JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

A REVIEW STUDY ON FACE GENDER RECOGNITION USING DEEP LEARNING

Priyanka
Madhav Institute of Technology & Science
Department of Computer Science & Engineering
Gwalior, India
priyankapvk1@gmail.com

Jaimala Jha
Madhav Institute of Technology & Science
Department of Computer Science & Engineering
Gwalior, India
jaimala.jha@mitsgwalior.in

Abstract— **Today, automatic gender identification influences the usage of social networking websites and social media in various software and hardware. Despite this, the current system's performance with real-world face photos is poor, particularly when compared to the results of facial recognition tasks. Researchers showed significant interest in the field of soft biometrics to fill the gaps between humans and machines by increasing real-world application. Soft biometrics consist of gender, ethnicity, height, facials and so on. This study offers a detailed discussion on the role of researchers in deep learning in the field of gender classification. Deep learning and auto encoders are most of the labor. For an effortless interpretation of tabular correlation study, different parts relating to the neural network model are included, such as data set, findings, calculative metrics, and findings.**

Keywords— Deep learning, Gender classification CNN, SIFT, SVM, etc.

I. INTRODUCTION

Biometrics is a fast-growing field with applications from accessing computers to entering a nation. To determine an individual's identification, biometric systems use physical and behavioral features such as fingerprints, face, speech, and hand geometry. The use of biometric large-scale systems in both commercial and public applications raise public awareness of this technology [1]. Rapid increase also underlines the limitations of the design and deployment of biometric systems. Indeed, the biometric recognition problem is itself a major challenge. Over the past five years, biometric research has grown substantially and has led to the creation of innovative sensors, strong and fast extracting and matching algorithms, improved test methods and new applications. These developments have led to durable, precise, safe, and affordable biometric systems. Incredible demands to aid combat misconduct and psychological oppression are solid facial recognition frameworks [2]. Various applications include providing client confirmation to ensure improved security in real and virtual spaces. In any case, it is still exceedingly difficult to distinguish a man by taking an image of an information comparison and coordination with the known face images in a database [3]. This is due to the changes in human faces, for example, lighting, revolutions, appearances, camera view focuses, maturing, cosmetics and glasses under different operating situations. When the frameworks are needed to coordination against large databases, these various situations often affect extraordinary implementation of the face acknowledgement frameworks. This low compliance with confronting recognition keeps frameworks widespread in real applications when misleading such as the FRR and the FRR are considered in advance. FAR is likely to misrepresent an unapproved person in the framework, whereas FRR is likely to falsely reject an approved person in the framework. The first challenge in psychophysical studies was the gender classification; this focus is on the quest to better understand human vision processing and discover the key characteristics that are used to define men and women [1]. Research has demonstrated that the difference between facial masculinity and femininity can be used to increase the performance of face-reconnaissance applications in the fields of biometrics. Gender identity is a personal gender experience [2]. The identity of the sexes can correlate or diverge from the allocated at birth [3]. All societies have a set of categories of gender capable of forming the social identity of a person with respect to other society members [3]. In most communities, gender qualities [4] are fundamental and contain expectations of men and women in the entire sex and gender context: biological sex, gender identity and gender expression. The gender is attributable to men and women [4]. Some people do not identify with some of the gender features of their biological sex. Some of these people are sexual, sexual, or non-binary. Some companies have 3rd category of gender. Core sex identity typically consists of three years of age [2]. It is extremely difficult to modify after three years [3] and efforts to reassign it can lead to sexual dysphoria [3]. It was proposed to impact the formation of both biological and social variables. Since the arrival of web-based lives that adds huge volumes of information has dramatically increased large data. There is the hidden potential in this material to find vital knowledge to improve our life. These learning materials can make data easier and more useable, which can contribute to changes in item creation and arrangement details, thereby adding to organizational development [3]. A good deal of this information is in the arrangement of content and is largely created by people. Web-based living provides social networking and correspondence steps. Furthermore, there was an almost exponential increase in the rate of image transfer to the Internet [4]. This newly discovered wealth of knowledge has allowed PC researchers to deal with PC vision problems that were previously inconsequential or intractable. We have thus seen the start of extraordinarily accurate and efficient systems of facial identification that leverage coevolutionary neural circuits in the motor. Applications for these frameworks include all aspects, from who to "tag" in Facebook images to people who explore on foot in self-driving cars. This breakthrough is subject to extensive applications and the prospect of having an enormous impact [4]. Many languages, for example, have distinct words to use while ministering to a male vs a female. Computerized interpretation authorities and various sorts of age may, thus, contribute to enhancing the sexual characterization of subjects. Similarly, thinking on the sex of a subject simplifies the attempt to see the subject. This can be used to help vision devices break down or lose visual perception for those. The data on the age and sexual direction of the public could be employed online life sites like Facebook to better reflect the picture. For example, if a picture includes many people looking at it together [5], Facebook may subtitle the image with a "contemplate session." In the event, however, that the general populace also acknowledge that the complete man is in his mid-20s and that some have shirts with such letters, "college students studying in a brotherhood" may be envisaged. The traditional approach linked to face recognition, including face-based recognition of sexual orientation, generally covers phases such as photo acquisition and processing, reduction in dimensionality, extraction, and arrangement. Previous knowledge of the application is necessary to determine the optimal extractor element to plan. Similarly, the implementation of the recognition framework depends severely on the type of classifier chosen, which is therefore sensitive to the connected element extraction method. A classifier that best consolidates with the chosen highlight extractor is difficult to incorporate in such a way that an optimal characterization is obtained. Any advances to the area of problem need to be updated completely **[5].**

II. GENDER CLASSIFICATION

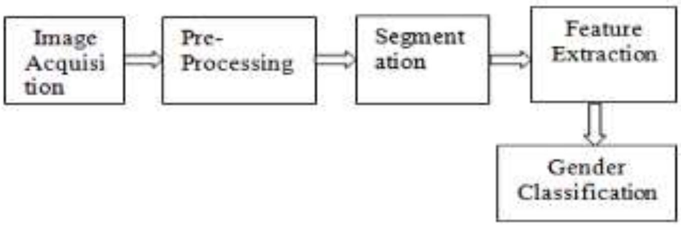

Figure.1.1 Block Diagram of human gender classification [6]

The block diagram of human gender, including the acquisition, classification, is illustrated in Fig. 1.

1) Image acquisition: the fundamental step in the classification of genders is to achieve efficient raw information. It is the process by which apparent qualities such as a physical scene or an internal structure of the object are digitally encoded. Images are obtained by illumination of the scene and by absorption of the energy that the existing items reflect. Various ways are used to classify gender depending on the characteristics acquired [7].

2) Classification

a) Gender Detection Classification

The Gender Detection Classifier saves photos to be classified for a similarity measure [8]. After the Discrete Cosine Transformation, a single dimensional array stores the four main highest values in every module. The distance from each point of the image to the training pictures by the classifier is determined thereafter. Hit and miss score increases rely on whether the average distance exceeds or falls below the predefined threshold. It relies on the score or miss of the resulting men or women. The picture should be taken as that when the hit value for specified labels is bigger (Male and Female) [9].

b) Local Binary Pattern

That method monitors points to see if they are greater or less than the center point and evaluates the surrounding points.

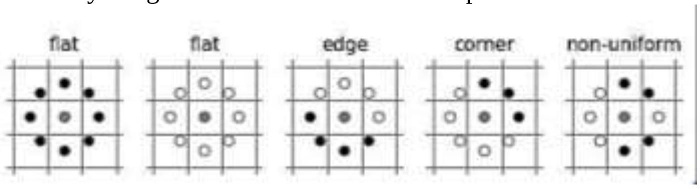

Fig1.2 Surrounding pixel intensity compared to center pixel [10]

Points are verified and tested around the central point if the points are larger or smaller. The above figure can be plainly seen to show this clearly. In comparison to the center pixel, pixels that are represented with black or white dots are seen as less or more intense. If the pixels are completely black or white, the picture area is termed flat and unchanged. Corners or borders are constants of black and white pixels, which are consistent patterns. Non-uniform patterns are created, however, when pixels between white and black pixels are changed [11].

c) Local Directional Pattern

As a gray-scale pattern, LDP is considered. The spatial shape of a local picture texture is also portrayed. Corner reaction values are calculated in all directions at each pixel, generating code from the relative magnitude of strength [12]. This is done through the calculation of Kirsch orientation masks (M0~M7) which focus on self-position [2] of a given pixel eight directional edge reactions. The illustration is shown in the figure below [2].

$$\underset{\text{East }(M_0)}{\begin{bmatrix}-3&-3&5\\-3&0&5\\-3&-3&5\end{bmatrix}}\quad\underset{\text{North East }(M_1)}{\begin{bmatrix}-3&5&5\\-3&0&5\\-3&-3&-3\end{bmatrix}}\quad\underset{\text{North }(M_2)}{\begin{bmatrix}5&5&5\\-3&0&-3\\-3&-3&-3\end{bmatrix}}\quad\underset{\text{North West }(M_3)}{\begin{bmatrix}5&5&-3\\5&0&-3\\-3&-3&-3\end{bmatrix}}$$

$$\underset{\text{West }(M_4)}{\begin{bmatrix}5&-3&-3\\5&0&-3\\5&-3&-3\end{bmatrix}}\quad\underset{\text{South West }(M_5)}{\begin{bmatrix}-3&-3&-3\\5&0&-3\\5&5&-3\end{bmatrix}}\quad\underset{\text{South }(M_6)}{\begin{bmatrix}-3&-3&-3\\-3&0&-3\\5&5&5\end{bmatrix}}\quad\underset{\text{South East }(M_7)}{\begin{bmatrix}-3&-3&-3\\-3&0&5\\-3&5&5\end{bmatrix}}$$

Figure 1.3 Kirsch edge response masks in eight directions [12]

d) Deformable Spatial Pyramid

A spatial deformable pyramid popular for dense pixel correspondence calculations. The pyramid graph model fits into several spatial degrees with uniformity. This strategy enhances the matching of the pixel level. The deformable element of the model has overcome the rigidity of the prior traditional pyramids [12].

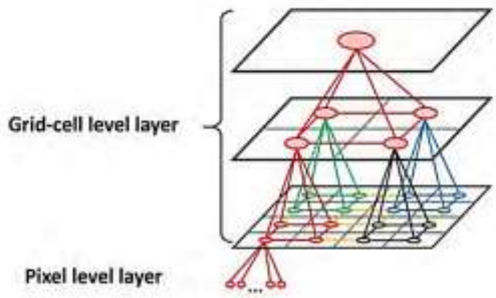

Fig 1.4 The Graph Structure of DSP model [12]

The whole image is divided into four grid cells. In addition, it is broken down until it reaches a certain level of the pyramid. Finally, there is an extra pixel layer, to give finest pixels a one-pixel width. The pyramid is shown by a plot. The objective was used to make a fixed scale or multi scale match. Because the time of calculation is huge, effective calculation is necessary.

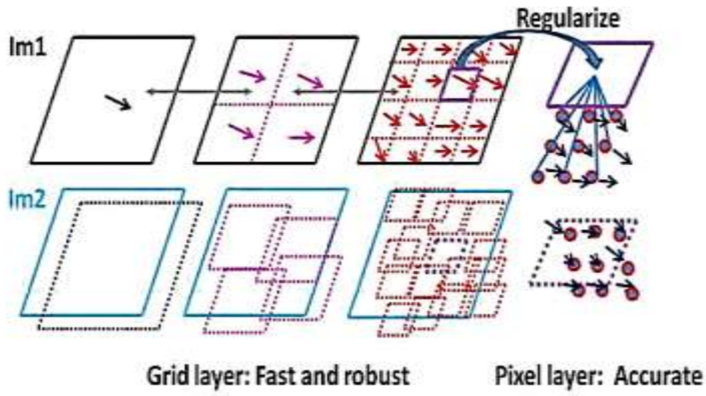

Fig 1.5 DSP matching method by dividing grid cells [13]

III. FACIAL GENDER CHALLENGES

In real-world applications, automation covers a wide range. Similarly, an algorithmic gender estimate can also be drawn up [13]. Techniques of gender classification can increase perceptional and interactional capacities of computers. Various gender classification applications can give users with a suitable, personalized gender-based service, including human computer interaction (HCI). The administration of electronic customer interactions is a technique based on the Internet, where personal data are reviewed without violating privacy for all classes of customers [14]. The main goal of gender automation is to estimate gender for each client, based on their camera-driven face pictures and demographic data [15]. Gender classification can provide knowledge to enhance gaming and telephone application user experience. It can also be utilized with soft biometric approaches for verification or authentication accuracies. Gender classification can control children's access to undesirable content on TV and the internet. In jobs like police, military and government jobs, gender calculations are required during recruiting and retirement

[16]. To prevent children's access to adult distributor systems such as (alcohol and cigarettes) and adult websites and to monitor fraud detections in terms of security and surveillance. It can play an important part in recognizing lost persons and in recognizing old people for the identification of their prior pictures. The estimate of gender faciality poses numerous challenges [17]. For two-class men or women, gender prediction is followed. Human beings can easily, but not machines can easily classify sex. Methods and models based on additional hairdo, body shape, clothes and face characteristics can be employed for gender classification. Although authentic as of now cannot be predicted in estimation. For example, clustering is still used with facial photos for prediction. Furthermore, there are limited numbers of good gender databases for rigorous research [18].

IV. GENDER CLASSIFIACTION AND ITS APPLICATION

A gender classification is based on its biometric indications to determine the gender of an individual. Most face photos are utilized for extracting features and a classifier is used to learn a gender recognizer with the features extracted [19]. It is an active field of research in the fields of computer vision and biometry. The result of the gender classification is frequently a binary value, such as 1 or 0, that is, male or female. A two-class classification challenge involves mostly gender recognition. While other biometric features, such as gait, can also be used to classify gender, facial techniques are still the most preferred for discrimination against gender [20].

V. RELATED WORKS

Alex Darborg [21] Male or female identification and confirmation is a method that is often known as gender prediction. This approach involves recognizing and confirming people in a photograph by their appearance. Researchers have recently begun to pay greater attention to this field, and they are continuously improving the models that underpin them. The purpose of this study is to develop a real-time face recognition system by using one-shot learning techniques. The phrase "one shot" refers to the process of learning from a single or a small number of training samples. Several methods to resolving the problem are discussed and contrasted in this article. Convolutional neural networks, as is well known, need large datasets in order to attain acceptable accuracy. The findings of the research are shown in the graph below. They proposed a method to solve this problem by reducing the number of training instances to one while still achieving an accuracy that was close to 100 percent. They did it by using the concept of transfer learning. [6].

Ramalakshmi K [22] Gender recognition is the technique of applying deep learning to recognize a person's gender from their face picture. Pose variation, lighting, and occlusion are only a few of the variables that influence face recognition. These are minimized by improving forecast accuracy. Convolutional Neural Network is the network that was utilized to train the system (CNN). Faces are identified and clipped from the picture to improve accuracy. Face detection is done using Open CV, which uses the frontal characteristics of the face to detect the face. This is done when the network is being trained. Cropped pictures were utilized in the training dataset. The suggested method can accurately estimate a person's gender without sacrificing accuracy.

The graph depicts the network's training accuracy and loss after it has been trained.[22]
Gil Levi and Tal Hassner [23] suggested an automatic age and sexual orientation technique that was relevant to an expanding use, particularly since social and internet life were on the rise. They showed the pictures with deep coevolutionary neural systems (CNN). On these assignments a critical increase was made in the execution. In this connection, they developed a fundamental coevolutionary network technology that could be used despite restrictions on the measurement of learning information. They evaluated the strategy for the current audience for sex assessment and showed it to be the finest current class technique in dramatic terms.
On the Audience benchmark, there is a confusion matrix for age estimation.

Makinen and R. Raisamo [24] provided an approach which included successful assessment of the sexual orientation of facial images obtained under genuine further improvements in the improvement of face identity. The suggested organizer, prepared with no arrangement on the enormous uncontrolled Celebes dataset, tries to find ways of evaluating the sexual orientation of real face images. Cross-database LFWA and CASIA-Web Face data collections show that our proposed technology predominates.

Shubham Patil [25] The main purpose of this article is to create an algorithm that properly guesses the sex of a person. Hair cascade is one of the most used methods. In this article, they have examined a model that can predict a person's gender using Haar Cascade's help. The model trained the classifier as positive and negative pictures using various male and female photos. Various face characteristics are removed. With the help of the Haar Cascade classifier the input picture is male or female. We have taken use of the neural network Deep Convolution. Even with little data, it functions effectively. The article uses a deep learning architecture for the approximation problem. Caffe has an architectural expression, extendable code. Over 60M pics per day can be processed by Caffe. It is one of the quickest possible convent implementations. [11].

Sandeep Kumar [26] It created a face image-based gender detection algorithm. In preparation, the brightness of a picture is preserved using dynamic inflatable histogram equalization (BPDFHE). +In this document, the extraction was done using the Invariable Fourier Transform (SIFT), and the classification was done with a support vector machine (SVM). The results of performance testing were 98 percent, 91 percent, and 94 percent, respectively, using live images, FEI, and SCIEN databases.

Jinhyeok Jang [27] Recurring learning with visual fastening depicts face attribute recognition. CNN has calculated face features and recurring network function development has been encoded. In general, the visual fixation was spaced across nose and lips between eyes or on the eyes. Adjustment of face attributes was also expanded using videos. The proposed system received a recognition rate of 89.8 from ADIENCE and 91.36 from MULTI-PIE. Computer facial recognition provides greater precision than people. The selection of features is difficult due to redundant and equal features.

The suggested multi-modal identification system T. Jabid and H. Kabir [28] combines two distinct facial and fingerprint functionalities to identify individuals. Since the BI system uses physical or conduction qualities to verify the identity of a person, it ensures significantly more security than passwords and numerical systems. However, occasionally one characteristic is not sufficiently accurate to identify, and the feature selected cannot always be read. This is far more accurate than single feature systems with its two modalities.

Hugo.et al [29] proposes an all-in-one extractor and classifier solution to the classification challenge using the CSN network. The results were hopeful that soft-biometric features can be extracted using a CNN end-to-end classification. The results were highly promising. The approach provided has obtained a decent generalization capacity and has correctly classified the three separate qualities.

A model of the convolutional neural network was described by Kukharenko.et al [30] enabling automatic simultaneous extraction of several features in a painting. A deep coevolutionary neural network with shared starting layers and various probabilistic results is the proposed model. They use sex, a moustache, and a beard as characteristics of a person's appearance. This neural network architecture can be utilized to simultaneously identify a higher number of features without substantial operation time increases.

VI. CONCLUSION

To tackle the real-time application challenges, an overall assessment of contributions to gender classification estimates might be used. Most of the research done in this study is on the Coevolutionary Neural Networks. 11 different kinds of neural networks were discussed with their MAE and model accuracy. Furthermore, in addition to the distinction between several functions, function removal is carried out by means of only one extractor or, perhaps, one-time classification along with several other works, fusion is followed by a separation process or perhaps extraction of attributes. In the future, good outcomes and years of opinion can also continue to be achieved using reliable transfer learning procedures.

REFERENCES

1) L. Prasad and S. Iyenqar, Wavelet Analysis with Applications to Image Processing. CRC-Press, 1997.
2) Juan E. Tapia and Claudio A. Perez, "Clusters of Features Using Complementary Information Applied to Gender Classification from Face Images", IEEE Access, VOLUME 7, 2019.
3) P. I. Kiratsa "Gender identification through facebook data analysis using machine learning techniques" November 2018
4) George Azzopardi, Antonio Greco, Alessia Saggese and Mario Vento, "Fusion of Domain Specific and Trainable Features for Gender Recognition from Face Images",IEEE Access, VOLUME 6, 2018.
5) Lin Yuan, Fanglin Chen, Ling-Li Zeng, Lubin Wang, and Dewen Hu,"Gender Identification of Human Brain Image with A Novel 3D Descriptor",IEEE/ACM Transactions on Computational Biology and Bioinformatics, VOL. 15, NO. 2, MARCH/APRIL 2018.
6) Ahmad Jamal KHDR and Cihan VAROL,"Age and Gender Identification by SMS Text Messages",978-1-5386-6878-8/18/©2018 IEEE.
7) Juan E. Tapia, Claudio A. Perez and Kevin W. Bowyer, "Gender Classification from the Same Iris Code Used for Recognition", IEEE Transactions on Information Forensics and Security, Vol. 11, No. 8, August 2018.
8) Koichi Ito, Hiroya Kawai∗ , Takehisa Okano∗ and Takafumi Aoki "Age and Gender Prediction from Face Images Using Convolutional Neural Network" Proceedings, APSIPA Annual Summit and Conference 2018
9) Basile, A., Dwyer, G., Medvedeva, M., Rawee, J., Haagsma, H., Nissim, M.: N-gram: New groningen author-profiling model. CoRR abs/1707.03764 (2017),
10) Miura, Y., Taniguchi, T., Taniguchi, M., Ohkuma, T.: Author Profiling with Word+Character Neural Attention Network—Notebook for PAN at CLEF 2017
11) Kodiyan, D., Hardegger, F., Neuhaus, S., Cieliebak, M.: Author profiling with bidirectional rnns using attention with grus. In: CLEF (2017).
12) Amirali Abdolrashidi , Mehdi Minaei , Elham Azimi3 , Shervin Minaee4" Age and Gender Prediction from Face Images Using Attentional Convolutional Network" 2017.
13) Basile, A., Dwyer, G., Medvedeva, M., Rawee, J., Haagsma, H., Nissim, M.: N-gram: New groningen author-profiling model. CoRR abs/1707.03764 (2017).
14) MIURA, Y., TANIGUCHI, T., TANIGUCHI, M., OHKUMA, T.: AUTHOR PROFILING WITH WORD+CHARACTER NEURAL ATTENTION NETWORK—NOTEBOOK FOR PAN AT CLEF 2017. IN: CAPPELLATO, L., FERRO, N., GOEURIOT, L., MANDL, T. (EDS.) CLEF 2017
15) KODIYAN, D., HARDEGGER, F., NEUHAUS, S., CIELIEBAK, M.: AUTHOR PROFILING WITH BIDIRECTIONAL RNNS USING ATTENTION WITH GRUS. IN: CLEF (2017).
16) Pau Rodrıguez , Guillem Cucurull, Josep M. Gonfaus , F. Xavier Roca, Jordi Gonz`alez "Age and Gender Recognition in the Wild with Deep Attention" June 29, 2017.
17) Sebastian Lapuschkin "Understanding and Comparing Deep Neural Networks for Age and Gender Classification" 2017.
18) Jiayan Qiu "Convolutional Neural Network based Age Estimation from Facial Image and Depth Prediction from Single Image" January 2016.
19) RANGEL, F., ROSSO, P.: ON THE IMPACT OF EMOTIONS ON AUTHOR PROFILING. INFORMATION PROCESSING & MANAGEMENT 52(1), 73 – 92 (2016).
20) SHAN SUNG LIEW , MOHAMED KHALIL-HANI, SYAFEEZA AHMAD RADZI , RABIA BAKHTERI "GENDER CLASSIFICATION: A CONVOLUTIONAL NEURAL NETWORK APPROACH" TURKISH JOURNAL OF ELECTRICAL ENGINEERING & COMPUTER SCIENCES, 2016.

21) Alex Darborg "Real-time face recognition using one-shot learning A deep learning and machine learning project" 2020, Department of Information and Communication Systems.

22) Ramalakshmi K , T. Jemima Jebaseeli , Venkatesan R "Prediction of Gender from Facial Image Using Deep Learning Techniques" Vol.-15, No.-2, February (2020) pp 118-128 ISSN (Print) 0973-897.

23) Gil Levi and Tal Hassner "Gender Prediction from Images Using Deep Learning Techniques" 2015.

24) MAKINEN AND R. RAISAMO "GENDER DETECTION USING MACHINE LEARNING TECHNIQUES AND DELAUNAY TRIANGULATION" 2015.

25) Shubham Patil, Bhagyashree Patil, Ganesh Tatkare "Gender Recognition and Age Approximation using Deep Learning Techniques" International Journal of Engineering Research & Technology (IJERT) ISSN: 2278-0181 IJERTV9IS040268 Vol. 9, Issue 04, April-2020.

26) Sandeep Kumar, Sukhwinder Singh and JagdishKumar, "Gender Classification Using Machine Learning with Multi-Feature Method",978-1-7281-0554-3/19/ @ 2019 IEEE.

27) Jinhyeok Jang, Hyunjoong Cho, Jaehong Kim, Jaeyeon Lee, andSeungjoon Yang, "Facial Attribute Recognition by RecurrentLearning With Visual Fixation",IEEE Transactions On Cybernetics, VOL. 49, NO. 2, FEBRUARY 2019.

28) T. Jabid and H. Kabir , "Gender classification using Local Directional Pattern (LDP)", IEEE International Conference on Pattern Recognition, pp. 2162 - 2165, August. 2010

29) Hugo "Gender classification using Interlaced Derivative pattern", IEEE transaction of pattern Recognition, pp. 1509 -1512, August 2010.

30) Kukharenko, "Gender classification using single frontal image per person," IEEE International Conference on Pattern Recognition, pp. 1192 - 1195, August. 2010.