International Journal of Scientific Research & Engineering Trends
Volume 9, Issue 5, Sep-Oct-2023, ISSN (Online): 2395-566X

A Critical Analysis of Machine and Deep Learning Techniques for Gender Identification

Yodhant Singh
Department of School of Computer Science and Information Technology
Symbiosis University of Applied Sciences , Indore, India
Yodhant@gmail.com

Abstract- Gender classification has become a topic of growing interest, primarily because it can provide valuable insights into the distinct social activities and behaviors associated with males and females. Particularly, when it comes to visual representations, gender classification, especially in facial recognition, presents a unique set of challenges. This process involves determining an individual's gender based on their physical appearance, and it has gained prominence due to the wealth of information gender can offer about societal behaviors. In recent years, the applications of automatic gender classification have expanded across various domains. For instance, in conservative societies, such a classification system finds utility in secure environments, where accurately identifying an individual's gender becomes crucial, particularly in sensitive areas, to prevent unauthorized access and maintain safety. Additionally, this technology is employed in scenarios involving gender segregation, such as in female railway compartments, gender-specific marketing strategies, and within certain cultural or religious contexts like temples. The evolving capabilities of gender classification systems hold the promise of facilitating a wide range of applications, with potential future developments aimed at enhancing accuracy and inclusivity while addressing privacy and ethical concerns.

Keyword:Gender Classification, Convolutional Neural Systems, SVM , LFW,FERET.

I. INTRODUCTION

Gender dynamics play a substantial role in shaping social interactions, with languages incorporating various linguistic nuances, greetings, and grammatical rules that distinguish between genders and age groups. Despite the prevalence of these gender-related characteristics in our daily lives, commercial applications have a considerable distance to cover in accurately and swiftly recognizing these cues from facial photographs. This challenge becomes particularly perplexing when considering the critical importance of facial recognition for various applications. Previous methods for estimating and identifying gender and age often relied on distinctive facial features and customized facial patterns. Some methods have been developed for age and gender prediction. However, only a few of these earlier methods have ventured into addressing the intricacies introduced by unaltered images taken in real-world scenarios.

These images can be marked by extreme lighting conditions, occlusions, pose variations, motion artifacts, and other unpredictable factors. Bridging the gap between intuitive human visual perception and computational systems is a challenging endeavor. To tackle this challenge, we draw inspiration from the latest advancements in face recognition technology, specifically the use of complex convolutional neural networks (CNNs). CNNs have proven to be promising due to their inherent ability to analyze facial images accurately for age and gender identification. This promising aspect lies in their fundamental architecture, which allows for the precise analysis of age and gender from currently available facial images. Our approach leverages this architecture to determine gender from unaltered images featured in our latest Adience benchmark, outperforming existing state-of-the-art methods. While these results mark an important milestone, they also hint at the need for more sophisticated model architectures, indicating that gender categorization remains a challenging task, as evidenced by the diverse range of images captured by our audience. We aim to facilitate further advancements in this field by openly sharing our trained models and categorization system with the public, providing a foundation for more effective future approaches.

II. CLASSIFICATION OF OF MEN AND WOMEN

In the early stages of gender prediction, the primary focus was on estimating facial trait measurements, particularly the proportions of various facial features such as eyebrows, nose, lips, and their dimensions. This method relied on predefined norms to determine the ratios and lengths of these features. Similarly, recent years have seen a method employed to predict the gender of individuals under the age of 18. However, this technique presents a

International Journal of Scientific Research & Engineering Trends
Volume 9, Issue 5, Sep-Oct-2023, ISSN (Online): 2395-566X

significant challenge as it requires precise localization of facial features, making it unsuitable for analyzing wild and unstructured photographs typically found on social media. Another line of work explored alternative approaches, including subspace and multiplier methods.

These methods, though effective, require input photos to be accurately aligned and closely positioned, limiting their applicability to specific scenarios. In contrast, research delved into facial object representation using Gaussian Mixture Models (GMM), focusing on the distribution of facial regions. Instead of pixel maps, trustworthy descriptors were employed to depict regional face proportions, ultimately replacing GMM and Hidden-Markov Models with Supervectors.

Robust object descriptors, such as Fuzzy-LDA and Gabor image descriptors, were introduced for cases where facial images could belong to multiple gender groups. Gender evaluation techniques incorporated Biological Inspired Characteristics Museum (BIF) and sequential training methods. Additionally, Gabor and local binary patterns, along with hierarchical support vector machine (SVM) features, were used to categorize gender based on the entrance image, followed by age-approximation vector regression. Active Appearance Models, along with distance learning and dimensional reduction, were employed for modest and limited age estimations, demonstrating their utility in these scenarios. Local Binary Patterns (LBP) descriptor variations, in the absence of SVM classification, delivered state-of-the-art results in gender classification. These findings paved the way for the suggested strategy, aiming to apply these results to a more challenging audience with the same objective.

An early technique for gender classification involved constructing a neural network with a limited number of nearly frontal facial elements. Gender determination was based on the intensity of the item and 3D head anatomy captured by a laser scanner. SVM classifiers and AdaBoost were utilized directly for image intensities, and their relationship with age and sex was discussed.

The Webers local texturing descriptor, previously used for gender detection, achieved near-flawless performance in the FERET benchmark. This success was attributed to shared data encompassing frequency, shape, and texture characteristics. In conclusion, these diverse approaches have contributed to the evolving landscape of gender classification, with each method offering unique insights and performance in specific contexts. In most of the aforementioned techniques, the FERET benchmark served as a pivotal tool for concept model design and result assessment. The FERET dataset consists of captured photographs, and the conditions under which these photos are taken are notably less challenging compared to capturing real-world, uncontrolled facial images.

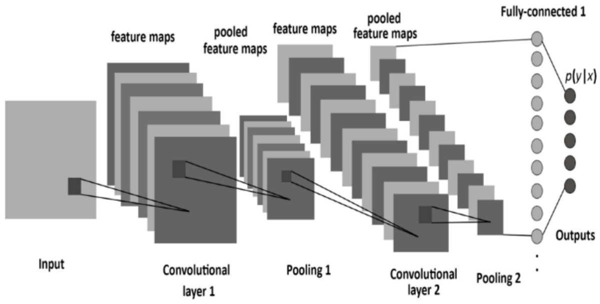

Figure 1. Illustration the basic CNN architecture [7]

The implications of this benchmark test highlight the concentrated efforts in developing new approaches that are relatively easy to implement. Consequently, evaluating the true comparative effectiveness of different tactics becomes a challenging task. To address this, the commonly recognized dataset known as "Labeled Faces in the Wild" (LFW) emerged as a valuable resource. LFW primarily focuses on recognizing faces and has become instrumental in various facial analysis tasks. In our technology, we leverage LBP (Local Binary Patterns) with AdaBoost grouping, following a robust approach to gauge performance. This approach ideally involves utilizing data from large training sets, encompassing a wide range of instances, for both age estimation and other facial analysis tasks, ultimately enhancing the accuracy and applicability of our methods.

III. LITRACTURE WORK

Zhou X et al. employed SVM and Gabor wavelet transformations in their work to identify gender. Local Binary Pattern (LBP) is another technique used to analyze pattern histograms generated by the LBP operator, which captures crucial regional texture properties of objects [3]. While humans possess an innate ability to discern a person's gender, computers still face challenges in achieving accurate gender identification from face photos. Gender identification is a critical preprocessing step for various applications, including face recognition, criminology, security technology, and surveillance.

Despite advancements in accuracy, gender classification applications often lag behind those focused solely on facial recognition. Two primary categories of applications exist: "geometric applications" and "regional applications," each targeting unique features for gender differentiation. Metcalfe manually ranked facial characteristics, and when integrated into the HyperBF network, the accuracy improved to 79%. To further enhance accuracy, techniques like Local Derivative Patterns (LDP) reflecting racial characteristics were introduced, followed by Support Vector Machine (SVM) classification, achieving a 95.05% success rate [11].

In a study involving 1,000 fingerprints (500 male, 500 female) from an internal database, the K-nearest neighbor

(KNN) method was employed for classification. Results showed that the Left-Winged Woman Fingers index achieved an 82.60% success rate, while the Left-Winged Fingers ranking achieved 82.90%. Additionally, men exhibited significantly longer finger lengths compared to women, with 80.40% versus 76.84% overall [12].

Researchers like Golomb et al. have explored neural networks for sex identification challenges. For instance, SexNet, a two-layer neural network, successfully classified images with a 91.9% accuracy rate. Various methods, including ICA and LDA, have also been applied for gender categorization, with SVMs achieving a 96.6% accuracy rate when using the FERET database. However, despite improvements in classification accuracy, generalization remains a challenge. Natural variations in factors like lighting, head tilt, and facial expressions can hinder classifier performance [13].

Speech signal mining and voice recognition play a crucial role in extracting meaningful information from massive datasets. Speech processing aims to distinguish between male and female voices, considering factors such as emotional content, intoxicated speech, autistic speech, and deviant language. Speech recognition designs focus on gathering speech signal data and learning to differentiate between male and female voices [14].

Gender categorization involves distinguishing between individuals based on their sexual identities, utilizing genetic or environmental mechanisms for physical determination. It plays a significant role in various fields, given its many potential applications. Historically, researchers relied on visual cues, but modern methods employ screens and lighting for gender identification. Utilizing facial characteristics for sex identification has shown promise and is considered a crucial topic in biometrics [15]. Recent approaches to gender identification often involve using techniques like the Wavelet Discrete Transform, as well as features related to object length and discrete cosine neural networks. These approaches aim to address challenges associated with capturing learning objects from various angles and lighting conditions [16].

Dealing with high-dimensional data in software description is challenging due to the "curse of dimensionality." Identifying redundant features that impact classification accuracy is crucial. In this context, a new classifier combining CHAID with a genetic algorithm has been proposed. The approach involves creating a decision tree using CHAID characteristics and comparing results with standard practices, ultimately seeking to improve classification accuracy and reduce the learning curve [17]. Studies exploring finger length, surface area, and rim properties have shown gender-related differences. SVM categorization has achieved high accuracy rates, and various features like ridge count, ridge thickness to valley thickness ratio (RTVTR), ridge length, and finger width have been used to distinguish between genders [18]. Face recognition plays a crucial role in determining the proximity of subjects within an image by identifying different faces. To achieve accurate results, it's essential to consider factors such as geometry, lighting, and image data. However, obtaining full facial images for face detection can be challenging. Face recognition methods can be categorized based on the utilization of image data, including shading contour or motion data, to discover faces in still images or image sequences [19].

Zhang et al. delve into the interpretation of facial expressions and provide detailed steps for analyzing the impact of automatically detected and matched heads on gender categorization [20], offering valuable insights into this area.

Roxo et al. introduce YY-Net, a method that successfully extracts facial regions from photos with varying image and subject conditions when conventional face detectors fail. YY-Net employs a channel-attention sub-network and a learnable fusion matrix to focus on critical body regions based on image and subject attributes, integrating face and body data. It outperforms five other PAR methods, reducing prediction errors by 24% in frontal data and achieving state-of-the-art results in gender recognition [4].
J. Chen and colleagues explore the application of gait biometrics for secure authentication, addressing the challenge of obtaining sufficient gait bioinformatics for pattern recognition. Their research utilizes age and gender recognition traits and phases, demonstrating that reliable age prediction within 5% accuracy and 97% gender recognition can be achieved with just three features extracted from pressure trajectory centroids [5].

AlShaye et al. emphasize the importance of reliable feature descriptors, representations, and classifiers in addressing recognition problems. They propose a model that combines handcrafted features with Convolutional Neural Networks (CNN) to overcome limitations related to image quality, illumination, and location while achieving superior results compared to state-of-the-art methods [6].
Susithra and coauthors discuss mood and gender detection using neural networks, breaking down emotions into four categories. Their approach includes systems for gender and emotion recognition, with a Feedforward neural network for gender recognition and a CNN for emotion recognition, achieving a 91.46% gender identification rate and an 86% emotion identification rate [7].

Selim et al. introduce an innovative approach that augments deep neural networks with a head orientation adapter, enhancing the accuracy of gender prediction models by 20%. This adaptation utilizes head angles to fine-tune deep learning neural networks and was evaluated using the AutoPOSE dataset, which provides precise measurements of head orientation [8].

1. Methods for Recognizing Human Faces

Facial region methods are intricate and lack a definitive sequential order, as they often intertwine and evolve continuously. In this context, we propose two criteria for strategic planning, separated by specific time intervals to adapt to the prevailing conditions. Data utilized in this context is categorized into four distinct buckets based on various factors, ensuring an appropriate context for analysis. A meticulous examination of the situation is imperative [21]. Currently, we possess the capability to capture images in controlled environments with stable structures and artificial lighting, enabling the recognition of facial features characterized by distinct shading patterns around their edges. Various methods for facial coloration exist, although they may lose effectiveness if subjected to abrupt changes in illumination. Moreover, human skin color undergoes significant variations, transitioning from white to gray, partly attributed to thermophysical distinctions. Achieving realistic human skin tones remains a formidable challenge, yet considerable efforts have been dedicated to establishing dependable facial features based on skin tone. The utilization of age-related data for facial recognition is now facilitated through continuous video recording, and many organizations mandate rigorous image retrieval practices. By adhering to specific guidelines, optimal results can be achieved in controlled testing scenarios [22].

Table 1 Comparative analysis different gender classification approaches using deep learning

Author	Algorithm /Methodology	Advantage	Disadvantage
Orken Mamyrbayev et al [23]	Convolution Neural Network	Characterization of a person's gender based on their voice	Analyze the algorithm's ability to classify people based on age and gender.
S. Arora et al.[24]	Convolutional Neural Networks, back-propagation and Adam optimization.	Performance in classification	Only a very little accuracy has been achieved compared to previous facial recognition algorithms.
Gök, E.C et al [25]	Multilayer Perceptron (MLP) gradient boosting and random forest in classification process	We were able to classify 96.22% of the data correctly.	The auditory properties were used to determine gender.
Y. Akbulut, et al [26]	LRF-ELM and CNN	Performance rate of 80% and 87.13%,	Very less accuracy
M. Marouf et al [27]	Deep Convolutional Neural Network (DCNN)	Uses a single left-hand radiograph to classify the gender and forecast the individual's age	Methods of transfer learning
T. V. Janahiraman et al [28]	VGG16, ResNet-50, and MobileNet	In terms of accuracy, VGG-16 was the most accurate.	Existing approaches are still unable to match real-time images in terms of performance.
S. Haseena et al [29]	deep convolution neural network (CNN),	The suggested network's correctness in terms of performance is evaluated using the LFW dataset.	In recent years, there has been a boom in the number of apps that can automatically classify face images according to gender. These applications use facial recognition technology.
A. Krishnan et al [30]	face-based gender classification system	Using facial landmarks, it was found that facial morphological differences were evident.	Automated sex identification and labelling there is a significant amount of space for advancement here.
K. S. Htet et al. [31]	R-CNN	Improving results with multi-IP cameras under SDN controller	Data with a large number of dimensions

IV. RESEARCH GAP

The process of capturing a photograph is inherently imperfect, and it offers no assurance of consistent conditions. The accuracy of gender recognition algorithms remains vulnerable to fluctuations in lighting, head orientation, facial expressions, potential obstructions like eyewear or hats, and variations in camera quality. This susceptibility to factors affecting accuracy has garnered significant attention, particularly within the realm of gender-detecting applications. These applications leverage facial recognition technology; however, they often overlook datasets that include unaltered images of individuals who have not recently groomed or applied touch-ups, as well as images devoid of facial expressions. This discrepancy highlights the limitations of current methods when compared to datasets containing photos influenced by aging, frequent grooming, cosmetics, and facial expression variability.

V. CONCLUSION

Gender categorization research holds immense potential for various applications, encompassing fields like computer vision systems, biometric identification systems, credit card verification systems, visual surveillance systems, data collection, and security systems, among others. This research has led to groundbreaking advancements, benefiting a wide array of disciplines including machine learning, image processing, and human-computer interaction.

Despite the proliferation of photo-gender-determination applications in recent years, there is a notable dearth of comprehensive literature on the subject. These applications rely on facial recognition technology but typically overlook datasets that encompass individuals without recent grooming or touch-ups, as well as images where subjects maintain expressionless faces. This gap underscores the limitations of current approaches when confronted with datasets that incorporate images altered by factors such as aging, regular grooming, cosmetic enhancements, and variations in facial expressions. Addressing these limitations represents an exciting frontier in gender categorization research.

REFERENCES

[1] S. Ortega Cisneros, J. M. Ruiz Varela, M. A. Rivera Acosta, J. Rivera Dominguez and P. Moreno Villalobos, "Pollen Grains Classification with a Deep Learning System GPU-Trained," in IEEE Latin America Transactions, vol. 20, no. 1, pp. 22-31, Jan. 2022, doi: 10.1109/TLA.2022.9662170.
[2] Gupta, S.K., Nain, N. Review: Single attribute and multi attribute facial gender and age estimation. Multimed Tools Appl (2022). https://doi.org/10.1007/s11042-022-12678-6
[3] Zhou X, Wang H, Xu C, Peng L, Xu F, Lian L, Deng G, Ji S, Hu M, Zhu H, Xu Y, Li G. Application of kNN and SVM to predict the prognosis of advanced schistosomiasis. Parasitol Res. 2022 Jun 29. doi:

10.1007/s00436-022-07583-8. Epub ahead of print. PMID: 35767047.

[4] T. Roxo and H. Proença, "YinYang-Net: Complementing Face and Body Information for Wild Gender Recognition," in IEEE Access, vol. 10, pp. 28122-28132, 2022, doi: 10.1109/ACCESS.2022.3157857.

[5] Y. -J. Chen, L. -X. Chen and Y. -J. Lee, "Systematic Evaluation of Features From Pressure Sensors and Step Number in Gait for Age and Gender Recognition," in IEEE Sensors Journal, vol. 22, no. 3, pp. 1956-1963, 1 Feb.1, 2022, doi: 10.1109/JSEN.2021.3136162.

[6] N. AlShaye, L. AlMoajil and M. Abdullah-Al-Wadud, "A Gender Recognition System Based on Facial Image," 2022 3rd International Conference on Artificial Intelligence, Robotics and Control (AIRC), 2022, pp. 21-25, doi: 10.1109/AIRC56195.2022.9836455.

[7] N. Susithra, K. Rajalakshmi, P. Ashwath, B. Ajay, D. Rohit and S. Stewaugh, "Speech based Emotion Recognition and Gender Identification using FNN and CNN Models," 2022 3rd International Conference for Emerging Technology (INCET), 2022, pp. 1-6, doi: 10.1109/INCET54531.2022.9824908.

[8] M. Selim, S. Krauß, T. A. Habtegebrial, A. Pagani and D. Stricker, "Deep Orientation-Guided Gender Recognition from Face Images," 2022 12th International Conference on Pattern Recognition Systems (ICPRS), 2022, pp. 1-6, doi: 10.1109/ICPRS54038.2022.9854066.

[9] B. Kwon and S. Lee, "Joint swing energy for skeleton-based gender classification", IEEE Access, vol. 9, pp. 28334-28348, 2021.

[10] A. Althnian, N. Aloboud, N. Alkharashi, F. Alduwaish, M. Alrshoud and H. Kurdi, "Face gender recognition in the wild: An extensive performance comparison of deep-learned hand-crafted and fused features with deep and traditional models", Appl. Sci., vol. 11, no. 1, pp. 89, 2021.

[11] Khan, S.A., Nazir, M., Riaz, N., Hussain, M., Naveed, N. (2012). Gender Classification Using Local Binary Pattern and Particle Swarm Optimization. In: Chowdhry, B.S., Shaikh, F.K., Hussain, D.M.A., Uqaili, M.A. (eds) Emerging Trends and Applications in Information Communication Technologies. IMTIC 2012. Communications in Computer and Information Science, vol 281. Springer, Berlin, Heidelberg.

[12] M. K. Shinde and S. A. Annadate, "Analysis of Fingerprint Image for Gender Classification or Identification: Using Wavelet Transform and Singular Value Decomposition," 2015 International Conference on Computing Communication Control and Automation, 2015, pp. 650-654, doi: 10.1109/ICCUBEA.2015.133.

[13] Ng, C.B., Tay, Y.H., Goi, BM. (2012). Recognizing Human Gender in Computer Vision: A Survey. In: Anthony, P., Ishizuka, M., Lukose, D. (eds) PRICAI 2012: Trends in Artificial Intelligence. PRICAI 2012. Lecture Notes in Computer Science(), vol 7458. Springer, Berlin, Heidelberg.

[14] Jagannath Jadhav, Sahana Devali, 2015, Speech Recognition to Distinguish Gender and A Review and Related Terms, International Journal Of Engineering Research & Technology (IJERT) ICESMART – 2015 (Volume 3 – Issue 19)

[15] Guarnera M, Hichy Z, Cascio MI, Carrubba S. Facial Expressions and Ability to Recognize Emotions From Eyes or Mouth in Children. Eur J Psychol. 2015 May 29;11(2):183-96. doi: 10.5964/ejop.v11i2.890. PMID: 27247651; PMCID: PMC4873105.

[16] Ms. Sushree Silpika Pattanayak, Ms. Sunita Dalai, Sujit Kumar Jena, 2015, Gender Classification using Distance Classifier and Neural Network, International Journal Of Engineering Research & Technology (IJERT) Volume 04, Issue 04 (April 2015), http://dx.doi.org/10.17577/IJERTV4IS040371

[17] S.R.Swarnalatha, Dr. G.M Kadhar Nawaz, 2014, Chaid and Genetic Algorithm-Based Hybrid Classifier for Pattern Classification, International Journal Of Engineering Research & Technology (IJERT) NCICCT – 2014 (Volume 2 – Issue 05),

[18] Prabhat M, Rai S, Kaur M, Prabhat K, Bhatnagar P, Panjwani S. Computed tomography based forensic gender determination by measuring the size and volume of the maxillary sinuses. J Forensic Dent Sci. 2016 Jan-Apr;8(1):40-6. doi: 10.4103/0975-1475.176950. PMID: 27051222; PMCID: PMC4799518.

[19] K C, Santosh and N, Pradeep, Development of Human Age and Gender Identification System from Teeth, Wrist and Femur Images (March 18, 2019). Proceedings of International Conference on Sustainable Computing in Science, Technology and Management (SUSCOM), Amity University Rajasthan, Jaipur - India, February 26-28, 2019.

[20] X. Zhang, S. Javed, A. Obeid, J. Dias and N. Werghi, "Gender Recognition on RGB-D Image," 2020 IEEE International Conference on Image Processing (ICIP), 2020, pp. 1836-1840, doi: 10.1109/ICIP40778.2020.9191068.

[21] Shan, C. (2010). Gender Classification on Real-Life Faces. In: Blanc-Talon, J., Bone, D., Philips, W., Popescu, D., Scheunders, P. (eds) Advanced Concepts for Intelligent Vision Systems. ACIVS 2010. Lecture Notes in Computer Science, vol 6475. Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-17691-3_30

[22] Greco, A., Saggese, A., Vento, M. et al. Gender recognition in the wild: a robustness evaluation over corrupted images. J Ambient Intell Human Comput

12, 10461–10472 (2021). https://doi.org/10.1007/s12652-020-02750-0

[23] Orken Mamyrbayev, Alymzhan Toleu, Gulmira Tolegen & Nurbapa Mekebayev | Duc Pham (Reviewing editor) (2020) Neural architectures for gender detection and speaker identification, Cogent Engineering, 7:1.

[24] S. Arora and M. P. S. Bhatia, "A Robust Approach for Gender Recognition Using Deep Learning," 2018 9th International Conference on Computing, Communication and Networking Technologies (ICCCNT), 2018, pp. 1-6, doi: 10.1109/ICCCNT.2018.8494194.

[25] Gök, E.C., Olgun, M.O. SMOTE-NC and gradient boosting imputation based random forest classifier for predicting severity level of covid-19 patients with blood samples. Neural Comput & Applic 33, 15693–15707 (2021).

[26] Yanhui Guo Abdul kadir Şengür Yaman Akbulut , "An effective color image segmentation approach using neutrosophic adaptive mean shift clustering ", MeasurementVolume 119, April 2018, Pages 28-40

[27] M. Marouf, R. Siddiqi, F. Bashir and B. Vohra, "Automated Hand X-Ray Based Gender Classification and Bone Age Assessment Using Convolutional Neural Network," 2020 3rd International Conference on Computing, Mathematics and Engineering Technologies (iCoMET), 2020, pp. 1-5, doi: 10.1109/iCoMET48670.2020.9073878.

[28] T. V. Janahiraman and P. Subramaniam, "Gender Classification Based on Asian Faces using Deep Learning," 2019 IEEE 9th International Conference on System Engineering and Technology (ICSET), 2019, pp. 84-89, doi: 10.1109/ICSEngT.2019.8906399.

[29] Haseena, S. Bharathi, I. Padmapriya and R. Lekhaa, "Deep Learning Based Approach for Gender Classification," 2018 Second International Conference on Electronics, Communication and Aerospace Technology (ICECA), 2018, pp. 1396-1399, doi: 10.1109/ICECA.2018.8474919.

[30] A. Krishnan, A. Almadan and A. Rattani, "Understanding Fairness of Gender Classification Algorithms Across Gender-Race Groups," 2020 19th IEEE International Conference on Machine Learning and Applications (ICMLA), 2020, pp. 1028-1035, doi: 10.1109/ICMLA51294.2020.00167.

[31] K. S. Htet and M. M. Sein, "Market Intelligence Analysis on Age Estimation and Gender Classification on Events with deep learning hyperparameters optimization and SDN Controllers," 2020 IEEE Conference on Computer Applications(ICCA), 2020, pp. 1-5, doi: 10.1109/ICCA49400.2020.9022854.