THE JOURNAL OF COMPUTER SCIENCE AND ITS APPLICATIONS
Vol. 23, No 1 June 2016

GENDER RECOGNITION USING LOCAL BINARY PATTERN AND NAIVE BAYES CLASSIFIER

R. S. Babatunde [1], S. O. Abdulsalam [2] S. R. Yusuff [3] A. N. Babatunde [4]
[1,2,3,4] Department of Computer Science, College of Information and Communication Technology, Kwara State University, Malete. Nigeria

[1]ronke.babatunde@kwasu.edu.ng;[2]sulaiman.abdulsalam@kwasu.edu.ng;
[3]shakirat.yusuff@kwasu.edu.ng; [4]akinbowale.babatunde@kwasu.edu.ng

ABSTRACT
Human face provides important visual information for gender perception. Ability to recognize a particular gender is very important for the purpose of differentiation. Automatic gender classification has many important applications, for example, intelligent user interface, surveillance, identity authentication, access control and human-computer interaction amongst others. Gender recognition is a fundamental task for human beings, as many social functions critically depend on the correct gender perception. Consequently, real-world applications require gender classification on real-life faces, which is much more challenging due to significant appearance variations in unconstrained scenarios. In this study, Local Binary Pattern is used to detect the occurrence of a face in a given image by reading the texture change within the regions of the image, while Naive Bayes Classifier was used for the gender classification. From the results obtained, the gender correlation was 100% and the highest accuracy of the result obtained was 99%.The system can be employed for use in scenarios where real time gender recognition is required.

Keywords: Gender, Local Binary Pattern, Naïve Bayes, Recognition

1. INTRODUCTION

Gender is a socially constructed definition of women and men. Gender can be referred to as the array of physical, biological, mental and behavioural characteristics which differentiates masculinity and femininity [1]. Automated facial gender recognition has become an interesting and challenging research problem in recent years [2].

Nowadays, researchers pay more attention to gender recognition in many potential application fields such as biometric authentication and passive demographic data collection. Gender is one of the important demographic features of human being [3]. Facial gender classification can significantly improve human identification in biometric recognition by speeding and increasing the accuracy as it reduces the process of matching the face in the databases to nearly the half and helps in potential applications in security industry and human computer interaction [2].

Although there are diverse parts of the human face which can be used to draw out conclusion on a particular gender, according to biometric identification systems all rely upon forms of random variation among persons [11]. The more complex the randomness the better, because more dimensions of independent variation produce signatures having greater uniqueness. But while desiring maximal between-persons

variability, biometric templates also need minimal within-person variability across time and conditions. Gender recognition is one of fundamental face analysis tasks. Most of the existing studies have focused on face images acquired under controlled environment [5], [6]. However, real-world applications require gender classification on real-life faces, which is much more challenging due to significant appearance variations in unconstrained scenarios.

Gender classification is an important task which in turn can enhance the performance of a wide range of applications including identity authentication, human-computer interaction, access control, and surveillance, involving frontal facial images [7]. A large majority of gender classification approaches are based on extracting features from face images and then giving these features to a binary classifier [13].

The face of human beings tells us a lot about the identity and emotional state of the person. Recognizing the human face has been a fascinating and challenging problem, and has brought about relevant applications in many areas such as authentication for banking, security system access, and personal identification among others [8].
Local Binary Pattern (LBP) is a textural feature extractor that gives a facial representation which is independent of expression and pose artefact. The LBP operators are easy to compute hence they are suitable for real time application. LBP is robust to texture feature description and capable of representing a face in a form in which illumination variations are suppressed [9]. At a given pixel position $(x_c,\ y_c)$, LBP is defined as an ordered set of binary comparisons of pixel intensities between the center pixel and its eight surrounding pixels. The decimal form of the resulting 8-bit word (LBP code) can be expressed using Eq. 1:

$$LBP(x_c,\ y_c - \sum_{n=0}^{7} s(i_n, i_c)\, 2^n) \qquad (1)$$

where i_c corresponds to the grey value of the center pixel $(x_c,\ y_c)$, i_n to the grey values of the 8 surrounding pixels.

Naive Bayes is a classification technique based on Bayes' Theorem with an assumption of independence among predictors [10]. In simple terms, a Naive Bayes classifier assumes that the presence of a particular feature in a class is unrelated to the presence of any other feature. Naive Bayes model is easy to build and particularly useful for very large data sets. Along with simplicity, it is known to outperform even highly sophisticated classification methods (Sunil, 2015).Bayes theorem provides a way of calculating posterior probability P(c|x) from P(c), P(x) and P(x|c) as shown in Eq.2.

$$P(c|x)\,\frac{P(x|c)P(c)}{P(x)} \qquad (2)$$

where P(c|x) is the posterior probability of class (c, target) given predictor (x, attributes), P(c) is the prior probability of class, P(x|c) is the likelihood which is the probability of predictor given class and P(x) is the prior probability of predictor.

Bayesian classifiers are statistical classifiers. They can predict class membership probabilities, such as the probability that a given sample belongs to a particular class. Naive Bayesian classifiers assume that the effect of an attribute value on a given class is independent of the values of the other attributes. A major advantage of the Naive Bayes is its efficiency in Real time Prediction**.** It is a fast eager learning classifier, thus, it could be used for making predictions in real time [11].

This paper aimed at developing an improved gender recognition system which employs the use of LBP to track the occurrence of a face in an image and Naïve Bayes Classifier for the recognition of gender.

2. RELATED WORKS

Gender recognition systems have been in existence over the years and various researchers have brought about the use of various algorithms in order to improve gender recognition [12]. Many techniques have been used for extracting discriminative features from facial images, which can be broadly

classified into either geometric and appearance based methods [13]. [14] demonstrated that geometric feature-based methods provide similar performance to appearance-based approaches.

[4] investigated the fusion of both global and local features for gender classification. Global features were obtained using the principal component analysis (PCA) and discrete cosine transformation (DCT) approaches. A spatial local binary pattern (LBP) approach augmented with a two-dimensional DCT approach was used to find the local features. The performance of the proposed approach was investigated on Face Recognition Technology (FERET) database. The approach gives a recognition accuracy of 98.16% on FERET database. Comparisons with some of the existing techniques revealed a remarkable reduction in number of features used per image to produce results more efficiently and without loss of accuracy for gender classification.

[15] investigates gender recognition on real-life faces using the recently built database, the Labelled Faces in the Wild (LFW). Local Binary Patterns (LBP) was employed to describe faces, and Adaboost was used to select the discriminative LBP features. The research obtained the performance of 94.81% by applying Support Vector Machine (SVM) with the boosted LBP features. The public database used in this study makes future benchmark and evaluation possible.

[16] developed an automatic gender recognition algorithm based on machine learning methods. Their work consists of two stages: adaptive feature extraction and support vector machine classification. The gender recognition algorithm was based on non-linear SVM classifier with RBF kernel. To extract information from image fragment and to move to a lower dimension feature space, an adaptive feature generation algorithm which was trained by means of optimization procedure according to LDA principle was used. The results obtained show a recognition performance of 91% on a database size of 5000 people and 79.6% on database size of 400.

[17] developed an Advanced Biometric Identification on Face, Gender and Age Recognition (ABIFGAR)algorithm for face recognition. The system yields good results on both large and small training set. It works with a training set as small as one image per person. The process consists of three phases: Preprocessing, Feature Extraction and Classification. The geometric features from a facial image were obtained based on the symmetry of human faces and the variation of gray levels, the positions of eyes, nose and mouth are located by applying the Canny edge operator. The gender and age are classified based on shape and texture information using Posteriori Class Probability and Artificial Neural Network respectively. It was observed that the face recognition is 100%, the gender and age classification is around 98% and 94% respectively.

[2] developed a facial gender recognition system using Eyes Images. In their research, feature extraction technique works only with eye and eyebrows region of the person. Three methods were used for feature extraction, which include 2D-Wavelet Transform, DCT and GLCM. SVM was used in the classification. The result from the feature extraction methods were compared and DCT gave the best recognition results over the two other methods on Face94 database used in the experiment

Although, numerous researches, including [12], [13], [15], obtained arguably high accuracy from images fetched from databases such as the Ferret database and Local Wide database, which undoubtedly would take a couple of seconds to fetch the image from the database. However, recognition systems are mostly effective in real-time scenarios such as authentication for banking, security system access, and personal identification where decisions are expected to be made in matter of nanoseconds

3. METHODS

The gender recognition system developed in this research consists of three main stages, which are:

3.1. Face tracking:

This involves determination of occurrence of face within an input set of image. Local Binary Pattern (LBP) was used for face tracking because of its robustness to texture feature description and capability to represent a face in a form in which illumination variations are suppressed [18]. The LBP was used to detect the occurrence of a face in a given image by reading the texture change within the regions of the image. Details of the operation of LBP can be found in [5]. Since the system uses a video stream, the occurrences of faces are being tracked using a green outline.

Once the LBP finds the occurrence of a face within the picture frame, a light-green boundary is created to map out the face region. From the mapped out region, the anthropometric measurements are being taken. These measurements constitute the global features used which include:

(i) Inter-ocular distance: The distance between the midpoint of right eye and midpoint of left eye in the face image.
(ii) Nose to Eyes: The distance between Nose tip to inter-ocular distance in the facial image.
(iii) Lips to Nose: The distance between nose tip and the midpoint of the lips pixel in the facial image.
(iv) Lips to Eyes: The distance between lips midpoint to inter-ocular in the facial image.

After the measurement is generated, the distance formula as used by [1]was then used to calculate the ratio of each face. Four major ratios are being calculated using Eqs. 3, 4, 5 and 6 to obtain the anthropometric measurements as itemised previously.

$$Ratio\ 1 = \frac{\text{Left eye to Right eye distance}}{\text{Eye to Nose Distance}} \quad (3)$$

$$Ratio\ 2 = \frac{\text{Eye to Nose distance}}{\text{Eye to Chin Distance}} \quad (4)$$

$$Ratio\ 3 = \frac{\text{Left eye to Right eye distance}}{\text{Eye to Chin Distance}} \quad (5)$$

$$Ratio\ 4 = \frac{\text{Eye to Lips distance}}{\text{Eye to Nose Distance}} \quad (6)$$

Once the face(s) has been tracked, there is need to bring out the discriminative features which are to be used in the gender recognition. From the face detected, the features needed which comprises of the eye region to the chin region as obtained from the four ratios in the above equations are passed on to the naïve bayes classifier. The prior probability is first calculated for both the male and the female which is then followed by the likelihood of both genders. Once this is done, each gender is calculated with respect to X which is the unknown and which forms the basis of our classification. The highest of the two becomes our classified gender.

The standard threshold values for female and male as illustrated by [1] are: ratio1>=1.1000&&ratio2>=0.7450||ratio3<= 1.3714&&ratio4>=0.6404and ratio1<=1.09 &&ratio2<=0.7440 || ratio3>=1.3714 &&ratio4<=0.6400 respectively.

To obtain the prior probability, all the four ratios are considered. The prior probability of male was obtained by dividing the value obtained for male attribute based on the threshold earlier stated by the total number of ratios which is four. The prior probability for female is also calculated likewise as shown in Eq. 7 and 8.

$$Prior\ probability\ of\ Male = \frac{\text{Number of Male attributee}}{\text{Total number of Ratio}} \quad (7)$$

$$Prior\ probability\ of\ Female = \frac{\text{Number of Female attributee}}{\text{Total number of Ratio}} \quad (8)$$

Having formulated our prior probability, we obtain the likelihood. The attributes are

restricted to only Ratio 1 and Ratio 2 and these ratios are regarded as X. The likelihood is calculated using Eq. 9 and 10.

$$Likelihood\ of\ X\ given\ Male = \frac{\text{Number of Male in X}}{\text{Total Number of Male Cases}} \quad (9)$$

$$Likelihood\ of\ X\ given\ Female = \frac{\text{Number of Female in X}}{\text{Total Number of Female Cases}} \quad (10)$$

The final classification was carried out by combining both sources of information, i.e., the prior and the likelihood, to form a posterior probability. Therefore, after obtaining the likelihood, the product of both the likelihood and the prior probability was calculated for both gender and the highest result obtained becomes the outcome of the recognition.

3.2 Classification

This stage basically involves deciding which gender the face that has been detected falls into based on the likelihood, after the face detected has been thoroughly evaluated by the naïve bayes classifier using the Bayesian theorem.

Figure 3.1 shows the model for the gender recognition system. The face tracking was the first operation to be performed which was carried out using LBP. Next is the anthropometric feature measurement and the distance computation. The result from the distance calculation is then further passed on to the naïve bayes classifier which decides the outcome of the recognition based on the highest probability of either a male or a female gender. The gender recognition system was developed using C# Programming Language. Face images were trained in real time. The face images were then saved in a database which was built using MySQL.

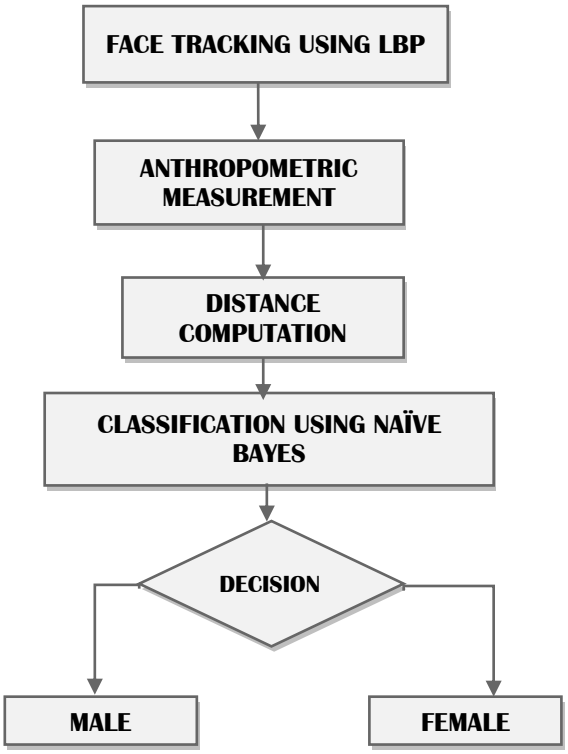


Fig. 3.1: Gender Recognition Model.

The GUI for the developed system is shown in Figure 3.2. The interface comprises of three main buttons.

i. A start button which is used to trigger the web cam in other to get the frame of an image.
ii. A save button which is used to save trained data
iii. A training set button which can be used to fetch and view all saved trained images.

The interface also contains a label which is used to indicate the gender and the accuracy of the result in percentage. Once the start button is clicked from the interface, the webcam is triggered and once it is active, the detection process begins. When a face is detected from an image frame, a green box outline is drawn on the detected face and the gender in turn is immediately recognized. Then the save button will have to be used in order to save the trained face to the database.

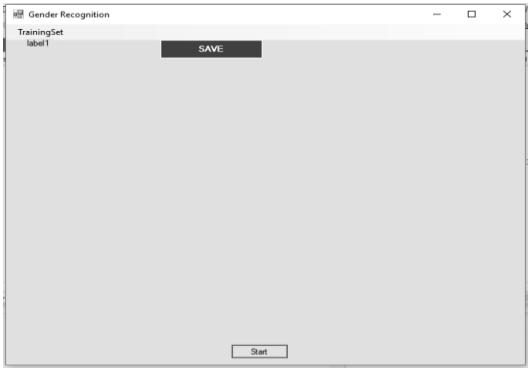


Fig. 3.2: Recognition System Interface



Fig. 4.1: Female training set(a)

The application which is an executable file must run on a computer system with webcam capability which can either be an inbuilt webcam or an attached webcam and running windows operating system ranging from windows vista, Windows 7, Windows 8, Windows 8.1 or Windows 10 with Microsoft .net Framework 2.0 or 3.5. Furthermore, the application can be run on either 64-bits or a 32-bits system.

4. RESULTS AND DISCUSSION

This study was experimented on real time training of some set of facial data obtained from students of Computer Science Department of Kwara State University, Malete. The images were captured in real time via webcam whereby an individual is made to position his/her self in front of the system to acquire a frame. A green outline on the face region indicated a tracked face in the given frame. The gender recognition takes effect in matter of nanoseconds once the face is detected.

From the various results obtained, the gender of the trained data was detected accurately in terms of whether the person is a male or a female but the percentage accuracy of the gender detected is mainly dependent on the image quality in terms of the resolution and the illumination of the image and also sometimes due to variation in facial pose. The greater the illumination, the greater the accuracy obtained. Figure 4.1 shows the accurate detection of female face which was trained in a low illuminated environment.

It can be observed that the system had the right gender correlation but with an accuracy of 94% due to the low illumination as at the time the face data was trained.

Figure 4.2 shows the recognition of the same person previously shown in Figure 4.1 but with a lower accuracy, also with the correct gender correlation. It can be observed that there is slight decrease in the illumination and also the distance between the person and the camera has changed a bit. The illumination and camera distance factor only affects the accuracy of the gender recognition and not the gender correlation in particular.

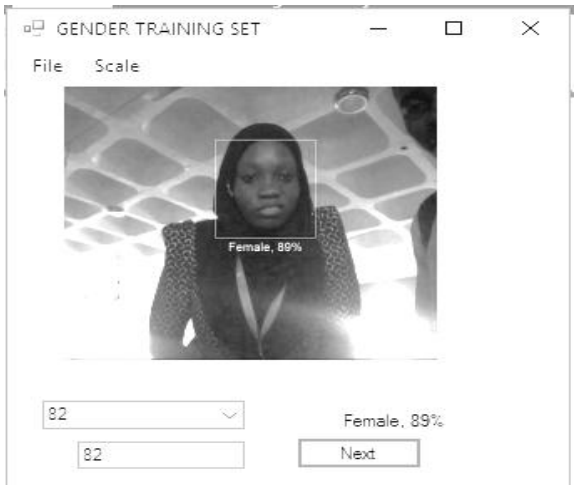


Fig. 4.2: Female training set(b)

From Figure 4.3 which captures the face of the same person as previously shown in Figure 4.1 and 4.2, it can be seen that the face has drawn closer compared to Figure 4.1 and the illumination has increased. This has caused the system to acquire a greater

accuracy.



Fig. 4.3: Female training set (c)

Figures 4.4, 4.5, 4.6 and 4.7 shows the testing of a male student with a 99% accuracy and correct gender recognition all through the various positions of capturing in terms of distance from the camera, slight head poses, but under the same condition of illumination. It can be deduced from the result obtained in the simulation that the quality of the image in terms of resolution and distance of image from camera (i.e. distance of capture) is not a major factor when it comes to the gender correlation.



Fig. 4.4: Male training set (a)

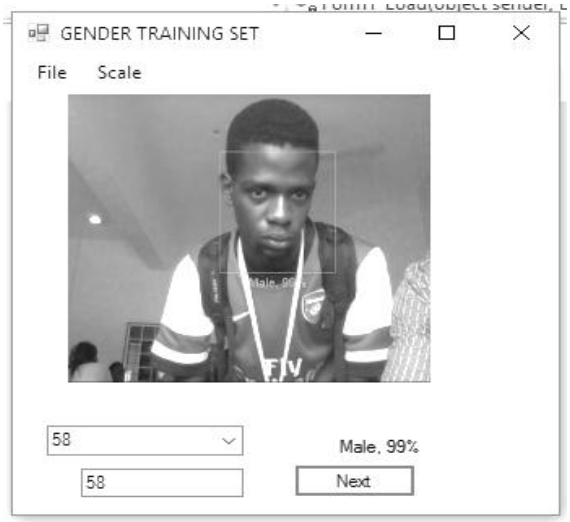


Fig. 4.5: Male training set (b)



Fig. 4.6: Male training set (c)

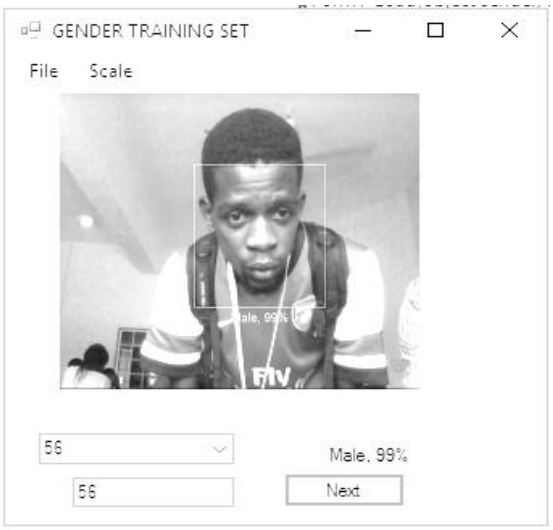


Fig. 4.7: Male training set (d)

However, different poses, illumination variation and facial expression might have a slight effect on the accuracy of the gender recognition as seen in the Figure 4.8 and 4.9.



Fig. 4.8: Male training set(e)

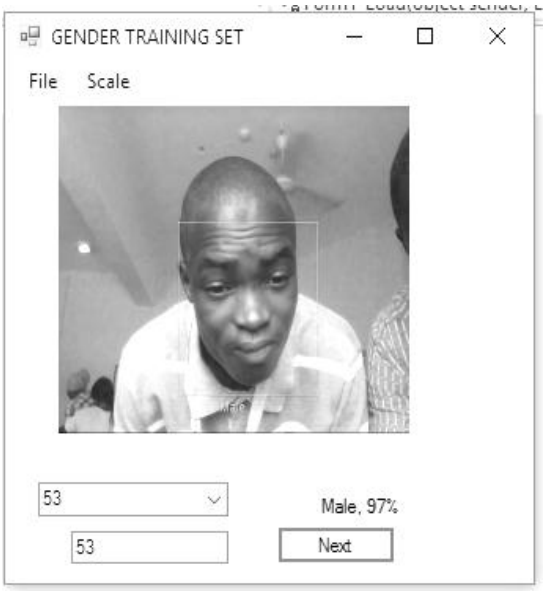


Fig. 4.9: Male training set(f)

5. CONCLUSION

This paper developed an automatic system capable of recognizing people's gender. From the results obtained, it can be deduced that the gender correlation is 100% and the accuracy of the result obtained is 99%, which is a great achievement being a system working in real time situation. Such systems can find useful application in different fields, such as robotics, human computer interaction, demographic data collection, video surveillance, security access control and the banking system. Further research can include the recognition of gender with high angular face pose and 3D faces.

ACKNOWLGEMENT

Special thanks to the Students of Kwara State University, Malete, Nigeria for their full support and cooperation during the capturing and testing of face images

6. REFERENCES

[1] Kalam, Swathi & Guttikonda, Geetha. (2014). Gender classification using geometric facial features. *International Journal of Computer Applications*, vol. *85* No.7.

[2] Alrashed, H. F., & Mohamed, B. A. (2013). Face gender recognition using eye images. *InternationalJournal of Advanced Research in Computer and Communication Engineering, 2*.

[3] Manoj, B., Pulkit, R., Annu, G. M., & Harsha, J. (2015).A Survey Paper on the Gender Recognition Techniques. Applications of Computers and Electronics for the Welfare of Rural Masses (ACEWRM). pp.22-25.

[4] Hussain, Mirza A. Almuzaini M. M., Muhammad H., G., , H Aboalsamh., and Bebis, G. (2013). Gender Recognition Using Fusion of Local and Global Facial Features. *Springer-Verlag Berlin Heidelberg. Part II, LNCS 8034*. 493–502.

[5] Babatunde, R.S., Olabiyisi, S.O., Omidiora, E.O., Ganiyu, R.A., & Isiaka, R.M. (2015). Assessing theperformance of Random Partitioning and K-Fold Cross Validation methods of evaluation of a Face Recognition System. *Advances in Image and Video Processing, 3* (6), 19-26.

[6] Choon, B. N., Yong, H. T., & Bok, M. G. Vision-based Human Gender Recognition: A Survey. Retrieved online at https://arxiv.org/ftp/arxiv/papers/1204/1204.1611.pdf

[7] Juan, E. T., Claudio, A. P. & Kevin, W. B. (2014). Gender classification from iris imagesusing fusion of uniform local binary patterns. *IEEE Transaction on Forensics and Security.*

[8] Tri, H., Rui, M., & Jean-Luc, D. (2012). An efficient LBP-based descriptor for facial depth images applied to gender recognition using RGB-D face data. Department of multimedia communications. Sophia Antipolis. Available at http://dx.doi.org/10.1007/978-3-642-37410-412

[9] Huang, D. S., Caifeng, Ardabilian, M., Wang, Yunhong, & Chen, L. (2011). Local Binary Patterns and Its Application to Facial Image Analysis: A Survey. *IEEE Transactions on Systems, Man and Cybernetics, Part C: Applications and Reviews, 41* (6), 765-781.

[10] Chai, K., Hn, H.T., Chieu, H. L. (2002). Bayesian Online Classifiers for Text Classification and Filtering. *Proceedings of the 25th annual international ACM SIGIR conference on Research and Development in Information Retrieval*, 97-104.

[11] Sunil, R. (2015). 6 Easy Steps to Learn Naive Bayes Algorithm - with code in Python. Available online at http//www.analyticsvidhya.com/blog/category/python-2/

[12] Lian, H., & Lu, B. (2013). Multi-view gender classification using local binary patterns and support vector machines. Department of computer science and engineering, Shanghai: Shanghai JIAO tong university.

[13] Muhammad, H., Ihsan, U., & Hatim, A. A. (2013). Gender recognition from face images with dyadic wavelet transform and local binary pattern. *International journal on artificial intelligence tools, 22 (*6), 1-18.

[14] Valstar, M. F., Jiang, B., Mehu M., Pantic, M., & Scherer, K. R. (2011). The First Facial Expression

Recognition and Analysis Challenge. *IEEE Int'l. Conf. Face and Gesture Recognition(FG'11).*

[15] Shan, C. (2011). Learning local binary patterns for gender classification on real-world face images. *Pattern recognition letters, 33*. 1-12

[16] Khryashchev, V., Priorov, A., Shmaglit, L., & Golubev, M. (2012). Gender Recognition via Face Area Analysis. *Proceedings of the World Congress on Engineering and Computer Science, San Francisco, USA.* Vol 1 pp1-5.

[17] Jeganlal, R., Gopi, V., & Rajeswari, S. (2013). Robust automatic face, gender and age recognition using ABIFGAR algorithm. *International journal of emerging trends in Electrical and Electronics (IJETEE), 4(*2), 41-44.

[18] Ramchand, H., Narendra, C., & Sanjay, T. (2013). Recognition of facial expressions using local binary patterns of important facial parts. *International journal of image processing (IJIP), 7* (2), 1-3.

[19] Bansal, A., Agarwal, R., & Sharma, R.K. (2014). Predicting gender using iris images. *Research Journal of recent sciences, 3(4)*, 21-26.

[20] Brian, O., & Kaushik, R. (2013). Facial recognition using modified local binary pattern and randomforest. *International journal of artificial intelligence & applications (IJAIA), 4 (2)*, 25-33.

[21] Christoper, M. B., (2006). Pattern recognition and machine learning. *Information science and statistics, Cambridge*: Microsoft Research Laboratory Ltd.

[22] Gupta, Varsha, & Sharma, D. (2014). A study of various face detection methods. *InternationalJournal of Advanced Research in Computer and Communication Engineering, 3(5).*

[23] Nils, J. N. (2005). Introduction to machine learning. Department of Computer Science, Stanford: Stanford University. 10-12.

[24] Rahim, A., Hossain, N., Wahid, T., & Azam, S. (2013). Face recognition using local binary patterns (LBP). *Global journal of computer science and technology graphics & vision, 13* (4), 1-9.