Gender classification using fisherface and support vector machine on face image

Muhammad Noor Fatkhannudin[1,*], Adhi Prahara[2]

Informatics Department, Universitas Ahmad Dahlan
Jalan Ring Road Selatan, Tamanan, Banguntapan, Bantul, Yogyakarta 55191, Indonesia
[1] muhammad1400018197@webmail.uad.ac.id
[2] adhi.prahara@tif.uad.ac.id
* corresponding author

ARTICLE INFO

Article history
Received
Revised
Accepted

Keywords
Classification
Gender Detection
Face Features
Fisherface
SVM

ABSTRACT

Computer vision technology has been widely used in many applications and devices that involves biometric recognition. One of them is gender classification which has notable challenges when dealing with unique facial characteristics of human races. Not to mention the challenges from various poses of face and the lighting conditions. To perform gender classification, we resize and convert the face image into grayscale then extract its features using Fisherface. The features are reduced into 100 components using Principal Component Analysis (PCA) then classified into male and female category using linear Support Vector Machine (SVM). The test that conducted on 1014 face images from various human races resulted in 86% of accuracy using standard k-NN classifier while our proposed method shows better result with 88% of accuracy.

1. Introduction

Biometric features such as face, fingerprints and gender now widely used in smartphone security verification. Biometrics is an approach for identifying one's identity based on physical traits or character. The utilization of biometric features has advantages because they have unique criteria. Biometric features also hard to emulate or stolen because they refer to a person's physical characteristics such as voice, face, fingerprints or eyes. Face is one of the easiest physiological measurement and it is often used to distinguish the identity of human beings. The human brain has the ability to recognize and distinguish human face quickly and easily. The information that can be obtained from a person's face are gender, expression, age, and human race.

Every human race has different facial characteristics that are not easy to imitated. Some of the characteristics are shape of face, nose, and hair, skin color, hair color, and eyes color. The most prominent difference that can be seen easily is the difference in skin color between human race. However, in some human races as in Mongoloid and Negroid, the facial characteristics of male and female are similar which make them difficult to identify the gender. This case is one of the challenge in gender classification from facial features. The other challenges are various face poses and the lighting condition when the face image is taken.

Gender classification has been developed by many researchers using various methods such as Local Directional Pattern (LDP) [1], Local Binary Pattern (LBP) [2], Convolutional Neural Network [3], and Fisherface [4] to represent facial features for gender classification. In [1], the area of face is divided into small regions. Face features are extracted to create LDP histogram. Support Vector Machines (SVM) then used to classify the features to predict gender. Experimental result using FERET face database achieved 95.05% accuracy [1]. The experimental result of Convolutional Neural

Network (CNN) shows that transferred deep CNN outperform the GilNet CNN model on the Adience dataset. The performance increases 4.5% in accuracy [3]. Fisherface method was chosen because of its advantages over limited data in the systems. The accuracy of facial recognition using fisherfaces is 90% [4].

Gender classification using Support Vector Machine (SVM) are investigated on low resolution "thumbnail" faces with size 21-by-12 pixels. The model is trained from 1,755 images of the FERET face database. The performance of SVM is superior to traditional classifiers such as Linear, Quadratic, Fisher Linear Discriminant, Nearest-Neighbor, Radial Basis Function (RBF) and large ensemble-RBF networks. SVM also tested with the same task on 30 test subjects, ranging in age from mid-20s to mid-40s, resulted 32% average error rate for the thumbnails faces and 6.7% with higher resolution images [5]. SVM also used in other topics of research as in [6]–[13].

In this research, the gender classification is done using Fisherface and SVM. Fisher developed Linear Discriminant Analysis (LDA) in 1930. Linear/Fisher Discriminant Analysis (LDA/FLD) have shown a promising results as in [4], [14]–[26]. The method applies LDA to find a set of basis images that maximizes the ratio of inter-class to the intra-class scatter. In face recognition, the problem of LDA is the within-class scatter matrix is almost always singular since the number of pixel in an image is larger than the number of images. This situation increases the error rate if there is a significant variation in pose or lighting condition. In order to overcome the problem of a singular matrix, many algorithms have been proposed [4-10]. The Fisherface model takes advantage of within-class information, minimize the variation within each class, and maximize the class separation. Therefore, the problem with different lighting conditions can be overcome [27].

2. Methodology

The proposed gender classification method uses facial features extracted using Fisherface then classified using SVM into male and female category. The input is profile face image of various human races. According to [28], human race is divided into three major races which are Caucasoid, Mongoloid and Negroid as shown in Fig. 1. The profile face image is resized and converted into grayscale color space to reduce the image dimension.

(a) Caucasoid

(b) Mongoloid

(c) Negroid

Fig. 1. Face image of different human race (SFA (Skin Face Analysis) dataset [29]).

2.1. Feature extraction using Fisherface

The facial features are extracted using Fisherface [30] which is a combination of PCA (Principal Component Analysis) and LDA/FLD (Linear Discriminant Analysis/Fisher Linear Discriminant). PCA finds a linear combination of features that maximizes the total variance. However, PCA does not consider any classes so many discriminative information may be lost when reducing the components. The components identified by PCA do not contain any discriminative information. Therefore, LDA is used to find the combination of features that separates well between classes. The difference between

PCA and LDA/FLD is shown in Fig. 2(a). From Fig. 2(a), PCA tends to mix the classes while LDA makes the classes separated.

The basic principle of LDA is to maximize the ratio of distance between classes against the intra-class in a features vector. Features in the same classes are clustered together while different classes are keep as far as possible from each other as shown in Fig. 2(b). Fig. 2(b) illustrates the scatter matrices of S_B and S_W for three class problems. The greater the ratio between classes, the generated characteristic vectors are not sensitive to changes of lighting. Therefore, it can produce a better classification [14], [31], [32]. The Fisherface algorithm is calculated in Equation (1) to (8). Assume there is X which shown in Equation (1) as a set of random vector with samples drawn from c classes.

$$X = \{X_1, X_2, \dots, X_c\}, \quad X_i = \{x_1, x_2, \dots, x_n\} \tag{1}$$

From X, the scatter matrices S_B and S_W are calculated as in Equation (2) and (3) respectively.

$$S_B = \sum_{i=1}^{c} N_i(\mu_i - \mu)(\mu_i - \mu)^T \tag{2}$$

$$S_W = \sum_{i=1}^{c} \sum_{x_j \in X_i} (x_j - \mu_i)(x_j - \mu_i)^T \tag{3}$$

where:

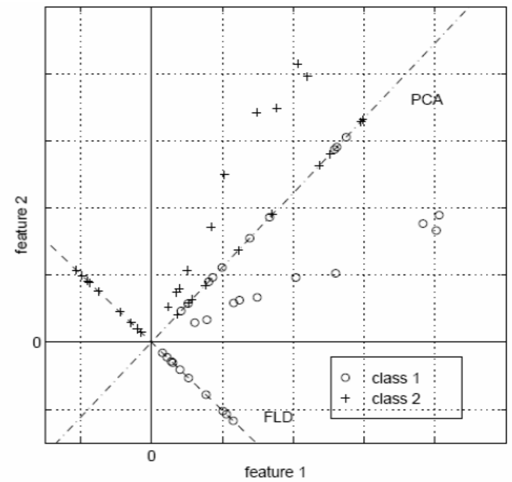
μ is the total mean: $\mu = \frac{1}{N}\sum_{i=1}^{N} x_i$ and μ_i is the mean of class $i \in \{1, \dots, c\}$: $\mu_i = \frac{1}{|X_i|}\sum_{x_j \in X_i} x_j$

Then a projection W that maximizes the class separability criterion is calculated from W_{pca} and W_{fld} as shown in Equation (6) – (8).

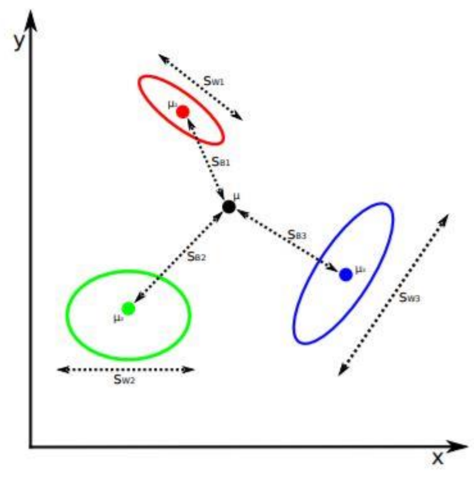
$$W_{pca} = arg\max_W |W^T S_T W| \tag{6}$$

$$W_{fld} = arg\max_W \frac{|W^T W_{pca}^T S_B W_{pca} W|}{|W^T W_{pca}^T S_W W_{pca} W|} \tag{7}$$

$$W = W_{fld}^T W_{pca}^T \tag{8}$$



(a) The difference between PCA and LDA/FLD



(b) Illustration of scatter matrices S_B and S_W

Fig. 2. The illustration of process in a Fisherface algorithm [33].

2.2. Classification using Support Vector Machine

Support Vector Machine (SVM) is a machine learning method that implements Structural Risk Minimization (SRM) which aims to find the best hyperplane that separates two classes in the input space. The concept of SVM classification originated from the two classes that requires training data in positive and negative samples. SVM tries to find the best hyperplane to separate two classes and maximizes the margin between the two classes. The decision function of SVM is shown in Equation (9) and (10) [5] and illustrated in Fig. 3. In the training step, if there are given training data $x_i \in$

$R^n, i = 1, \dots l$ in two classes and label $y \in R^l$ such that $y_i \in \{1, -1\}$, it can be solved using Equation (9).

$$\min_{w,b,\xi} \frac{1}{2} w^T w + C \sum_{i=1}^{l} \xi_i \tag{9}$$

$$subject\ to\ y_i(w^T \phi(x_i) + b) \geq 1 - \xi_i, \xi_i \geq 0, i = 1, \dots, l$$

where w is weight vector, b is bias, ξ_i is slack variables, $\phi(x_i)$ maps x_i into higher dimensional space and $C > 0$ is the regularization parameter and the decision function is shown in Equation (10).

$$sgn(w^T \phi(x) + b) = sgn\left(\sum_{i=1}^{l} y_i \alpha_i K(x_i, x) + b\right) \tag{10}$$

where $K(x_i, x_j)$ is the kernel function. After training process, parameter $y_i \alpha_i \forall i$, b, label names, support vectors, and kernel parameter saved as trained SVM model.

For the classification step, voting strategy is performed for each data *x*. The data will be designated to be in a class which has maximum votes. Optimal parameter is selected using *k*-fold cross validation. After training process, the classification process can be done by calculates kernel, calculates decision function using Equation (10). For multi class problem, repeat the previous step for other classes. Finally, determine the class by function which give maximum value.

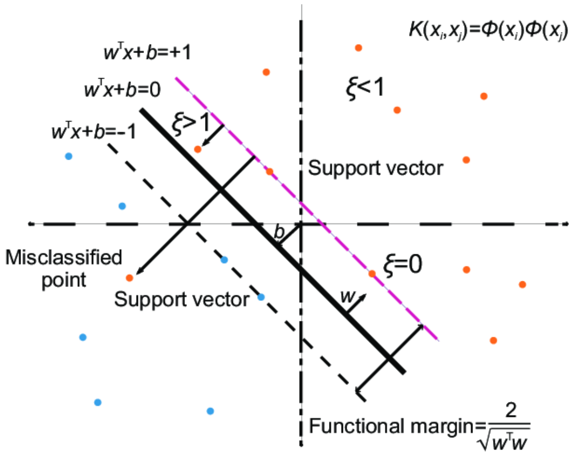


Fig. 3. Illustration of linear SVM.

2.3. Performance evaluation metrics

Confusion matrix is a method to measure the performance of classification. Basically, it compares the actual category and the predicted result. Confusion matrix uses four terms as a representation of the results of classification namely True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN). Those terms are used to calculate accuracy, precision, and recall of the proposed method using Equation (11), (12) and (13) respectively. The category of classification performance is explained as follows: 0.91 – 1.00 is excellent, 0.81 – 0.90 is good, 0.71 – 0.80 is fair, 0.61 – 0.70 is poor, and below 0.60 is a failure.

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

$$precision = \frac{TP}{TP+FP} \tag{12}$$

$$recall = \frac{TP}{TP+FN} \tag{13}$$

3. Result and Discussion

The proposed gender classification method is developed using Matlab and runs on Laptop with Intel Core i5 processor and 16 GB of RAM. The general procedure to apply the proposed gender classification method is shown in Fig. 4. From Fig. 4, face image dataset are divided into training and test data. In the training step, face images are resized to 100x100 pixels and converted to grayscale to reduce the image dimension. Features are obtained using Fisherface algorithm which further reduce the features dimension to 100 components. The features are trained using linear SVM to generate trained gender classifier. In the testing step, from the image acquisition until features extraction process are the same as in the training step. The features then classified into male or female category using previously trained gender classifier.

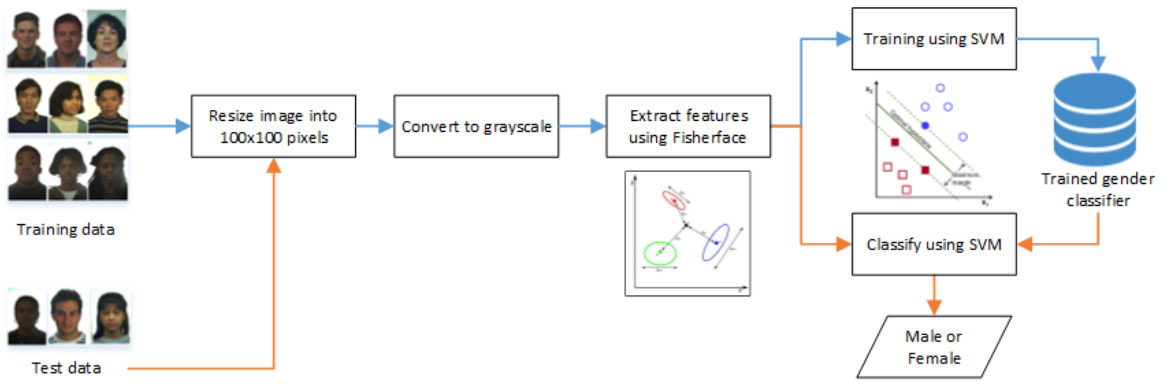


Fig. 4. The general procedure of the proposed gender classification method.

3.1. Face image dataset

In the training step, we use face image dataset from IMDB-WIKI [34] and several face images grabbed from the internet then choose 1200 images as training data. The training data consist of 600 male and 600 female face images. The test data consist of 1014 images divided into 507 female and 507 male face images. All face images in .jpg format. In the pre-processing step, images are resized to 100x100 pixels and converted to grayscale to reduce the image dimension before entering feature extraction step. Fig. 5 shows the sample of face image dataset used in this research.

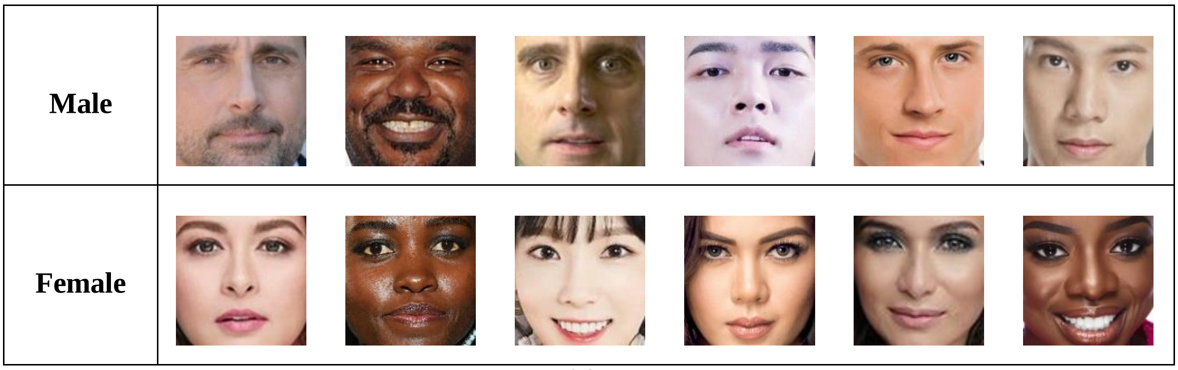


Fig. 5. Sample of face image dataset.

3.2. Features dimensionality reduction

Fisherface method is a combination of PCA and LDA which allow dimensional reduction at the PCA stage. The training input dimension is 1,200x10,000 (from 100x100 pixels). After analysis with PCA using cumulative explained variance ratio as shown in Fig. 6, approximately 100 components already represent the 90% of the data. It means from 100 components we can reproduce all the data used for training. Therefore, the features are reduced to 100x10,000. The LDA stage is used to optimize the result from PCA to separate the distance between classes. It creates a final weight features that differentiate the male and female category.

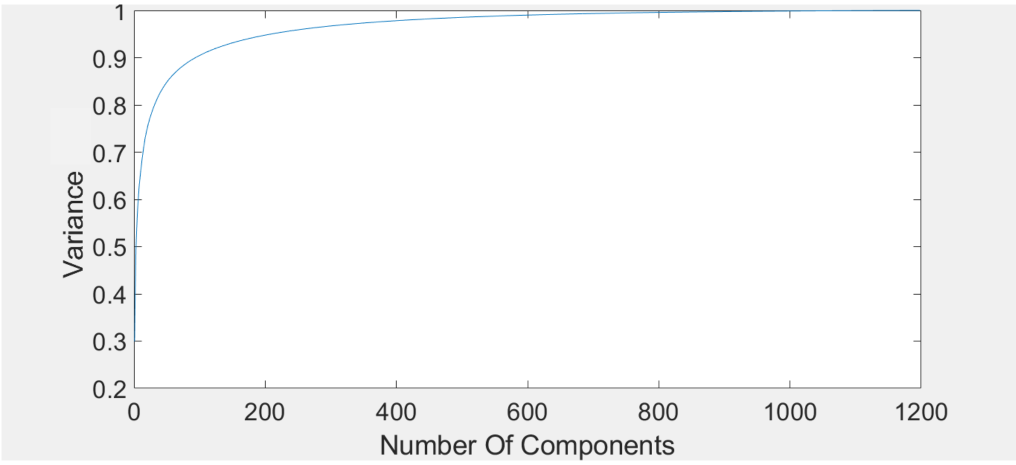
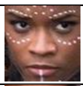
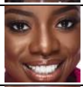
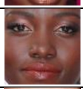
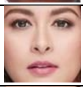
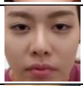
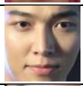
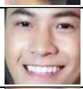
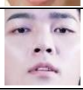


Fig. 6. Plot of cumulative explained variance ratio.

3.3. Gender classification

The proposed gender classification uses SVM to classify face image into male or female category. Fisherface commonly followed by K-NN since the features result are already differentiate. However, K-NN model needs all of training data as gender classifier while SVM only chooses the support vector that lies in the hyperplane to separate the features. Hence, it will be faster and compact. Table 1 shows the result of proposed gender classification on several samples of test data.

Table 1. The result of gender classification.

No	**Sample**	**Actual**	**Predicted**	**Confidence Score**	
				Female	**Male**
1		Female	Female	0	-1.8154
2		Female	Female	-0.28894	-0.71106
3		Female	Male	-2.6355	0
4		Female	Female	0	-2.9112
5		Female	Male	-2.0472	0
6		Male	Male	-1.5752	0
7		Male	Male	-0.60716	-0.39284
8		Male	Female	0	-1.372
9		Male	Male	-1.7792	0
10		Male	Male	-2.5067	0

From Table 1, if the confidence score is close to 0 that means the system is confidence that the decision is correct otherwise if the confidence score falls toward the negative side, then the decision is likely to be doubted as shown in sample number 2 and number 7. However, we still take the maximum value between confidence score of each category to make a decision. Sample number 3, 5 and 8 is wrongly classified although the system is confident about the decision. This is maybe due to the facial features of face image that similar to each other.

3.4. Performance evaluation

We use confusion matrix to measure the accuracy, precision and recall as performance evaluation metrics on 1014 test data. The confusion matrix of proposed gender classification method is shown in Table 2. From Table 2, the value of accuracy, precision, and recall are 0.8817, 0.8639, and 0.8957 respectively. All of these values are higher than 0.81 which means it is considered as good classification performance.

Fig. 7 shows the performance comparison of the default Fisherface classifier which is K-NN with K=5 and our proposed method using SVM on a plot with the number of components vs accuracy. From Fig. 7, SVM is slightly better than K-NN by 2% in 100 components and produce similar value when its closer to use all of the components. This result shows that our proposed method is superior than the default K-NN classifier. Moreover, SVM is compact and perform well even using small set of training data.

Table 2. The result of confusion matrix of the proposed method.

Predicted / Actual	Female	Male
Female	0.8639 (TP)	0.1361 (FN)
Male	0.1006 (FP)	0.8994 (TN)
Accuracy	0.8817	
Precision	0.8639	
Recall	0.8957	

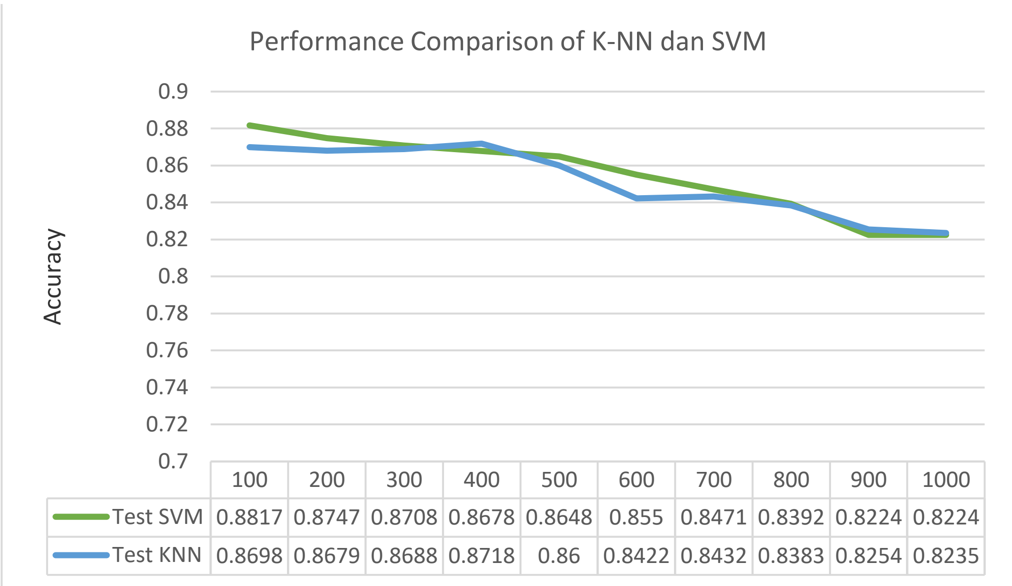


Fig. 7. The performance comparison of K-NN with *K*=5 vs SVM.

4. Conclusion

Based on the performance results of gender classification using Fisherface and SVM on face image, the proposed method gains good classification with 0.8817 of accuracy, 0.8639 of precision and 0.8957 of recall. The Fisherface features not only suitable to be used in gender classification but also effective because it has mechanism to reduce the features dimension. The use of SVM classifier than K-NN classifier increase the accuracy by 2% even with small training data. For the future work, we plan to increase the accuracy by adding more face image data and also we plan to work on human race classification to complete the gender classification system.

References

[1] T. Jabid, M. H. Kabir, and O. Chae, "Gender Classification Using Local Directional Pattern (LDP)," in *2010 20th International Conference on Pattern Recognition*, 2010, pp. 2162–2165.

[2] J. E. Tapia, C. A. Perez, and K. W. Bowyer, "Gender Classification from Iris Images Using Fusion of Uniform Local Binary Patterns," in *European Conference on Computer Vision.*, vol. 9913, G. Hua and H. Jégou, Eds. Cham: Springer International Publishing, 2015, pp. 751–763.

[3] G. Ozbulak, Y. Aytar, and H. K. Ekenel, "How Transferable Are CNN-Based Features for Age and Gender Classification?," in *2016 International Conference of the Biometrics Special Interest Group (BIOSIG)*, 2016, vol. P-260, no. 113, pp. 1–6.

[4] D. Arisandi, M. F. Syahputra, I. L. Putri, S. Purnamawati, R. F. Rahmat, and P. P. Sari, "A real time mobile-based face recognition with fisherface methods," *J. Phys. Conf. Ser.*, vol. 978, no. 1, p. 012038, Mar. 2018.

[5] B. Moghaddam and M.-H. Yang, "Sentiment Classification with Support Vector Machines," *Proc. Fourth IEEE Int. Conf. Autom. Face Gesture Recognit. (Cat. No. PR00580)*, no. 0-7695-0580–5, pp. 583–592, 2000.

[6] N. Halpern *et al.*, "Clinical course and outcome of patients with high-level microsatellite instability cancers in a real-life setting: a retrospective analysis," *Onco. Targets. Ther.*, vol. Volume 10, pp. 1889–1896, Mar. 2017.

[7] Y. Saatci and C. Town, "Cascaded Classification of Gender and Facial Expression using Active Appearance Models," in *7th International Conference on Automatic Face and Gesture Recognition (FGR06)*, 2006, pp. 393–400.

[8] J. S. Alowibdi, U. A. Buy, and P. Yu, "Empirical Evaluation of Profile Characteristics for Gender Classification on Twitter," in *2013 12th International Conference on Machine Learning and Applications*, 2013, vol. 1, no. 1, pp. 365–369.

[9] J. E. Tapia and C. A. Perez, "Gender Classification Based on Fusion of Different Spatial Scale Features Selected by Mutual Information From Histogram of LBP, Intensity, and Shape," *IEEE Trans. Inf. Forensics Secur.*, vol. 8, no. 3, pp. 488–499, Mar. 2013.

[10] A. Mukherjee and B. Liu, "Improving Gender Classification of Blog Authors," *Proc. 2010 Conf. Empir. Methods Nat. Lang. Process.*, no. October, pp. 158–166, 2010.

[11] Shiqi Yu, Tieniu Tan, Kaiqi Huang, Kui Jia, and Xinyu Wu, "A Study on Gait-Based Gender Classification," *IEEE Trans. Image Process.*, vol. 18, no. 8, pp. 1905–1910, Aug. 2009.

[12] G. Levi and T. Hassner, *Sicherheit und Medien*. Wiesbaden: VS Verlag für Sozialwissenschaften, 2009.

[13] E. Mäkinen and R. Raisamo, "An experimental comparison of gender classification methods," *Pattern Recognit. Lett.*, vol. 29, no. 10, pp. 1544–1556, Jul. 2008.

[14] P. Hespanha, D. J. Kriegman, and P. N. Belhumeur, "Eigenfaces vs . Fisherfaces : Recognition Using Class Specific Linear Projection," vol. 19, no. 7, pp. 711–720, 1997.

[15] M. Anggo and La Arapu, "Face Recognition Using Fisherface Method," *J. Phys. Conf. Ser.*, vol. 1028, no. 1, 2018.

[16] Yangrong Ling, Xiangrong Yin, and S. M. Bhandarkar, "Sirface vs. Fisherface: recognition using class specific linear projection," in *Proceedings 2003 International Conference on Image Processing (Cat. No.03CH37429)*, 2003, vol. 2, pp. III-885–8.

[17] Shiguang Shan, Bo Cao, Wen Gao, and Debin Zhao, "Extended Fisherface for face recognition from a single example image per person," in *2002 IEEE International Symposium on Circuits and Systems. Proceedings (Cat. No.02CH37353)*, 2002, pp. II-81-II–84.

[18] Hyung-Ji Lee, Wan-Su Lee, and Jae-Ho Chung, "Face recognition using Fisherface algorithm and elastic graph matching," in *Proceedings 2001 International Conference on Image Processing (Cat. No.01CH37205)*, 2002, vol. 1, pp. 998–1001.

[19] J. A. Suykens and J. Vandewalle, "Improved sparse least-squares support vector machine classifiers," *Neural Process. Lett.*, vol. 9, no. 3, pp. 293–300, 1999.

[20] S. Gurumurthy, C. Ammu, and B. Sreedevi, "Council for Innovative Research," *J. Adv. Chem.*, vol. 10, no. 1, pp. 2146–2161, 2015.

[21] R. Patel and S. B. Yagnik, "A Literature Survey on Face Recognition Techniques," *Int. J. Comput. Trends Technol.*, vol. 5, no. 4, pp. 189–194, 2013.

[22] Z. Abidin and A. Harjoko, "A Neural Network based Facial Expression Recognition using Fisherface," *Int. J. Comput. Appl.*, vol. 59, no. 3, pp. 30–34, 2013.

[23] S. Jaiswal, S. Singh Bhadauria, and R. Singh Jadon, "Comparison Between Face Recognition Algorithm-Eigenfaces, Fisherfaces and Elastic Bunch Graph Matching," *J. Glob. Res. Comput. Sci.*, vol. 2, no. 7, pp. 3–9, 2011.

[24] K. N. Prakash, "Face Recognition using Extended Fisherface with 3D Morphable Model," *Int. J. Comput. Appl.*, vol. 1, no. 16, pp. 46–57, Feb. 2010.

[25] A. Majumdar and R. K. Ward, "Pseudo-Fisherface method for single image per person face recognition," in *2008 IEEE International Conference on Acoustics, Speech and Signal Processing*, 2008, pp. 989–992.

[26] K.-C. Kwak and W. Pedrycz, "Face recognition using a fuzzy fisherface classifier," *Pattern Recognit.*, vol. 38, no. 10, pp. 1717–1732, Oct. 2005.

[27] J. S. Bedre and S. Sapkal, "Comparative Study of Face Recognition Techniques:A Review," *IJCA Proc. Emerg. Trends Comput. Sci. Inf. Technol. (ETCSIT2012)etcsit1001*, vol. ETCSIT, no. 1, pp. 12–15, 2012.

[28] H. Lazi, R. Efendi, and E. P. Purwandari, "Model Warna Cielab Neural Network Untuk Identifikasi Ras Manusia (Studi Kasus Ras : Kaukasoid , Mongoloid , Dan Negroid)," *J. Rekursif*, vol. 5, no. 2, pp. 121–133, 2017.

[29] J. Casati, D. Moraes, and E. Rodrigues, "SFA: A Human Skin Image Database based on FERET and AR Facial Images," *IX Work. Visao Comput.*, 2013.

[30] R. A. FISHER, "THE USE OF MULTIPLE MEASUREMENTS IN TAXONOMIC PROBLEMS," *Ann. Eugen.*, vol. 7, no. 2, pp. 179–188, Sep. 1936.

[31] W. Zhao, R. Chellappa, P. J. Phillips, and A. Rosenfeld, "Face Recognition: A Literature Survey," *ACM Comput. Surv.*, vol. 35, no. 4, pp. 399–458, 2003.

[32] Y. Tao, "Automated Estimation of Human Age," *EE368 Digit. Image Process. Final Proj. Rep.*, 2014.

[33] D. Hong, Y. Ruohe, and L. Kunhui, "Research on face recognition based on PCA," *Proc. - 2008 Int. Semin. Futur. Inf. Technol. Manag. Eng. FITME 2008*, no. 2007, pp. 29–32, 2008.

[34] R. Rothe, R. Timofte, and L. Van Gool, "DEX: Deep EXpectation of Apparent Age from a Single Image," in *2015 IEEE International Conference on Computer Vision Workshop (ICCVW)*, 2015, pp. 252–257.