Real-time age-range recognition and gender identification system through facial recognition

Carlos Cruz-Colan, David Lopez-Herrera, Ernesto Paiva-Peredo, Kevin Acuña-Condori
Department of Electronics Engineering, Faculty of System and Electronics Engineering, Universidad Tecnológica del Perú, Lima, Peru

Article Info

Article history:

Received Mar 17, 2024
Revised Nov 14, 2024
Accepted Nov 24, 2024

Keywords:

Age classification
DeepFace
Face detection
Gender classification
MediaPipe
Real time
Red siamesa

ABSTRACT

Facial recognition and age estimation are being implemented in apparel retailing which is undergoing significant changes due to fashion and technology. To improve interaction with customers and refine marketing strategies. The paper proposes an approach based on a Siamese neural network and the use of tools such as MediaPipe for face detection and DeepFace for age and gender estimation. In addition, the four stages of the research work, real-time image capture, ID assignment, facial feature extraction, and data storage, are described. Early approaches to age estimation were based on biometric features, such as eyes, nose, mouth, and chin, resulting in limited accuracy and low performance in older adults. To improve accuracy, additional elements, such as the presence of wrinkles, were considered and a diverse database of images was used. The proposed methodology achieves a positive result for real-time age classification and gender ID. The results include information on gender, age, ID, time and date for each person identified.

Corresponding Author:

Ernesto Paiva-Peredo
Department of Electronics Engineering, Faculty of System and Electronics Engineering
Universidad Tecnológica del Perú
Calle Natalio Sánchez N° 125, Urb. Santa Beatriz, Cercado de Lima, Lima, Peru
Email: C22395@utp.edu.pe

1. INTRODUCTION

Today, apparel retailing is constantly changing, influenced by fashion trends and technological advances. Because of this change, malls and stores are constantly looking for innovative ways to improve their customers' shopping experience. By getting to know their customers better, they can recommend products according to individual preferences. Among the many factors that define the customer profile, age and gender stand out as crucial aspects. These two elements are particularly significant because of the different preferences and styles exhibited by various demographic groups depending on their age and gender.

Therefore, it has become necessary to classify ages in groups of four years, as well as to identify the gender of the person and collect this information through the use of neural networks. This technique of age classification and gender identification (ID) plays a fundamental role in shopping malls and stores to interact with their customers and refine their marketing strategy. Furthermore, accurate age and gender classification using neural networks not only benefits marketing strategies but also provides the opportunity to personalize the customer experience. This personalization translates into the ability to offer specific products and services tailored to each demographic group, which contributes to improved consumer satisfaction. Consequently, the use of these technologies is seen not only as a strategic enhancement but also as a means to strengthen customer and retailer relationships.

In recent years, facial recognition and age estimation have experienced remarkable growth, this increased interest is due to its broad potential in a variety of commercial applications, ranging from targeted advertising to visual monitoring and robotics, among others [1]–[5]. It is essential to highlight that age and gender classification are present in several sectors of commerce to improve sales [2], [6]. In addition, its application extends to compliance with legal regulations, such as restricting the sale of alcoholic beverages or prohibited products to minors [7], [8].

The ages of individuals are considered important biometric traits for ID [6], [9]. Early studies on age estimation were based only on certain biometric features such as eyes, nose, mouth, and chin, thus generating a classification with a low estimation percentage [2], [5]. In addition, accuracy decreased for adults over the age of 65, due to decreased elasticity and firmness of the skin [10]. For best results, Zighem *et al.* [7] mentioned for a better estimation of ages not only considering the features of eyes, nose, mouth, and chin, it began to consider additional elements such as the presence of wrinkles. On the other hand, it also mentions the use of databases that should be vast and varied, which should include images such as race, gender, and descent from different parts of the world [11]. This research has a low sample size, which suggests increasing the sample size of the population [12]. Other challenges presented by facial recognition for age estimation include illumination, full face coverage, as well as the presence of facial accessories [13], [7]. On the other hand, Dozdor *et al.* [14] proposed an age estimation method that involves cropping the image at neck level, and they also chose to detect the face in different positions to ensure wide and accurate coverage.

The research in [15]–[17] proposed solutions to combat the problems of unaligned profiles in the image and body postures at different camera angles. For example, the research in [1], [13], [15] chose to use the radial basis function with support vector machine (RBF-SVM) classifier method to extract facial features from the face such as eyes, eyebrows, and nose. Also, a multiple convolutional neural network (CNN) was used to train each of the neural networks with diverse sets of facial features [8], [18], [19]. The latter method stands out for its good performance and high percentage accuracy for age estimation. In comparison, Opu *et al.* [20] mentions that he worked with a lightweight CNN, which does not require much computational demand but the estimation accuracy is low. To obtain a better result, Guo and Mu [21] recommends the use of a MORPH-II dataset, because it presents a wide variety of images, to improve the accuracy of the result.

In conclusion, the review of the literature on age and gender estimation and classification highlights the need for an extensive database to achieve accurate results. The main objective of this article is to identify and characterize individuals by age and gender in real-time, with subsequent storage of the data in an archive. Determining age and gender ranges are complicated to determine due to several factors, such as the location of the person and the surrounding environment. Our project consists of five fundamental stages. First, we capture the image in real time using a camera, this is done through OpenCV which is a tool that allows us to capture what happens in real-time. In the second stage, we use MediaPipe to perform face detection, which allows us to accurately locate each face within a frame. In the third stage, we assign a unique ID to each identified person. This assignment is performed by a Siamese neural network, ensuring that the same person is not assigned different IDs. Then, in the fourth stage, we extract the facial features to determine the age and gender of each individual, which will be carried out using DeepFace which allows facial recognition and facial tribute analysis. Finally, in the last stage, the acquired data is sent and stored in their respective groups. After this process, we obtain visual results that show the image of the person along with detailed information about their gender, age and an associated unique ID.

2. METHOD

This paper presents a method for age and gender ID based on DeepFace technology [22]. This technology can detect 300 faces simultaneously and consists of 176 face reference points. A Siamese net was also used [23], for verification and ID assignment to each subject. This work recognizes the person's face as soon as it is in range of the camera and displays the data on the screen. For this work, public domain images were used, and tests were carried out with four hundred images, one hundred of each category.

The ID of age and gender has been divided into five essential stages, as shown in Figure 1, the diagram of the methodology is presented. In the first stage, image capture is performed through the camera. In the second stage, we employ the MediaPipe library for accurate face detection in the captured images in real-time. The third stage involves the comparison of the detected image with the existing database. If no matches are found, the image is automatically saved and assigned an unique user ID. In the fourth stage, data related to age and gender are accurately extracted using the DeepFace library. This fundamental step provides detailed information about each identified individual. Finally, in the fifth stage, the acquired data is submitted and organized into a table, allowing clear and accurate visualization of the classification results.

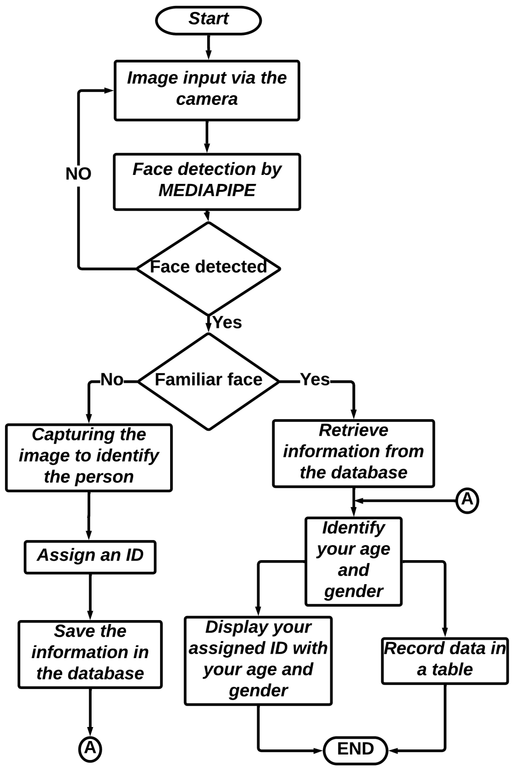


Figure 1. Methodology flowchart

2.1. Real-time image capture

The real-time capture stage is performed by computer vision, an open-source library. Real-time video capture is performed by a camera, which records a sequence of images in rapid succession, allowing real-time processing and analysis of visual data. Subsequently, the image is displayed on a graphical interface that allows users to visualize in real time what the camera is capturing, thus facilitating the transition to the next stage of detection.

2.2. Face detection via MediaPipe

Facial recognition is carried out using artificial vision. The captured frame goes through a CNN model, MediaPipe, developed by Google open source [24]. This model not only detects the face in real-time but also identifies specific facial features, such as the eyes, nose, and mouth [25]. The ability of this model to recognize and locate these facial features is crucial to identifying the region of interest, which in this case is focused on the accurate detection of people's faces while being able to detect several faces at once.

2.3. ID assignment

At this stage, each identified face goes through the process of assigning a unique ID. To perform this task, a Siamese neural network is implemented, an architecture that allows comparing two different inputs and evaluating the similarity between them. The network uses two branches that share the same set of weights. Each branch processes the input data independently through its layers, using the same set of weights. This architecture is fundamental to obtaining a representation that indicates the similarity between the resulting vectors, which results in the conclusion of whether the original inputs are similar or not [23]. Once the similarity has been established, a check is made in the database. If a match is found, the information is extracted. If not, a new ID is assigned to the face and the database is updated for future comparisons. This approach ensures accuracy and efficiency in the assignment and management of IDs for each detected face.

2.4. Age and gender classification

Age classification presents greater complexity due to the variability in the facial aging process, influenced by factors such as gender, ethnic descent and the person's quality of life. In this work, we use the DeepFace library [22], for age estimation. In this work, we classified ages into four groups: child (0-12 years), adolescent (13-18 years), young adult (19-35 years), and older adult (36-100 years). This categorization is done due to the complexity of determining the exact age of a person, since each experiences a unique aging process, for this reason determining age presents a challenge, grouping the ages would not present a large range of error in age estimation.

Gender ID is presented as a low cognitive load task for people because we can visually recognize gender through facial features. This process of gender classification is simplified by dividing people into two distinct categories: male or female. The implementation of a binary model in this context is natural, as there are only two possibilities. To carry out this process, the DeepFace library, recognized for its open codes and the availability of previously trained models, is used. The use of this library facilitates the accurate ID of gender from facial features captured in real-time [16].

DeepFace represents a specialized library that focuses on the ID of various attributes, including age, gender, emotion, and race. Its functionality is based on a pre-trained deep learning model, consisting of 16 convolutional layers (CNN) and 3 connected layers, which has been rigorously trained on a large dataset spanning up to four million faces. This training process has culminated in an impressive 97.35% accuracy on the labeled faces in the wild (LFW) dataset benchmark. The robustness and accuracy of the model make DeepFace a formidable tool for detailed analysis and accurate ID of facial features in a variety of applications [26].

To determine age and gender, the process starts with the detected face in the face detection stage. Before DeepFace analyzes the image, it is adjusted to the dimensions of the pre-trained model, which are 224x224 pixels. Then, the pixels are normalized within a range of 0 and 1. For feature extraction, DeepFace uses a CNN, these features may include details of the shape and texture of the face, as a result, the estimation of age in numerical values and gender is obtained.

2.5. Record the data

The storage of data records is essential for our project. Figure 2 shows the data logging flowchart. We start this process by creating a DataFrame, a tabular data structure that acts as an organized container. This data frame is composed of five key columns: "ID, age, gender", date and time, providing a structured format for storing the results of our detections.

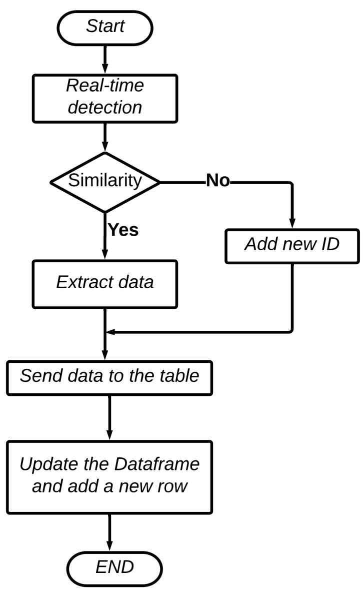


Figure 2. Data logging flowchart

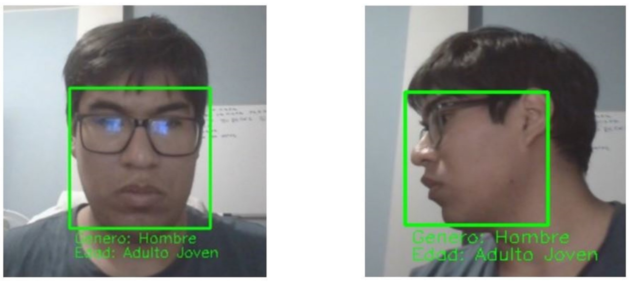
The aforementioned collected data are directed into a table where they are carefully organized in the corresponding columns. During program execution, each new detection contributes to the creation of an additional row. The addition of ”index=false” during this process ensures that no unnecessary columns are added, keeping the data structure clean and ready for further analysis. This strategic approach not only allows for the efficient capture and storage of information during program execution but also facilitates the visualization and analysis of the detections made. The ability to keep a detailed record of each detection made during runtime facilitates understanding the process of identifying people in real-time.

3. RESULTS AND DISCUSSION

The implemented model can predict ages and classify them into four groups: children, adolescents, young adults, and older adults, in comparison with [3], [11], [18], which group them into eight age classes (”0-2”, ”4-6”, ”8-13”, ”15-20”, ”25-32”, ”38-43”, ”48-53”, and ”60-80”). Since these authors employ the same pre-trained neural network model. In turn, by comparing it with the approach of [8], although the latter shows the exact age of the person, it has a higher margin of error in its predictions, reaching 85% in general. It also performs gender classification, identifying between men and women by analyzing facial features in real-time. This model was trained with an extensive dataset consisting of four million images, which contributes to a higher accuracy in the results. It is worth mentioning that, due to time constraints, we chose to use a previously trained model.

In the validation of the model, a real-time manual evaluation of the faces was carried out using individual tests to assess the accuracy of age and gender detection. The model demonstrated its ability not only to detect the face and estimate age and gender frontally, as shown in Figure 3(a) but also to perform this detection in real-time from a side view of the face, as illustrated in Figure 3(b). This lateral detection capability is a significant improvement over previous work by [8], that he could only effectively detect from a frontal view.

Figure 3 presents the results of gender and age classification in real-time, where the person is facing the camera. The results show an accuracy in estimating gender and age correctly to the person, who is 27 years old, in the corresponding young adult group. This test highlights the model’s ability to make real-time predictions accurately and efficiently. The combination of gender and age classification demonstrates the versatility and applicability of the model in practical situations.



(a) (b)

Figure 3. Gender and age prediction results: (a) frontal view and (b) lateral view

To expand the coverage of the model tests, evaluations were carried out with a larger group of people spanning various ages and genders. The results of these tests are presented in Figure 4, which was carried out with a sample of 100 images for each category, taken from public persons, with an ID accuracy of 76%, gender of 85% and age of 92% in the children’s category. The same sample size and procedure are applied to the rest of the categories. The results of 87%, 86%, and 91% for adolescents, 93%, 95%, 97% for young adults, and 88%, 85%, and 89% for older adults, as compared to the above mentioned in Abirami which provides an overall accuracy of 68.89% in correctly predicting age and gender. It is important to note that, when predicting age and gender, negative results were observed for certain individuals due to varying facial characteristics, as well as external conditions such as light, as illustrated in Figure 5. Despite these variations, the overall accuracy of the model demonstrates its effectiveness in the classification task.

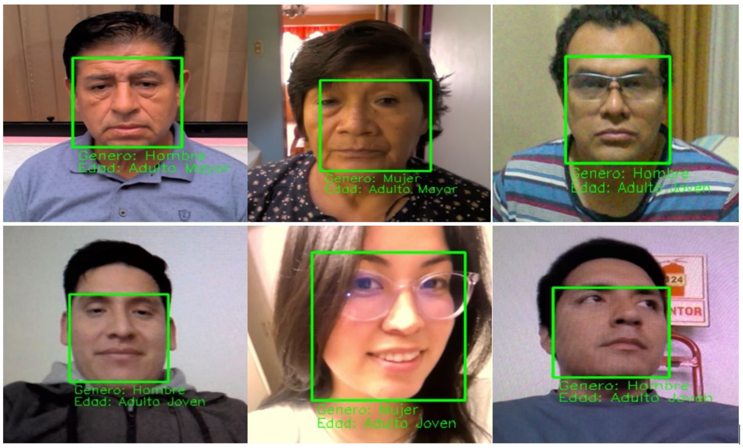


Figure 4. Gender and age prediction results

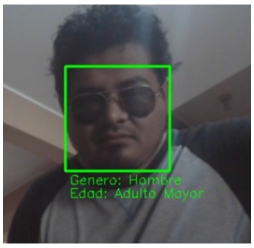


Figure 5. Negative results in age estimation

Figure 6 shows the table that stores the information of the people recognized through the camera. The process of storing data in a file involves taking the information collected on the faces detected in real-time and saving it in a structured format. To achieve this, ID matching using Siamese neural networks is used, in case a face is not found in the database, it is assigned a unique ID and added to the table along with details such as age, gender, date, and time of detection. This approach ensures the organization of the information collected during the process of identifying people in real-time.

1	ID	Edad	Género	Fecha	Hora
2	PERSONA_1	Adulto Joven	Hombre	2023-11-07	18:06:11
3	PERSONA_2	Adulto Mayor	Hombre	2023-11-07	18:10:20
4	PERSONA_3	Adulto Mayor	Mujer	2023-11-07	18:12:44
5	PERSONA_4	Adulto Joven	Hombre	2023-11-07	18:13:25
6	PERSONA_5	Adulto Joven	Hombre	2023-11-07	18:17:51
7	PERSONA_6	Adulto Joven	Mujer	2023-11-07	18:30:39
8	PERSONA_7	Adulto Joven	Hombre	2023-11-07	18:38:59
9	PERSONA_8	Adulto Joven	Mujer	2023-11-07	18:40:03
10	PERSONA_9	Adulto Mayor	Hombre	2023-11-07	18:43:15
11	PERSONA_10	Adulto Joven	Mujer	2023-11-07	18:52:37

Figure 6. Results in the excel-generated dataset

Little variation is observed in the age and gender predictions, mainly attributable to external factors. To improve accuracy, it is suggested that a more rigorous model be implemented in future iterations. The effectiveness of this detection network lies in its ability to recognize faces both frontally and laterally, as well as the detection of several faces simultaneously, making it a suitable choice for crowded environments. However, it is important to note one limitation: the network may have difficulty recognizing faces at long distances. In situations requiring long-distance recognition, it is recommended to explore other networks that offer optimal results.

4. CONCLUSION

The results obtained in gender and age classification have yielded positive results. However, it is crucial to recognize that age classification is affected by a variety of external factors, such as lighting, facial expressions, skin tones, and the person's gender. Despite these influences, the overall accuracy of the model remains remarkable. In this research, specific tools were employed to address each component of the process. Using MediaPipe, efficient and accurate real-time face detection was achieved 100%. In addition, DeepFace played a key role in gender and age estimation, providing satisfactory results 88.75%. Additionally, a unique strategy was implemented to assign a unique ID to each person detected. Through the use of a Siamese neural network, effective matching and assignment of IDs was achieved 86%, thus contributing to uniqueness in the ID of individuals over time. This combination of approaches provides a comprehensive and robust solution for the real-time ID of individuals. The result of this study is the combination of real-time gender classification and age classification from live camera streams, which represents an achievement of the stated objectives. Although much research has been conducted in these fields independently, no similar study has been found that combines all of these applications in the field of computer vision.

REFERENCES

[1] S. Mane and G. Shah, "Facial recognition, expression recognition, and gender identification," *Advances in Intelligent Systems and Computing*, vol. 808, pp. 275–290, 2019, doi: 10.1007/978-981-13-1402-5_21.

[2] K. R. Hassan and I. H. Ali, "Age and gender classification using multiple convolutional neural network," *IOP Conference Series: Materials Science and Engineering*, vol. 928, no. 3, 2020, doi: 10.1088/1757-899X/928/3/032039.

[3] A. Salihbašic and T. Orehovacki, "Development of android application for gender, age and face recognition using OpenCV," in *2019 42nd International Convention on Information and Communication Technology, Electronics and Microelectronics, MIPRO 2019*, 2019, pp. 1635–1640, doi: 10.23919/MIPRO.2019.8756700.

[4] A. Yousaf, M. J. Khan, M. J. Khan, A. M. Siddiqui, and K. Khurshid, "A robust and efficient convolutional deep learning framework for age-invariant face recognition," *Expert Systems*, vol. 37, no. 3, 2020, doi: 10.1111/exsy.12503.

[5] R. Suguna, M. S. Devi, A. Kushwaha, and P. Gupta, "An efficient real time product recommendation using facial sentiment analysis," in *2019 IEEE International Conference on Electrical, Computer and Communication Technologies (ICECCT)*, 2019, pp. 1–6, doi: 10.1109/ICECCT.2019.8869300.

[6] S. Kumar *et al.*, "Face spoofing, age, gender and facial expression recognition using advance neural network architecture-based biometric system," *Sensors*, vol. 22, no. 14, 2022, doi: 10.3390/s22145160.

[7] M. E. N. Zighem, A. Ouafi, A. Zitouni, Y. Ruichek, and A. Taleb-Ahmed, "Two-stages based facial demographic attributes combination for age estimation," *Journal of Visual Communication and Image Representation*, vol. 61, pp. 236–249, 2019, doi: 10.1016/j.jvcir.2019.03.025.

[8] A. Mustafa and K. Meehan, "Gender classification and age prediction using CNN and ResNet in real-time," in *2020 International Conference on Data Analytics for Business and Industry: Way Towards a Sustainable Economy (ICDABI)*, 2020, pp. 1–6, doi: 10.1109/ICDABI51230.2020.9325696.

[9] T. T. Lu, S. C. Yeh, C. H. Wang, and M. R. Wei, "Cost-effective real-time recognition for human emotion-age-gender using deep learning with normalized facial cropping preprocess," *Multimedia Tools and Applications*, vol. 80, no. 13, pp. 19845–19866, 2021, doi: 10.1007/s11042-021-10673-x.

[10] I. Boutet and B. Meinhardt-Injac, "Measurement of individual differences in face-identity processing abilities in older adults," *Cognitive Research: Principles and Implications*, vol. 6, no. 1, 2021, doi: 10.1186/s41235-021-00310-4.

[11] B. Sukh-Erdene and H. C. Cho, "Facial age estimation using convolutional neural networks based on inception modules," *Transactions of the Korean Institute of Electrical Engineers*, vol. 67, no. 9, pp. 1224–1231, 2018, doi: 10.5370/kiee.2018.67.9.1224.

[12] W. Wu, Y. Yin, X. Wang, and D. Xu, "Face detection with different scales based on faster R-CNN," *IEEE Transactions on Cybernetics*, vol. 49, no. 11, pp. 4017–4028, 2019, doi: 10.1109/TCYB.2018.2859482.

[13] S. A. Rizwan, A. Jalal, and K. Kim, "An accurate facial expression detector using multi-landmarks selection and local transform features," in *2020 3rd International Conference on Advancements in Computational Sciences (ICACS)*, 2020, pp. 1–6, doi: 10.1109/ICACS47775.2020.9055954.

[14] Z. Dozdor, T. Hrkac, K. Brkic, and Z. Kalafatic, "Facial age estimation models for embedded systems: a comparative study," *IEEE Access*, vol. 11, pp. 14282–14292, 2023, doi: 10.1109/ACCESS.2023.3244059.

[15] S. Kumar, S. Singh, and J. Kumar, "Automatic live facial expression detection using genetic algorithm with haar wavelet features and SVM," *Wireless Personal Communications*, vol. 103, no. 3, pp. 2435–2453, 2018, doi: 10.1007/s11277-018-5923-y.

[16] S. Kumar, S. Singh, and J. Kumar, "Multiple face detection using hybrid features with SVM classifier," *Advances in Intelligent Systems and Computing*, vol. 847, pp. 253–265, 2019, doi: 10.1007/978-981-13-2254-9_23.

[17] S. Kumar, S. Singh, and J. Kumar, "A study on face recognition techniques with age and gender classification," in *2017 International Conference on Computing, Communication and Automation (ICCCA)*, 2017, pp. 1001–1006, doi: 10.1109/CCAA.2017.8229960.

[18] B. Abirami, T. S. Subashini, and V. Mahavaishnavi, "Gender and age prediction from real time facial images using CNN," *Materials Today: Proceedings*, vol. 33, pp. 4708–4712, 2020, doi: 10.1016/j.matpr.2020.08.350.

[19] J. C. Xie and C. M. Pun, "Chronological age estimation under the guidance of age-related facial attributes," *IEEE Transactions on Information Forensics and Security*, vol. 14, no. 9, pp. 2500–2511, 2019, doi: 10.1109/TIFS.2019.2902823.

[20] M. N. I. Opu, T. K. Koly, A. Das, and A. Dey, "A lightweight deep convolutional neural network model for real-time age and gender prediction," in *2020 Third International Conference on Advances in Electronics, Computers and Communications (ICAECC)*, 2020, pp. 1–6, doi: 10.1109/ICAECC50550.2020.9339503.

[21] G. Guo and G. Mu, "Human age estimation: What is the influence across race and gender?," in *2010 IEEE Computer Society Conference on Computer Vision and Pattern Recognition - Workshops*, 2010, pp. 71–78, doi: 10.1109/CVPRW.2010.5543609.

[22] V. K. Verma, V. Kansal, and P. Bhatnagar, "Patient identification using facial recognition," in *2020 International Conference on Futuristic Technologies in Control Systems & Renewable Energy (ICFCR)*, 2020, pp. 1–7, doi: 10.1109/ICFCR50903.2020.9250002.

[23] K. P. Kumar, K. S. Vijaya, and A. Jukuntla, "Efficient deep learning technique to person reidendification in content based video system," in *2020 International Conference on Computational Intelligence for Smart Power System and Sustainable Energy (CISPSSE)*, 2020, pp. 1–6, doi: 10.1109/CISPSSE49931.2020.9212271.

[24] D. S. Brar, A. Kumar, Pallavi, U. Mittal, and P. Rana, "Face detection for real world application," in *2021 2nd International Conference on Intelligent Engineering and Management (ICIEM)*, 2021, pp. 239–242, doi: 10.1109/ICIEM51511.2021.9445287.

[25] C. S. T. Hii *et al.*, "Automated gait analysis based on a marker-free pose estimation model," *Sensors*, vol. 23, no. 14, 2023, doi: 10.3390/s23146489.

[26] Y. Taigman, M. Yang, M. Ranzato, and L. Wolf, "DeepFace: Closing the gap to human-level performance in face verification," in *2014 IEEE Conference on Computer Vision and Pattern Recognition*, 2014, pp. 1701–1708, doi: 10.1109/CVPR.2014.220.

BIOGRAPHIES OF AUTHORS

Carlos Cruz-Colan is student as a electronic engineering at the Technological University of Peru. His learning interests include cybersecurity. He currently holds the position of IT planning and control intern. He can be contacted at email: 1520263@utp.edu.pe.

David Lopez-Herrera is student as an electronic engineer from the Technological University of Peru. His learning interests include industrial automation and telecommunications systems. Currently, he holds the position of intern at the company Matysger S.A.C. He can be contacted at email: 1520254@utp.edu.pe.

Ernesto Paiva-Peredo is graduated as an electrical mechanical engineer from the Universidad de Piura in Peru in 2013. He pursued further studies and obtained a master's degree in electrical mechanical engineering with a specialization in automation and optimization, which was supported by CONCYTEC and awarded by the Universidad de Piura in 2016. During his academic journey, he served as a research assistant at the Department of Technology and Innovation (DTI) at SUPSI. Presently, he holds the position of a Professor-Researcher at the Universidad Tecnológica del Perú. He can be contacted at email: epaiva.peredo2@gmail.com or C22395@utp.edu.pe.

Kevin Acuña-Condori received his B.Eng. degree in electrical engineering from Universidad Nacional Mayor de San Marcos, Peru, in 2015. He was awarded the CONCYTEC scholarship for his master's studies, which he completed in mechatronic engineering at Pontificia Universidad Católica del Perú in 2017. As a researcher at Universidad Tecnológica del Perú, he has authored publications in bioengineering, artificial intelligence, and control. His research interests include bioengineering, artificial intelligence, brain-computer interfaces, and neuroprosthetics. He has participated in multidisciplinary projects funded by CONCYTEC and co-founded CIRSYS, a tech development company focused on scientific and technical innovations for societal benefit. He can be contacted at email: C17419@utp.edu.pe.