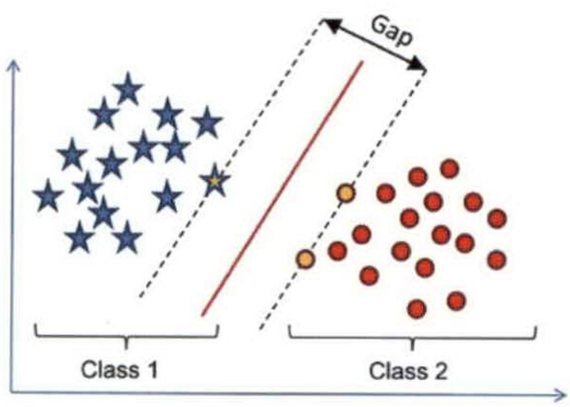

Fig. 5. Basic Concept of SVM

		Actual (as confirmed by experiment)	
		positives	negatives
Predicted (predicted by the test)	positives	TP True Positive	FP False Positive
	negatives	FN False Negative	TN True Negative

Fig. 6. Confusion Matrix

SVM Based Classification

The SVM classifier has been trained on 1,582 images from FG-NET and UTD databases by using Leave-One-Out technique. Consequently, when the HOG features are used with SVM, age prediction accuracy was 98.60%, whereas, when LBP features are used with SVM, the accuracy was 98.29%. Table 2 shows the performance of the proposed methods. In addition, the classifiers are evaluated by using Confusion Matrix (CM), which provides details and visualization about predicted and actual classes that are accomplished by the SVM classifier with HOG and LBP features, as shown in Tables 3 and 4.

As can be seen from the tables, the errors occur on the neighbour classes. For example, the error on the 56-60 age-range class is on (up to 60) class. This shows that the person on the age range of 56-60 is predicted to be in up to 60 age range.

k-NN Based Classification

The k-NN classifier was applied on 1,582 images from FG-Net and UTD databases by using Leave-One-Out technique. k-NN classifier performance is highly sensitive to the number of k value and the results are affected by any changes in it. Moreover, determining k value is not easy, because it is effected by the parameters like number of samples that obtained in training set, and the type of used feature extractor algorithm. Therefore, in this study, many extensive experimentations have been done in order to determine the best optimal k value that can give high performance (Fig. 7).

As can be seen from the Fig. 7, changing k value from 1 to 30 is leading to attain different performance. In addition, it is observed that the best performance can be achieved when k value is equal to 12 and 19 in case of using HOG and LBP features, respectively. Consequently, when the HOG features are used with k-NN, age prediction accuracy were 98.23%. Similarly, when LBP features are used with k-NN, the accuracy were 88.05%, in case of considering k value = 19. Table 5 shows the summary of the performance of the proposed method. In addition, the evaluation of classifiers is performed by using Confusion Matrix (CM), which provides simple details and visualization about predicted and actual classes that accomplished by the k-NN classifier with HOG and LBP features, as shown in Tables 6 and 7.

DISCUSSION AND CONCLUSION

In order to predict the age range of any person from his/her face image, many extensive experimentations were carried out to make the classifiers obtain high accuracy and performance. In this paper, an efficient and accurate approach was proposed by processing extracted HOG and LBP features from images, while SVM and k-NNare used for classification. Moreover, dimensions alignment that used to reduce the computation cost, and Histogram Equalization technique that used to minimize the illumination effects in different images, had been applied successfully on all images to obtained promising and accurate results. Furthermore, the extensive experiments confirm that using proposed method with correct k value-when using k-NN classifier-lead to achieve excellent performance.

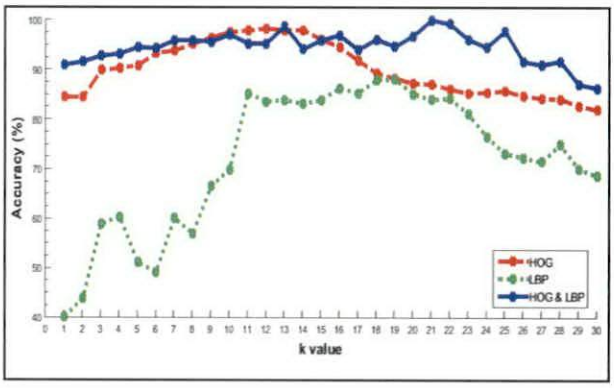

Fig. 7. The Performance of k-NN Based Classification According to 'k' Value

Table 2. SVM Based Age-Classification of FG-NET and UTD Databases

Method	Dataset	Accuracy
HOG + SVM	FG-NET + UTD	98.60%
LBP + SVM	FG-NET + UTD	98.29%

Table 3. Confusion Matrix Evaluation of HOG + SVM

		Actual Classes										
	0-15	16-20	21-25	26-30	31-35	36-40	41-45	46-50	51-55	56-60	Up 60	
Predicted Classes	0-15	574	1	0	0	0	0	0	0	0	0	0
	16-20	1	206	1	0	0	0	0	0	0	0	0
	21-25	0	1	211	0	0	0	0	0	0	0	0
	26-30	0	0	0	102	0	0	0	0	0	0	0
	31-35	0	0	0	0	60	0	0	0	0	0	0
	36-40	0	0	0	0	1	47	1	0	0	0	0
	41-45	0	0	0	0	0	1	43	0	0	0	0
	46-50	0	0	0	0	0	0	0	26	0	0	0
	51-55	0	0	0	0	0	0	0	0	24	0	0
	56-60	0	0	0	0	0	0	0	0	0	7	0
	Up 60	0	0	1	1	1	2	1	3	4	2	260
Total		**575**	**208**	**213**	**103**	**62**	**50**	**45**	**29**	**28**	**9**	**260**

Table 4. Confusion Matrix Evaluation of LBP + SVM

		Actual Classes										
	0-15	16-20	21-25	26-30	31-35	36-40	41-45	46-50	51-55	56-60	Up 60	
Predicted Classes	0-15	575	1	0	0	0	0	0	0	0	0	0
	16-20	0	205	0	0	0	0	0	0	0	0	0
	21-25	0	0	211	0	0	0	0	0	0	0	0
	26-30	0	0	0	101	0	0	0	0	0	0	0
	31-35	0	0	0	0	60	0	0	0	0	0	0
	36-40	0	0	0	0	0	48	0	0	0	0	0
	41-45	0	0	0	0	0	0	43	0	0	0	0
	46-50	0	0	0	0	0	0	0	27	0	0	0
	51-55	0	0	0	0	0	0	0	0	25	0	0
	56-60	0	0	0	0	0	0	0	0	0	0	0
	Up 60	0	2	2	2	2	2	2	2	3	9	260
Total		**575**	**208**	**213**	**103**	**62**	**50**	**45**	**29**	**28**	**9**	**260**

Table 5. k-NN Based Age-Classification of FG-NET and UTD Databases

		Actual Classes										
	0-15	16-20	21-25	26-30	31-35	36-40	41-45	46-50	51-55	56-60	Up 60	
Predicted Classes	0-15	575	5	0	0	0	0	0	0	0	0	0
	16-20	0	202	0	0	0	0	0	0	0	0	0
	21-25	0	1	212	1	0	0	0	0	0	0	0
	26-30	0	0	1	102	0	0	0	0	0	0	0
	31-35	0	0	0	0	62	0	0	0	0	0	0
	36-40	0	0	0	0	0	50	0	0	0	0	0
	41-45	0	0	0	0	0	0	45	8	0	0	0
	46-50	0	0	0	0	0	0	0	20	2	0	0
	51-55	0	0	0	0	0	0	0	1	26	1	0
	56-60	0	0	0	0	0	0	0	0	0	0	0
	Up 60	0	0	0	0	0	0	0	0	0	8	260
Total		**575**	**208**	**213**	**103**	**62**	**50**	**45**	**29**	**28**	**9**	**260**

Table 6. Confusion Matrix Evaluation of HOG + k-NN

		Actual Classes										
	0-15	16-20	21-25	26-30	31-35	36-40	41-45	46-50	51-55	56-60	Up 60	
Predicted Classes	0-15	575	127	2	0	0	0	0	0	0	0	0
	16-20	0	76	6	0	0	0	0	0	0	0	0
	21-25	0	5	204	4	0	2	0	0	0	0	0
	26-30	0	0	0	99	0	0	0	0	1	0	0
	31-35	0	0	0	0	49	0	0	0	0	0	0
	36-40	0	0	0	0	0	30	0	0	0	0	0
	41-45	0	0	0	0	0	0	43	0	0	0	0
	46-50	0	0	0	0	0	0	0	26	0	0	0
	51-55	0	0	0	0	1	0	0	0	25	0	0
	56-60	0	0	0	0	0	0	0	0	0	6	0
	Up 60	0	0	1	0	12	18	2	3	2	3	260
Total		**575**	**208**	**213**	**103**	**62**	**50**	**45**	**29**	**28**	**9**	**260**

Table 7. Confusion Matrix Evaluation of LBP + k-NN

Method	Dataset	Accuracy
HOG + k-NN (k = 12)	FG-NET + UTD	98.23%
LBP + k-NN (k = 19)	FG-NET + UTD	88.05%

Consequently, the experimental results show that when SVM is used the performance is on the range of 98% for each feature extractor (HOG and LBP). However, comparing with other similar studies like (Guo *et al*, 2008 and Bauckhage *et al*, 2010) that are discussed previously, our results are promising and significant, where the best result achieved by (Guo *et al*, 2008) was 94.93% success age estimation by applying LARR + SVM on 500 images from FG-Net database. Similarly, the best accuracy that achieved by (Bauckhage *et al*, 2010) was 85% by applying HOG + Random-forests on UTD and FG-Net databases. Whereas, the age prediction accuracy of all 1,582 experimental images has been achieved upto 98% when using our proposed methods.

However, LOO technique has a disadvantage that it may consumes longer-processing time when applying it on large amount of data, because it evaluates all images we have in the dataset one by one. Another disadvantage is that we directly used facial images to test the performance of the proposed methods, so detecting faces in the images is out of scope to this work.

RECOMMENDATION

In future work, it would be much better results if the researcher plan to focus on predicting the exact age of the people instead of age-range.

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