Facial recognition software for identification of powered wheelchair users.

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Abstract. The research presented in this paper investigates the use of facial recognition software as a potential system to identify powered wheelchair users. Facial recognition offers advantages over other biometric systems where wheelchair users have disabilities. Facial recognition systems scan an image or video feed for a face, and compare the detected face to previously detected data. This paper reviews the software development kits and the libraries available for creating such systems and discusses the technologies chosen to create a prototype facial recognition system. The new prototype system was trained with 262 identification pictures and confidence ratings were produced from the system for video feeds from twelve users. The results from the trials and variance in confidence ratings are discussed with respect to gender, presence of glasses and make up. The results demonstrated the system to be 95% efficient in its ability to identify users.

Keywords: Face Recognition, User Identification, Camera, Wheelchair, SDK.

1 Introduction

The work presented in this paper describes the results from the creation of a facial recognition system to identify users of powered wheelchairs. The identification system was required to identify a user from a pool of 262 identification (ID) pictures. The input to the system was via a video camera. The system returned a confidence value for each match. Variations in confidence values are discussed for test case scenarios based on gender, the presence or non-presence of glasses and make up.

The work described here is part of broader research carried by the authors at Chailey Heritage Foundation and the University of Portsmouth funded by the Engineering and Physical Sciences Council (EPSRC) [1]. The aims of this research are to use AI techniques to improve the quality of life and to increase mobility of disabled powered wheelchair users providing improved self-reliance and confidence.

Studies have revealed that approximately 15% of the world population were suffering from some sort of disability, part of them were diagnosed with significant mobility problems [2,3]. People with disabilities often suffer from lower quality of life than others [4].

Powered mobility often included assistive devices such as powered wheelchairs or scooters and is becoming more important to people with disabilities [5]. Researchers have developed systems to enhance mobility and improve the quality of life of disabled users through the use of sensors to control veer [6], scanning ultrasonic sensors for collision avoidance [7] and expert system to analyse users' hand tremor and improve steering [8].

Self-reliance factors have been studied to create a system that shared control between ultrasonic sensors and wheelchair users. Sanders et al. [9, 10, 11] considered rule-based systems to provide steering routes for wheelchairs. Ultrasonic sensor arrays have been used as inputs to Multi-Criteria Decision Making deciders combined with user desired directions to provide collision free routes for wheelchairs [12-15].

Intelligent Human Machine Interfaces [16,17] and a deep learning neural network has been created to provide a safe steering direction for a powered wheelchair [2]. Tewkesbury et al. applied high level task programming methodologies to the programming of powered wheelchairs [18].

Many researchers have created systems to study and improve powered wheelchair driving [19-21]. Haddad et al. [22-24] used cameras and microcomputers to translate drivers hand movements to digital commands used to operate powered wheelchairs.

Interviews conducted by the authors with operational therapists, helpers and carers at

Chailey Heritage Foundation/School showed that many students used the same powered platform to practice driving a powered wheelchair. Each powered wheelchair user had their own settings and preferences. Changing user settings often required time and effort. Helpers/carers often struggled with changing wheelchair settings when changing users. Different users often required different interfaces, sensors and input devices. Identifying users of a powered wheelchair from a video stream could therefore be used to automatically configure wheelchair settings.

This paper presents an overview of the leading technologies available for facial recognition at the time of the study. The selection process of the technology for use in this research is covered in Section 2 and the results from user trials of the new system created are presented in section 3 with an analysis of the effects of gender, the presence of glasses and make up. Discussion, conclusions and future work are presented within Section 4.

1.1 Facial Recognition Systems

A simple facial recognition system operates in three steps: Firstly, an image is scanned for anything that resembles a human face. If a face is detected, then feature data is extracted and stored digitally. This data can then be used to verify an image against a database of images.

Facial recognition software relies on the same methods and theory as all other forms of object recognition, however before a face can be recognised it must first be detected. One of the most important developments in the detection of faces in digital images was the Viola-Jones object detection framework. This framework allows a system to recognise patterns in an image that might constitute a face without being computationally expensive, allowing for real time face detection [25]. The patterns that the framework attempts to detect are the same patterns that human brains are able to recognise. For example, a few of the properties common to human faces are that the region surrounding the eyes is darker than that of the upper cheeks, and that the nose bridge region is brighter than that of the eyes [26].

The regions of light and dark formed on an image by averaging the intensity of the pixels are known as Haar features. Training a program to look for the Haar features associated with human faces in turn, detects faces [27].

By mapping the geometries of these regions, such as the distance between the eyes or the length of the nose, the identity of a face can be profiled digitally using a vector that represents the makeup of a face known as an Eigenface [28]. The similarity between two faces can then be found by use of mathematical algorithms to compare their relative similarity to an Eigenface [29].

Improved methods for the detection and recognition of faces have been developed since the emergence of the Viola-Jones method, including detection through the use of 3D images as opposed to 2D, and the use of high detail digital skin prints capable of detecting subtle differences present in the faces of identical twins [30]. However, the traditional Viola-Jones method, and other improved methods based on it remain the most commonly used method for detection in facial recognition systems, primarily because their simplicity allows them to be used with relatively low computational requirements in comparison to other methods that may require the use of complex systems such as neural networks [31].

The potential solutions for a facial recognition of powered wheelchair users range from fully fledged systems that include both the necessary hardware and software for facial recognition, to APIs and software libraries that require integration into a working program and system.

1.2 API

Microsoft's Azure Face API offered both free and paid pricing tiers depending on the amount of calls to the API that were required; a free account could call the API up to a maximum of 20 times per minute and up to 30,000 times per month, however the ability to store images on Microsoft servers instead of locally required a paid subscription. [32].

Amazon's Rekognition API (a component of Amazon Web Services) offered real time facial recognition for both images and live video. Similar to Microsoft, Amazon offered both free and paid subscription. The free tier for Rekognition could, (per month) analyse 5000 images, store up to 1000 images, and analyse 1000 minutes of live video. However, the free tier of this service was limited to one year [33].

Google also produced an API; "Cloud Vision". However, at the time of this study, they had yet to publicly release a build capable of facial recognition, claiming that: "facial recognition merits careful consideration to ensure its use is aligned with our principles and values, and avoids abuse and harmful outcomes" [34]. Cloud Vision was only capable of detecting faces and could not be used to attach identities.

A relatively new entrant to the facial recognition market was Kairos, which like Amazon's Rekognition was capable of applying facial recognition to video. A useful additional feature Kairos offered was the ability to self-host the API on local servers using their Software Development Kit (SDK). Kairos was only available through paid pricing tiers, which cost a monthly fee on top of 'per transaction' charges. It was not possible to test the system without a paid license [35].

China's facial recognition 'Face++' API, was a publicly available version of the software that was used in China's 170 million camera strong 'SkyNet' mass surveillance system [36]. The free pricing tier of Face++ allowed for a maximum of 3 API calls per second with no limits on usage outside of this. Face++ charged extra for additional API request bandwidth instead of charging more for total requests [37].

1.3 Software Libraries

An alternative to calling APIs was to use a local software library. These collections of pre-written code allow a system for facial recognition to be run on a local machine, without internet connectivity. This however comes with the requirement for more powerful hardware. A low cost embedded system may not have sufficient power for more demanding applications. Whilst technically identical to SDKs, software libraries are free and open source, thus offering more flexibility in their implementation. In comparison to an externally hosted API they are more intricate to program into a system and require applications utilising them to be sufficiently streamlined so as to not hinder performance.

The most popular software libraries in the field of facial recognition were OpenCV and Accord.NET. Both were capable of real time facial recognition on live video and their respective implementations were well documented online, with various books and tutorials available for both [38,39].

2 Facial Recognition System

A facial recognition system capable of efficient identification of powered wheelchair users required development from the ground up using commercially available APIs or libraries. These handle the task of detecting and recognising faces, but what a system does with the returned data is entirely dependent on the application they are built in to.

The development of the facial recognition system began with a comparison of the various available solutions to determine the one most suitable for use. The early stages of development that followed concerned the implementation of the chosen solution in a simple system, for example: in an application that was only capable of applying facial detection on an image. Continued development aimed towards a more advanced system capable of facial recognition on a video feed.

An important factor for determining the most feasible API was ease of implementation. Azure Face was by far the most flexible, with several in depth examples about how to effectively utilise it in a system available on Microsoft's website or through third party programming tutorial/hobbyist sites. Rekognition's documentation was deemed to be less accessible, being marketed more towards seasoned developers of Amazon Web Service, but as with Azure Face it had the benefit of being easily importable into a Visual Studio project through the Nuget package manager. Kairos and Face++ did feature notable documentation, but they were not as comprehensive as that of Azure or Rekognition.

With these factors in mind, the decision made was to use Azure Face API for the developmental system. Rekognition's greater TPS bandwidth made it the superior candidate for use in a real-world system, however it was not selected for use due to the likelihood of its complexity of implementation hindering development.

Alongside the development of a prototype system utilising an API, an experimental system utilising the OpenCV library was also developed. These two systems eventually merged to form a final system that utilised both Azure Face API and OpenCV.

3 Results

The system needed to be able to recognise wheelchair users from a webcam video feed after being trained with the facial data extracted from an identification (ID) photo or the images on their electronic record card. The images were a mixture of quality and resolution. The aging of wheelchair users was also considered and the confidence value returned by the system was a useful metric for this.

The system was trained with 12 known user faces and with an additional 250 unknown faces, all from the same source of ID photos.

Of the 250 untested faces trained in the system, the ID photos of 3 faces were unable to be trained by the system due to its inability to detect a face (i.e. locate a face in the picture); a failure rate of 1.2%. These images were discarded and replaced with images that the system could use.

Testing consisted of having users present themselves to the system via a webcam feed. The system then attempted to recognise the user in the same way it did the images used in preliminary testing.

Where possible, elements of the testing were kept constant. All users were tested using the same webcam under as consistent as possible lighting conditions. The test was repeated on each user 3 times. In one test users were asked to present a neutral expression, in another test users were asked to smile, and in the final test users were asked to attempt to mimic the expression of the training photo. If a user wore glasses, they were tested for an additional three instances without wearing glasses so that the difference in confidence values returned could be compared.

Three confidence values were obtained for each user tested, with an additional three also obtained for users who wore glasses. These values were compiled into two separate average values, as shown in Table 1.

The size of collection of trained faces had no effect on returned confidence values. The system was able to correctly identify all users at least once and no users were misidentified (i.e. as a different user).

Table 1. Results of users testing in descending order of average confidence value.

Average Confidence Values		Gender	Confidence Values			Glasses Confidence Values		
			Neutral	Smile	Mimic	Neutral	Smile	Mimic
75.6%		M	77.7%	73.8%	79.1%	N/A	N/A	N/A
72.8%		M	70.0%	73.9%	74.6%	N/A	N/A	N/A
70.5%		M	71.1%	69.9%	73.7%	N/A	N/A	N/A
65.3%		M	62.1%	65.3%	68.5%	N/A	N/A	N/A
53.3%	62.8%	M	54.3%	50.8%	54.8%	63.5%	59.1%	65.9%
62.5%	53.1%	F	59.1%	63.4%	65.1%	52.7%	53.5%	55.5%
62.0%	54.0%	F	58.3%	62.4%	65.3%	53.4%	54.1%	54.5%
61.7%	52.6%	M	59.9%	61.0%	64.3%	51.4%	53.8%	54.2%
60.7%	0%	M	61.4%	58.2%	62.5%	0%	0%	0%
51.2%	56.1%	F	51.3%	50.8%	51.6%	56.3%	55.8%	62.1%
54.6%		F	52.8%	53.4%	57.7%	N/A	N/A	N/A

A single user was not recognised by the system whilst wearing glasses, but was correctly identified every time when not wearing glasses (The user's ID photo featured them without glasses). Other users also returned a lower value whilst wearing glasses compared to not wearing glasses. Excluding the unidentifiable student, the differences in confidence values returned for glasses-wearing students are shown in Table 2.

Table 2. A comparison of the difference in confidence values for glasses-wearing users.

No Glasses	Glasses	Difference
53.3%	62.8%	9.5%
62.5%	53.1%	9.4%
62.0%	54.0%	8%
61.7%	52.6%	9.1%
51.2%	56.1%	4.9%

The average difference between these results was 8%, enough to bring a user below the 50% recognition threshold if their confidence value was already low without the addition or removal of glasses.

Varying facial expressions had a similar but lesser effect on returned confidence values. If a student's expression in their ID photo was neutral or smiling, a higher confidence value was returned when asked to present with the same expression. User's attempts at mimicking the exact expression of their ID photo resulted in higher confidence values. The differences in confidence values as a result of facial expression can be seen below in Table 3.

Table 3. A comparison of the differences in confidence values for different expressions.

Confidence Values			Differences in Values	
Neutral	Smile	Mimic	Neutral/Smile	Mimic
77.70%	73.80%	79.10%	3.90%	1.40%
70.00%	73.90%	74.60%	3.90%	0.70%
71.10%	69.90%	73.70%	1.20%	2.60%
62.10%	65.30%	68.50%	3.20%	3.20%
54.30%	50.80%	54.80%	3.50%	0.50%
59.10%	63.40%	65.10%	4.30%	1.70%
58.30%	62.40%	65.30%	4.10%	2.90%
59.90%	61.00%	64.30%	1.10%	3.30%
61.40%	58.20%	62.50%	3.20%	1.10%
51.30%	50.80%	51.60%	0.50%	0.30%
52.80%	53.40%	57.70%	0.60%	4.30%
63.50%	59.20%	65.90%	4.30%	2.40%
52.70%	53.50%	55.50%	0.80%	2.00%
53.40%	54.10%	55.50%	0.70%	0.40%
51.40%	53.80%	54.20%	2.40%	0.40%
56.30%	55.80%	62.10%	0.50%	5.80%

The average difference between the higher and lower confidence values of the neutral and smile expressions was 2%, the difference between the higher of these two values and the value of the mimic expression was an additional 2%.

A factor that had a more significant effect on the confidence value was the gender of the participants. The difference in confidence values can be noted from Table 1, with no female user scoring above 63% average confidence value, whereas 4 male users scored well over that. The difference between the average male value and the average female value was 7%.

4 Discussion and Conclusions

The results demonstrated the system to be 95% efficient in ability to identify wheelchair users with the applied test data. The research presented here has focused on two of the six possible solutions identified in the literature survey. Further work may evaluate the relative efficiency of the other solutions and evaluate if they are superior to the results obtained during this research.

Overall, the project has successfully determined that a facial recognition system reliant on ID photos or the images on electronic record cards could be used to identify powered wheelchair users, to configure the devices for the needs of that particular user.

It was possible for the Azure Face API to return additional data such as emotional values or estimated physical characteristics but that data was not used during this study, however, this type of data may prove to be useful in the future for other studies.

The identity of the face detected, along with a confidence value were returned for each test. The results suggested that the API was biased towards recognising male faces, with only one female scoring above 70% confidence value. This discrepancy might have been due to the use of ID photos as the source data for the test: the images of female individuals used featured them wearing notably different levels of makeup, thus negatively impacting on the system's ability to recognise them when comparing the two images. This is reinforced by 3 of the 5 lowest confidence values that were returned during the test having come from females who wore in one image heavy makeup, and in the other image no makeup. Notable differences in lighting conditions could also have been a significant factor.

The ID photos used in the study were selected and supplied by the users, however in a real clinical situation these photos are likely to have been provided at the time of first use of the wheelchair, or from clinical records, where there is likely to be more consistency in the level of makeup.

References

1. Sanders D, Gegov A. Using artificial intelligence to share control of a powered-wheelchair between a wheelchair user and an intelligent sensor system. EPSRC Project, 2019 – 2022. 2018.
2. Haddad, M.J., Sanders, D.A., 2020. Deep Learning architecture to assist with steering a powered wheelchair. IEEE Transactions on Neural Systems and Rehabilitation Engineering.
3. Krops, L.A., Hols, D.H., Folkertsma, N., Dijkstra, P.U., Geertzen, J.H. and Dekker, R., 2018. Requirements on a community-based intervention for stimulating physical activity in physically disabled people: a focus group study amongst experts. Disability and Rehabilitation, 40(20), pp.2400-2407.
4. Bos, I., Wynia, K., Almansa, J., Drost, G., Kremer, B. and Kuks, J., 2019. The prevalence and severity of disease-related disabilities and their impact on quality of life in neuromuscular diseases. Disability and rehabilitation, 41(14), pp.1676-1681.
5. Frank, A.O. and De Souza, L.H., 2018. Clinical features of children & adults with a muscular dystrophy using powered indoor/outdoor wheelchairs: disease features, comorbidities & complications of disability. Disability and rehabilitation, 40(9), pp.1007-1013.
6. Sanders D A, Langner M, Tewkesbury G E. Improving wheelchair-driving using a sensor system to control wheelchair-veer and variable-switches as an alternative to digital-switches or joysticks. Ind Rob: An int' jnl. 2010;32(2):157-167.
7. Langner, M., 2012. Effort Reduction and Collision Avoidance for Powered Wheelchairs: SCAD Assistive Mobility System (Doctoral dissertation, University of Portsmouth).
8. Sanders, D.A. and Bausch, N., 2015, August. Improving steering of a powered wheelchair using an expert system to interpret hand tremor. In International Conference on Intelligent Robotics and Applications (pp. 460-471). Springer, Cham.
9. Sanders, D.A., 2016. Using self-reliance factors to decide how to share control between human powered wheelchair drivers and ultrasonic sensors. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 25(8), pp.1221-1229.
10. Sanders D A, Gegov A, Haddad M, Ikwan F, Wiltshire D, Tan Y C. Adv. Intell. Syst. Comput. Vol. 868. Cham: Springer; 2019. Rule-based Expert System to decide on direction and speed of a powered wheelchair; p. 822-832.
11. Sanders, D.A., Haddad, M., Tewkesbury, G.E., Thabet, M., Omoarebun, P. and Barker, T., 2020, August. Simple expert system for intelligent control and HCI for a wheelchair fitted with ultrasonic sensors. In 2020 IEEE 10th International Conference on Intelligent Systems (IS) (pp. 211-216). IEEE.
12. Haddad M, Sanders D, Gegov A, Hassan M, Huang Y, Al-Mosawi M. Adv. Intell. Syst. Comput. Vol. 1037. Cham: Springer; 2019. Combining multiple criteria decision making with vector manipulation to decide on the direction for a powered-wheelchair; p. 680-693.
13. Haddad M, Sanders D, Langner M, Ikwan F, Tewkesbury G, Gegov A. Steering Direction for a Powered-Wheelchair Using the Analytical Hierarchy Process. Proceedings of the 2020 IEEE 10th International Conference on Intelligent

Systems (IS); 2020 Aug 26-28; Varna, Bulgaria; 2020. p. 229-234.
14. Haddad M, Sanders D, Thabet M, Gegov A, Ikwan F, Omoarebun P, Tewkesbury P, Hassan M. Use of the Analytical Hierarchy Process to Determine the Steering Direction for a Powered Wheelchair. In: Arai K, Kapoor S, Bhatia R, editors. Intelligent Systems and Applications. IntelliSys 2020. Advances in Intelligent Systems and Computing, Vol. 1252. Springer, Cham; 2021. p. 617-630.
15. Haddad M J, Sanders D A. Selecting a Best Compromise Direction for a Powered Wheelchair Using PROMETHEE. IEEE T Neur Sys Reh. 2019;27(2):228-235.
16. Haddad, M., Sanders, D., Ikwan, F., Thabet, M., Langner, M. and Gegov, A., 2020, August. Intelligent HMI and control for steering a powered wheelchair using a Raspberry Pi microcomputer. In 2020 IEEE 10th International Conference on Intelligent Systems (IS) (pp. 223-228). IEEE.
17. Haddad, M., Sanders, D., Langner, M., Bausch, N., Thabet, M., Gegov, A., Tewkesbury, G. and Ikwan, F., 2020, September. Intelligent control of the steering for a powered wheelchair using a microcomputer. In Proceedings of SAI Intelligent Systems Conference (pp. 594-603). Springer, Cham.
18. Tewkesbury, G., Sanders, D., Haddad, M. J. M., Bausch, N., Gegov, A., & Okonor, O. M. (2019). Task programming methodology for powered wheelchairs. In Y. Bi, R. Bhatia, & S. Kapoor (Eds.), *IntelliSys 2019 Intelligent Systems and Applications: Proceedings of the 2019 Intelligent Systems Conference* (Vol. 1, pp. 711-720).
19. Haddad, M., Sanders, D., Langner, M., Thabet, M., Omoarebun, P., Gegov, A., Bausch, N. and Giasin, K., 2020, September. Intelligent system to analyze data about powered wheelchair drivers. In Proceedings of SAI Intelligent Systems Conference (pp. 584-593). Springer, Cham.
20. Haddad, M., Sanders, D., Langner, M., Omoarebun, P., Thabet, M. and Gegov, A., 2020, August. Initial results from using an intelligent system to analyse powered wheelchair users' data. In 2020 IEEE 10th International Conference on Intelligent Systems (IS) (pp. 241-245). IEEE.
21. Sanders, D., Haddad, M., Tewkesbury, G., Bausch, N., Rogers, I. and Huang, Y., 2020, August. Analysis of reaction times and time-delays introduced into an intelligent HCI for a smart wheelchair. In 2020 IEEE 10th International Conference on Intelligent Systems (IS) (pp. 217-222). IEEE.
22. Sanders, D., Haddad, M., Langner, M., Omoarebun, P., Chiverton, J., Hassan, M., Zhou, S. and Vatchova, B., 2020, September. Introducing time-delays to analyze driver reaction times when using a powered wheelchair. In Proceedings of SAI Intelligent Systems Conference (pp. 559-570). Springer, Cham.
23. Haddad et al. Steering a powered wheelchair using a camera module and image processing algorithms. In: Arai K, Kapoor S, Bhatia R, editors. Intelligent Systems and Applications. IntelliSys 2021. Advances in Intelligent Systems and Computing. Accepted and in Press.
24. Haddad et al. Novel Approach to Steer a Powered Wheelchair Using Image Processing Algorithm and Raspberry Pi. In: Arai K, Kapoor S, Bhatia R, editors. Intelligent Systems and Applications. IntelliSys 2021. Advances in Intelligent Systems and Computing. Accepted and in Press.
25. Viola, P. and Jones, M. Rapid Object Detection using a Boosted Cascade of Simple Features. *Proceedings of the 2001 IEEE Computer Society Conference on Computer Vision and Pattern Recognition. 2001*, Kauai, HI, USA, 2001, pp. I-I, doi: 10.1109/CVPR.2001.990517.
26. Ming-Hsuan Yang, D. J. Kriegman and N. Ahuja, "Detecting faces in images: a survey," in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 24, no. 1, pp. 34-58, Jan. 2002, doi: 10.1109/34.982883.
27. Wang, C. (2018). What's the Difference Between Haar-Feature Classifiers and Convolutional Neural Networks?. *Towards Data Science,* [online] Accessed Jan-2021 Available at: https://towardsdatascience.com/whats-the-difference-between-haar-feature-classifiers-and-convolutional-neural-networks-ce6828343aeb
28. Sirovich, L. and Kirby, M. (1986). Low Dimensional Procedure for the Characterisation of Human Faces. *Journal of the Optical Society of America* [online], Volume 4, p.519.
29. Georgescu, D. (2011). A Real-Time Facial Recognition System Using Eigenfaces. *Journal of Mobile, Embedded and Distributed Systems*, Volume 3(4), p.199. ISSN 2067 – 4074
30. Williams Pontin, M. (2007). Better Face-Recognition Software. MIT Technology Review, Accessed Jan-2021, Available at: https://www.technologyreview.com/s/407976/better-face-recognition-software/

31. Enriquez, K. (2018) 'Faster Face Detection using Convolutional Neural Networks & the Viola-Jones Algorithm', Accessed Jan-2021, Available at: https://www.csustan.edu/sites/default/files/groups/University%20Honors%20Program/Journals/01_enriquez.pdf
32. Microsoft, (2019). Cognitive Services pricing – Face API. Accessed Jan-2021, Available at: https://azure.microsoft.com/en-gb/pricing/details/cognitive-services/face-api/
33. Amazon, (2019). Amazon Rekognition pricing. Accessed Jan-2021, Available at: https://aws.amazon.com/rekognition/pricing/
34. Google, (2018). *AI for Social Good in Asia Pacific.* [blog], Accessed Jan-2021, Available at: https://www.blog.google/around-the-globe/google-asia/ai-social-good-asia-pacific/amp/
35. Kairos, (2019). KAIROS FACE RECOGNITION PRICING GUIDE. Accessed Jan-2021, Available at: https://www.kairos.com/pricing
36. Jacobs, H. and Ralph, P. (2018). Inside the creepy and impressive startup funded by the Chinese government that is developing AI that can recognize anyone, anywhere. *Business Insider,* Accessed Jan-2021, Available at: https://www.businessinsider.com/china-facial-recognition-tech-company-megvii-faceplusplus-2018-5
37. Face++, (2021). Face++ Facial Recognition API Prices. Accessed Jan-2021, Available at: https://www.faceplusplus.com/v2/pricing/
38. OpenCV, (2021). Open Source Computer Vision Library. Accessed Jan-2021, Available at: https://opencv.org/about.html
39. Accord.NET, (2021). Machine Learning Made in a Minute. Accessed Jan-2021 Available at: http://accord-framework.net/