

Towards Facial Recognition Limitation in the Era of Pandemic

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Abstract— This paper gives a detailed examination of artificial intelligence (AI) and face recognition algorithms against COVID-19 and various subsequent variants such as omicron and BA.2, each of which introduces a new challenge to overcome. The primary ways in which Face Recognition may help in the fight against pandemics are outlined. Face mask adaption offered a new difficulty for commercial biometric facial recognition algorithms already in use in applications like facial recognition login management and public security inspections. In this article, we will discuss in depth the limitations of face recognition techniques, as well as the solutions and practices that can be implemented effectively and efficiently.

Keywords—Face recognition, artificial intelligence, COVID-19, Pandemic, Omicron, face mask, limitations, AI.

I. INTRODUCTION

In recent decades, Face recognition has been a major research issue all around the world. Furthermore, with the advancement of High Tech tools and the rapid evolution in AI, significant advancements have been made. Resulting of mentioned above both public and commercial organizations employ face recognition technology to identify and manage access to individuals in airports, schools, businesses, and other locations. Government institutions, on the other hand, have adopted many biosafety measures to minimize infections as a result of the expansion of the pandemic. Among these is the need of wearing face masks in public areas, which has been proved to be useful in protecting people and others around them. Because the virus spreads by physical touch, traditional identification techniques (such as fingerprints) or inputting a password on a computer are rendered unsecure. As a result, since they do not need physical contact as in previous circumstances, face recognition systems are indeed the ideal solution. Nevertheless, since 50% of the face is hidden throughout facial recognition, using a face mask within these systems has provided a substantial challenge for artificial vision. Resulting in the loss of numerous important data points. This obviously indicates the necessity for algorithms that can distinguish a person while wearing a face mask [1].

Face identification has been a well-known and challenging subject amongst computer vision researchers since ages. Face recognition technology has progressed at a remarkable rate in recent years, thanks to the rapid expansion of AI. In comparison to traditional card identification, iris scanning, and fingerprinting identification, the new facial recognition-based attendance system has a number of advantages. Contactless, high concurrency, and systems that are user-friendly are examples of facial recognition approaches. The facial recognition system has several uses, including government employment, Governmental institutions, protection, Electronic commerce, shopping, and others. The introduction of deep learning model has considerably benefited the advancement of face recognition algorithms. Large data are accessible for the development of deep learning systems for facial recognition [2].

Traditional biometric systems based on passwords or fingerprints are no longer safe since COVID-19 may be transmitted through contact and contaminated surfaces. Because it removes a need to contact any device, recognition software is more secure. Recent coronavirus study has shown that wearing a face mask reduces transmission of the virus across both healthy and sick patients, on the other hand, produces the following issues:

- 1) The mask is used by scammers and criminals to steal and commit crimes while staying unnoticed.
- 2) Face identification and public access control become very difficult when a mask conceals a major section of a face.

3) Whenever a mask is used, existing facial recognition algorithms are unsuccessful because the entire face image cannot be described.

4) Face recognition requires exposing the nasal region since it is used for face standardization, positioning adjustment, and facial similarity. As a consequence of these concerns, facial masks have significantly impeded existing face recognition systems [3].

Some separated 2 roles to handle these issues: facial mask recognition and masked face recognition. The first decides if the person is wearing a mask or not in the second option. Such a technology may be used in urban locations when wearing a mask is required [4]. Face recognition with a mask, on the other hand, focuses on recognizing a face primarily just on eyes and forehead areas, and we will also discuss other limitations such as the cost of implementing such a technology and the technological barriers that may arise when implementing these technologies, particularly in developing countries

II. RELATED WORK

Face recognition technology implementation presents several operational issues. Face recognition system threats are considered the most significant of these problems, and they receive the bulk of study attention. These assaults may include morphing assaults [5, 6], presenting Threats & attacks [7, 8], and other unorthodox Breaches.

Facial recognition deploy ability is further influenced by biometric sample acquisition [9, 10], particularly face occlusions. Regarding the sector of computer vision, occluded face identification is a well-studied case. A paper presented by Oiptiz et al is such glaring indication of obstructed face recognition they presented a method based on a unique grid loss to target the accurate recognition of occluded faces. Ge et al. [11] concentrated on identifying faces (rather than face Identification) using mask occlusions in naturalistic circumstances. Their research focused at face coverings in general, rather than simply facial masks for medical or hygienic reasons. Such findings are especially pertinent to face recognition since recognizing faces (with wearing a mask) is a crucial preprocessing step when face recognition algorithms might fail, as our analysis results show.

As previously stated, the recognition of occluded faces is among the challenges in implementing biometric facial technologies.

on the contrary, face authentication of covered faces is a much more challenging problem. One of the most recent efforts to solve this issue is Song et al, which intended to improve face recognition effectiveness under generalized occlusions. Song et al. offer a technique for detecting and removing damaged characteristic elements from the detection phase that may be connected to occlusions. A novel research on masked faces was published by Wang et al. [12]. Their study presented crawling databases for face identification and detection, and also simulated masked faces, in a brief and under-detailed presentation. The authors claim to have enhanced validation efficiency from 50% to 95%; however, they give no data on the baseline utilized, recommended algorithmic specifics, or clarification on the assessment database used. Anwar and Raychowdhury [13] published a library of 296 face pictures, partly with genuine masks, of 53 identities in a recent preprint. The photographs in the database were acquired in the wild since they were scraped from Web pages and do not reflect a collaborative face recognition situation. To improve assessment performance, they recommended finetuning an existing facial recognition network. On a greater level, (NIST) National Institute of Standards and Technology had As part of the ongoing Face Recognition Vendor Test (FRVT), issued a special report (FRVT—Part 6A) on the impact of respirators on the effectiveness of biometric authentication supplied by vendors [14]. Algorithmic performance using covered faces was shown to be much worse in the NIST study.

Other major research drawbacks is using simulated masked pictures affected by dubious premise that their impact mimics genuine face masks, which is addressed in this article. All of the studies referenced did not include a face verification assessment, which might lead to the necessity for a second masked reference image, a concern that is also addressed in this article.

Other studies have identified occlusion as an essential component, since it is a major shortcoming 2D face detection and recognition techniques in the real world IT commonly occurs as a consequence of wearing hats, sunglasses, wigs, or any other item that obscures part of the face while leaving the rest visible. As result of mentioned before, since it circumscribes a substantial area of the facial, such as the nose, wearing a mask is considered the most difficult facial occlusion difficulty. Other solutions have been presented to address this issue. They are classified into three types: local matching approaches, restoration approaches, and occlusion removal approaches. The matching technique compares the similarity of pictures using a matching procedure. In general, the facial picture is divided into a number of identically sized patches. Each patch is subsequently subjected to feature extraction. Finally, a matching technique is used to match the probe and gallery faces. The benefit of this method is that the sampled patches are not overlapping, which prevents occluded sections from influencing the other

relevant parts. Martinez and Aleix [15], for example, sampled the facial area into a predefined number of local patch. The similarity metric is then applied using matching.

Other approaches, rather than using local patches, identify critical points in a facial picture. For example, Weng et al. [16] advocated recognizing people of interest based on their partial faces. To do this work, they first identified critical spots and extracted textural and geometrical characteristics from them. The collected features are then matched using point set matching.

Eventually, the similarity of the two faces is computed based on the closeness of two aligned selected features. Duan et al. [17] provide a key point-based matching approach. To pick the suitable key points, the SIFT key point descriptors are used. The Gabor ternary patterns and features sets matching are utilized to correlate the localized main points for incomplete face recognition. Unlike the previously stated approaches based on predetermined patch matching or key point identification, without any sampling, McLaughlin et al. [18] utilized the largest matching area at each place of the face image.

Approaching restoration, occluded portions of probing faces are restored here in accordance with the gallery ones. Bagchi et al. [19] advocated, for example, restoring face occlusions. By quantizing the depth map values of the 3D image, the occluded regions are discovered. After that, the restoration is accomplished using Principal Component Analysis (PCA) [20]. There are also other methods that rely on predicting the occluded areas. Drira et al. [21] employed a statistical generative model to anticipate and reconstruct the partial face curves. The iterative closest point (ICP) approach was used in [22] to remove blocked regions. The restoration is done with the use of a curve, which uses a statistical approximation of the curves to deal with the obstructed areas. The PCA approach's curves model is being used to complete partly observed curves.

Method for removing occlusions: To prevent a faulty reconstruction procedure, these techniques try to identify occluded faces areas picture then remove it entirely from of the feature extraction and classification process. One of the better ways is the multipathing strategy, which identifies the obstructed zone initially and then only utilizes the non-occluded part in following stages. Priya and Banu [23], for example, split the facial picture into tiny local areas. They then used the svm classifier to find the occluded area and reject it. Finally, the non-occluded regions are subjected to a mean based weight matrices for face recognition. Alyuz et al. [24] employed an obstruction removal and recovery strategy. They used a global masked projection to remove the occluded zones. After that, eigenvectors are utilized to restore the partial Gappy PCA. With the publication of the AlexNet architecture by Krizhevsky et al. [25] in late 2012, Deep CNN has become a widely used approach in face Identification. It's also been utilized effectively in face Identification with occlusion variation [26]. The deep learning-based technique is based on the fact that visual system normally skips obstructed regions and only focuses on those that aren't. Song et al., for example, [27] suggested a mask learning strategy to remove the masked region's feature components during the identification phase.

Other research explored the wireless network, and Figure 1 Describes the main facial recognition diagram.

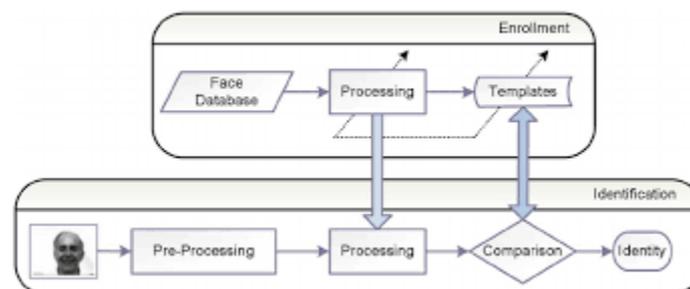


Fig. 1. Face Recognition System General Diagram

During registration, the photos of registered members are processed into caricature patterns by the face recognition system's particular algorithms, As a result, these templates have been saved. The templates may be seen as modified user photographs that have been encoded using the proper processing methods. The processing techniques and templates are also being changed at the same time. While the case of confirmation or recognition, the face recognition gets a new picture, defines and saves it using the same method, and compares it to the templates. All types of classifiers may be used in the decision-making process. If indeed, the classifier is indeed a learning algorithm whose structure must be educated, A

enrollment database, which may include a neural network or a Bayesian network, may be separated into two sections, one for building patterns and another for training the classification structure [28].

Also Regarding The cost of Implementing Such a solutions A.Zharovskikh mentioned certain considerations must be made during the construction of face recognition software. Before beginning a project, a tech solutions company should evaluate hardware setup, webcams and edge devices, databases, and other key factors. Continue reading to discover more about what this kind of project entails and why the price of face recognition software is so expensive.

- **Configuration of Hardware:**

When designing a face recognition security system, bear in mind that there is no ideal hardware configuration that is suited for every application. For any business job, appropriate hardware should be carefully selected. If the selected hardware is insufficiently powerful for specific tasks, this may result in either very unacceptable processing delays or a decline in the quality of such solution. For some jobs that do not need a large amount of processing resources, selecting excessively powerful hardware may result in an overpriced solution that is no longer in the market due to its high cost.

- **The Location of cameras and Their Choice:**

Without a doubt, comprehensive design of a face recognition security system for a certain purpose and area would include establishing the kind and position of cameras. The selection of this arrangement is heavily influenced by the necessary image resolution, angle of view, and transmission range. However, while deciding on video quality and the amount of cameras, network bandwidth must be considered, since it is often one of the major obstacles in developing high-quality face recognition systems. High-quality equipment has an influence on the price of facial recognition software's.

- **Application of Edge Devices**

Many face recognition algorithms rely on large, deep neural networks. However, such systems often need the use of GPUs for fast assessment. As a result, advanced face recognition systems need the use of computers equipped with a CPU and GPU. These servers need special assistance in terms of time and location in order to function successfully. Jetson devices are a solution that may be utilized to lessen support for end-users. It might assist to reduce the need for human support while also lowering the overall cost of the system.

- **Datasets for Software Challenges**

Deep learning-based algorithms are often utilized to construct powerful face recognition software. Deep learning algorithms, on the other hand, are infamous for being data-hungry. training data and Personification and the Pretrained Model's Potential Bias also evaluate the demographic information of the system users you want to create is highly affect the cost. Because most open-source datasets are mostly composed of white adults, the overall result is likely to be biased and may not operate effectively on other races and/or ages. To get around this problem, you gather an extra private dataset with a comparable demographic profile with the one you'd anticipate in real life. Fine-tuning based on the acquired data may aid in reducing the model's bias.

- **Scalability of software**

If a corporation wishes to install a face recognition system, it most likely expects it to be scalable and expandable to a larger audience. This necessitates a high level of flexibility in the software as well as a well-thought-out system architecture.

- **Image Retrieval Speed**

Image retrieval is a significant bottleneck for several face recognition systems, since such systems often execute searches in a database containing millions of data samples. Since a result, a corporation must ensure that such algorithm used to scan through a dataset is efficient and scalable, as the database may be continually increasing [29].

III. METHODOLOGY

The main problem to address during the feature extraction step is obtaining representative features with low within the variation of the class as well as high among class variance. The retrieved features are divided into two categories: handcrafted features and learnt features. Hand-made features are those that are retrieved via classic pre-processing and similar procedures, and they may be divided into appearance-based features, geometry-based features, and hybrid-based characteristics. The world or sub-sectional portion of the face image is captured by the appearance-based feature, which is primarily concerned with

the picture's color and texture. Local Binary Pattern -LBP-, Histogram of Oriented Gradient -HOG-, and Gabor Texture are all terms that you should be familiar with these terms which are the most often used features in this category (GT). These approaches must account for intrinsic problems such as head postures and lighting variations.

A. Local Binary Pattern

Local Binary Pattern operator useful for (TA)texture analysis because picture texture Local spatial and gray scale contrasting, which seem to be complementary measures, maybe used to define it. [30]. LBP employs 3x3 grayscale pixels and thresholds every neighbor pixel with the center pixel to form a binary sequence using the binary thresholding function provided in (1) and then computes the decimal equivalent again for center pixel using (2).

If G_p is the grey scale amount in pixel and G_c is the grey scale values in pixel then the threshold function is as follows:

$$s(x) = \begin{cases} 0, & x < 0 \\ 1, & x \geq 0 \end{cases} \text{ where } x = g_p - g_c \quad (1)$$

$$LBP_{R,P} = \sum_{P=0}^{P-1} S(X)2^P \quad (2)$$

Local Binary Pattern version of such input picture is shown in Figure 2. LBP's strength rests in its ability to discriminate, its computational simplicity, its great tolerance for poor picture resolution, and its insensitivity to changes un light. According to Shahreen et al. [32], applying the LBP feature on an SVM classifier of seven phrases in the JAFFE database enhanced system performance by 22%. Although the results were not generalizable since they were only tested on a particular database. Similarly, [33] conducted a research using linear programming on LBP features utilizing JAFFE database, and the results indicated an average accuracy of 93.8 percent. LBP is hampered by issues such as rotation, increases in computing cost as feature size grows in terms of time and space, and tiny features.

As it would not address magnitude information but just pixel difference, it has a low range represented set and a restricted data representation. These drawbacks prompted the development of variations. [34] used one of the LBP variants dubbed CLBP, which took into account the sign & magnitude data of the disparities between the center and neighbor gray values. It outperformed various previous appearances-based approaches A study by[35] provides information on the LBP variations.

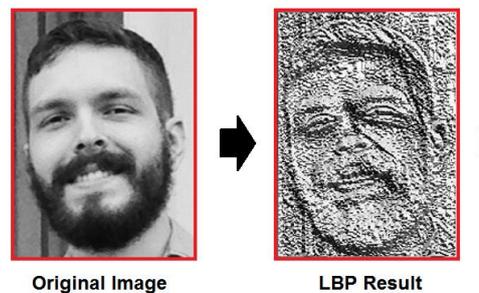


Fig. 2. Original image and the Corresponding LBP image [31]

B.Histogram of Oriented Gradient

The Histogram of Oriented Gradients (HOG) is indeed a feature descriptor used in a variety of domains where object characterization via form is critical. The arrangement of local intensity gradients along with edge directions may frequently explain the look and form of a local item. The concept of the histogram of directed gradients descriptors seems to be that the distribution of intensity gradients & associated edge directions may reflect the appearance and shape of local objects inside a picture [36]. The image is divided into small connected pieces called cells, and a histogram of gradient directions is generated for the pixels within each unit. The description is the sum of these histograms

. Because various photos may have varying contrast, contrast leveling is required to optimize efficiency. As a consequence of this normalization, the invariance to changes in light and shadowing is improved. Other engineers [37] collected HOG features from active face patches and put them into SVM for

categorization into neutral or six universal expressions, yielding an average accuracy of 95.01% with 5 folds cross-validation in the expanded Cohn Kanade (CK+) dataset. HOG outperforms several other algorithms in terms of performance. Nevertheless, it is computationally demanding and so increases calculation time.

C.Gabor Filter Texture

This method is widely used for feature extraction; it is just a wavelet transform approach with excellent directional selectivity, shift variance sensitivity as well as spatial localization, and information maximization within both space and frequency domains. A Gabor filter seems to be a function that captures the appropriate frequency spectrum in all directions by amplitude modulating a sinusoid with a Gaussian function in a spatial domain. Equation (3) formally defines it (4). Considering the following parameters: (x,y) being the spatial domain pixel location, λ to become the pixel wavelength, θ to be the orientation, and S_x, S_y to become the standard deviation all along x and y direction;

$$G(x, y) \exp \left[-\frac{1}{2 \left(\frac{x'^2}{s_x^2} + \frac{y'^2}{s_y^2} \right)} \right] \exp \left[j \frac{2\pi x'}{\lambda} \right] \quad (3)$$

$$\text{Where: } x' = x \cos \theta + y \sin \theta \quad y' = -x \sin \theta + y \cos \theta \quad (4)$$

The Gabor filter was used to features extracted, and the resulting Gabor decompositions have been encoded with radial grids with claim that this really increase the performance of expression recognition within local classifiers. Nonetheless, this method incurs computation cost and massive space consumption in its quest to maximize available information.

D.Geometric Features

This algorithm is statistically scrapped characteristics from face Characteristics displacement. The hypothesis behind this technique is that while there are subgroups of face components that are more prominent in facial expression analysis, and that obtaining the metrics connection of these components might effectively represent the feature vectors [36]. Geometric characteristics are unaffected by illumination, are simple to record, and operate well for certain Action Units. They are, however, unsuitable for representing action units that do not result in landmark displacement. Other Engineers [37] used displacements relying on graph matching displacement estimate using elastic bunch to automatically retrieve geometric features from video frames.

E.Hybrid Features

it allow the investigation of the introduced issue of how best to combine characteristics for maximum performance. Others [38] proposed an algorithm that fused LBP and HOG features extracted from the CK+ and JAFFE databases and lowered the extracted features dimensionality to PCA. After permuting the fusion on several classifiers, he discovered that the fused features on the softmax classifier produced 97.99 percent on the CK+ database and 89.91 percent on the other database. As a consequence, there's really evidence that the use of appropriate hybrid features may greatly increase performance of the system.

F.Learned characteristics and features

The Artificial Neural Network is blamed for the learnt features (ANN). Throughout this scenario, the ANN learned from the input the features that it might express even without help of a person.. Learned characteristics may well be the best since they are unaffected by light, rotation, head attitude, and other factors. However, the main issue is a lack the adequate Info for the network to train, that may result in overfitting. Other scientists [39] employ deep learning visualization tools to examine the type of feature that CNN is utilizing for classification, and he saw that the characteristics at the low level resembled low level Gabor filters. CNN learnt characteristics match to (FACs), according to Khorrami et al. [40]. LBP and SIFT have been added into 1D layer CNNs to increase their performance [41]. They outperformed the CNN network's performance when just handcrafted or learnt features were used. Complementing learnt features with handcrafted characteristics is still a research priority in FEA that has to be considered.

Upon what all that had been mentioned above we will investigate The methods, features and classifiers that had been implemented in previous Researches and studies to Determine Each Model

Performance and Database type as well as implementation cost through Analyzing each model we will Carefully Describe the limitations that had been found in each system

TABLE I. METHODS, PERFORMANC AND LIMITATION Analysis

AUTHOR	METHODOLOGY (ALGORITHMS & CLASSIFIER)	PERFORMANCE	TYPE -DATABASE	LIMITATIONS	IMPLEMENTATION COST
Sandbach et al. [42]	3D motion based feature +HMM	81.82%	BU-4DFE (Spontaneous)	It falls into the Local optimum Solution trap since it is a generative model.	High cost to Reach High Reliability
K. SikKa et al [43].	HMM+SVM	74.99%	OULU-CASIA VIS (Spontaneous)	When faced with a binary challenge, SVM outperforms a multiclass problem such as expression recognition.	Medium cost But it will need more investment to Reach accuracy more than 91%
		94.01%	CK+ (Posed)		
Feng et al [44].	LBP + Linear Programming	94%	JAFFE(posed)	The dataset supplied for system training in a real-time situation may lead to the system being misled.	High Cost and take more time to implement
Huang et al [45].	LBP + AdaBoost	85.1%	CK+ (posed)	It's likely that important data may be lost.	While costs need to be treated differently in each Project but we could consider it Medium cost
Eleyan et al [46].	PCA+SVM	87.03%	MUFE	SVM is susceptible to noise because it affects hyperplane parallelism & hyperplane tangent like a support vector.	High Cost but it's manageable to be Decreased
Anggraeni et al[47]	Hand crafted Preprocessing stages +CNN	96.96%	CK+ (posed), JAFFE (posed) and MUG (posed)	Due to a lack of training data, there is a tendency to overfit.	Low Cost Due to saving sampling, sensing and personnel used to gather the data
Kumar et al [48].	HOG+SVM	95.07%	CK+(posed)	Because more time required extracting HOG characteristics, it is computationally demanding.	Consider Medium Cost Solution
Liu et al [49].	Hybrid (LBP&HOG) +Softmax	97.99%	CK+(posed)	The optimum combinations of features are currently being researched but no proof for it's efficiency yet	High Cost Due to Multiple Technology Implementation
		89.91%	JAFFE(posed)		
Yang et al [50].	LBP + CNN (fine tune with VGG16)	Better performance than either methods	CK+, JAFFE & Oulu-CASIA	difficulty of generalization.	Medium Cost But LBP could save some Hardware Cost
Zhang et al[51].	SHIFT + CNN	Performance ,state of art	BU-3DFE and Multi-PIE datasets	difficulty of generalization.	Medium Cost and some consider it Cos-effective.

I. RESULTS

The results and findings from the mentioned papers and studies are highlighted in this section. The following justifications were given for the stated goals:

By applying our analysis on the following Studies which indicates “ Facial Recognition methods and Limitations and it was shown in table 1:

I. Discussion

the results of using several classifiers to categorize LBP. AdaBoost and Linear programming provided 85.1 percent and 94 percent accuracy, respectively. While expenses must be managed individually in each project, we may classify it as a medium-cost item that will require more time to install, adding to the overall cost. Similarly, SVM was used in order to categorize PCA and HOG, with the results revealing PCA had 87.03 percent accuracy with a High Cost of Implementation, while HOG had 95.07 percent accuracy with a Medium Cost of Implementation when compared to other alternatives. In addition, it was discovered that spontaneous databases had worse accuracy than posed databases. Although composite characteristics (LBP and HOG) exhibit varying accuracy on diverse posed datasets. Both hybrid characteristics and a mix of custom features are available with deep learning provide promising results, but total cost is taken into account. High for most methods, while low cost solutions provide very low performance, making the system unreliable. Therefore, more emphasis should be placed on determining the ideal mixture of handmade features or a mix of handcrafted and learnt characteristics to overcome limitations that appears in these models, especially in such critical times of pandemic.

However, using data engineering methods on the given dataset, this may be explained. Handcrafted approaches may also be used as supplementary information to help a network make predictions with all these limitations.

Not to mention the security and data privacy issues that might arise while getting or maintaining data, which must be considered as a primary concern and must be addressed as it is one of the most difficult and crucial limitations that can be discovered these days

II. Future Work

Pandemic Affect of growing demand for online and internet solutions Affect of growing demand for online and internet solutions There is a possibility that privacy and personal data restrictions would be loosened.

As a result, it is the responsibility of governments and biometrics providers to develop civil-centric solutions and implement appropriate data protection measures. It contains and monitors the outbreak of the virus, concentrating civilian personal information (PII) and biometrics, health, and personal data in the hands of a small number of unsupervised organizations with visibility, regulatory barriers, and unsupervised. Helps prevent global efforts to prevent. There are restrictions and there will be no biometric options in the near future. Data Privacy and Security must be thoroughly examined to determine the effect on users as well as the challenges that must be Overcome.

References

- [1] Dang, K.; Sharma, S. Review and comparison of face detection algorithms. In Proceedings of the 7th International Conference Confluence 2017 on Cloud Computing, Data Science and Engineering, Noida, India, 12–13 January 2017; pp. 629–633.
- [2] Mundial, I. Q., Hassan, M. S. U., Tiwana, M. I., Qureshi, W. S., & Alanazi, E. (2020, September). Towards facial recognition problem in COVID-19 pandemic. In 2020 4rd International Conference on Electrical, Telecommunication and Computer Engineering (ELTICOM) (pp. 210-214). IEEE.
- [3] M. L. Koudelka, M. W. Koch, and T. D. Russ. Aprescreeener for 3d face recognition using radial symmetry and the hausdorff fraction. In 2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'05)-Workshops, pages 168–168. IEEE, 2005.
- [4] A. Krizhevsky, I. Sutskever, and G. E. Hinton. Imagenet classification with deep convolutional neural networks. In Advances in neural information processing systems, pages 1097–1105, 2012.
- [5] Damer, N., et al.: On the generalization of detecting face morphing attacks

- as anomalies: Novelty vs. outlier detection. In: 2019 IEEE 10th International Conference on Biometrics Theory, Applications and Systems (BTAS), pp. 1–5. IEEE, Tampa (2019). <https://doi.org/10.1109/BTAS46853.2019.9185995>
- [6] Damer, N., et al.: Realistic dreams: Cascaded enhancement of GAN - generated images with an example in face morphing attacks. In: 2019 IEEE 10th International Conference on Biometrics Theory, Applications and Systems (BTAS), pp. 1–10. IEEE, Tampa (2019). <https://doi.org/10.1109/BTAS46853.2019.9185994>
- [7] Damer, N., Dimitrov, K.: Practical view on face presentation attack detection. In: Wilson, R.C., Hancock, E.R., Smith, W.A.P. (eds.) Proceedings of the British Machine Vision Conference 2016, BMVC 2016, 19–22. BMVA Press, York (2016). <http://www.bmva.org/bmvc/2016/papers/paper112/index.html>
- [8] Damer, N., et al.: Crazyfaces: Unassisted circumvention of watchlist face identification. In: 9th IEEE International Conference on Biometrics Theory, Applications and Systems, BTAS 2018, pp. 22 - 25. IEEE, Redondo Beach, CA, USA (2018). <https://doi.org/10.1109/BTAS.2018.8698557>
- [9] Damer, N., et al.: Deep learning - based face recognition and the robustness to perspective distortion, In: 2018 24th International Conference on Pattern Recognition (ICPR). pp. 3445–3450. IEEE, Beijing (2018). <https://doi.org/10.1109/ICPR.2018.8545037>
- [10] Damer, N., Samartzidis, T., Nouak, A.: Personalized face reference from video: Key-face selection and feature - level fusion. In: Ji Q., B. Moeslund T., Hua G., Nasrollahi K. (eds.) Face and Facial Expression Recognition from Real World Videos. FFER 2014. Lecture Notes in ComputerScience, vol. 8912. Springer, Cham (2015). https://doi.org/10.1007/978-3-319-13737-7_8
- [11] Ge, S., et al.: Detecting masked faces in the wild with l1 - cnns. In: IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2017, pp. 426–434. IEEE Computer Society, Honolulu (2017). <https://doi.org/10.1109/CVPR.2017.53>
- [12] Wang, Z., et al.: Masked face recognition dataset and application. arXiv. <https://arxiv.org/abs/2003.09093> (2020)
- [13] Anwar, A., Raychowdhury, A.: Masked face recognition for secure authentication, arXiv. <https://arxiv.org/abs/2008.11104> (2020)
- [14] Ngan, M.L., Grother, P.J., Hanaoka, K.K.: Ongoing face recognition vendor test (frvt) part 6b: face recognition accuracy with face masks using post - covid - 19 algorithms, National Institute of Standards andTechnology, Gaithersburg (2020).
- [15] Martínez, A.M.: Recognizing imprecisely localized, partially occluded, and expression variant faces from a single sample perclass. IEEE Trans. Pattern Anal. Mach. Intell. 24(6), 748–763 (2002).
- [16] Weng, R., Lu, J., Tan, Y.-P.: Robust point set matching for partial face recognition. IEEE Trans. Image Process. 25(3), 1163–1176 (2016).
- [17] Duan, Y., Lu, J., Feng, J., Zhou, J.: Topology preserving structural matching for automatic partial face recognition. IEEE Trans. Inf. Forensics Secur. 13(7), 1823–1837 (2018).
- [18] McLaughlin, N., Ming, J., Crookes, D.: Largest matching areas for illumination and occlusion robust face recognition. IEEE Trans. Cybernet. 47(3), 796–808 (2016).
- [19] Bagchi, P., Bhattacharjee, D., Nasipuri, M.: Robust 3d face recognition in presence of pose and partial occlusions or missing parts. arXiv preprint arXiv:1408.3709 (2014).
- [20] Wold, S., Esbensen, K., Geladi, P.: Principal component analysis. Chemom. Intell. Lab. Syst. 2(1–3), 37–52 (1987).
- [21] Drira, H., Ben Amor, B., Srivastava, A., Daoudi, M., Slama, R.: 3d face recognition under expressions, occlusions, and pose variations. Pattern Anal. Mach. Intell. IEEE Trans. 35(9), 2270–2283 (2013).
- [22] Gawali, A.S., Deshmukh, R.R.: 3d face recognition using geodesic facial curves to handle expression, occlusion and pose variations. Int. J. Computer Sci. Inf. Technol. 5(3), 4284–4287 (2014).
- [23] Priya, G.N., Banu, R.W.: Occlusion invariant face recognition using mean based weight matrix and support vector machine. Sadhana 39(2), 303–315 (2014).
- [24] Alyuz, N., Gokberk, B., Akarun, L.: 3-d face recognition under occlusion using masked projection. IEEE Trans. Inf. Forensics Secur. 8(5), 789–802 (2013).
- [25] Krizhevsky, A., Sutskever, I., Hinton, G.E.: Imagenet classification with deep convolutional neural networks. In: Advances in neural information processing systems, pp. 1097–1105 (2012).
- [26] Almadby, S., Elrefaei, L.: Deep convolutional neural networkbased approaches for face recognition. Appl. Sci. 9(20), 4397 (2019).
- [27] Song, L., Gong, D., Li, Z., Liu, C., Liu, W.: Occlusion robust face recognition based on mask learning with pairwise differential siamese network. In: Proceedings of the IEEE International Conference on Computer Vision, pp. 773–782 (2019).
- [28] http://en.wikipedia.org/wiki/Face_recognition, (2013).
- [29] Zharovskikh, A., 2021. How Much Does a Facial Recognition System Cost? - InData Labs. [online] InData Labs. Available at: <<https://indatalabs.com/blog/facial-recognition-system-cost/>> [Accessed 20 February 2022].
- [30] T. Ojala, M. Pietikäinen, and T. Mäenpää, “Gray Scale and Rotation Invariant Texture Classification with Local Binary Patterns,” Springer, Berlin, Heidelberg, 2000, pp. 404–420.
- [31] Salton, K. (2017). Face recognition: Understanding lbp algorithm. Towards Data Science, 10.
- [32] S. Kasim, R. Hassan, N. H. Zaini, A. S. Ahmad, and A. A. Ramli, “A Study on Facial Expression Recognition Using Local Binary Pattern,” Int. J. Adv. Sci. Eng. Inf. Technol., vol. 7, no. 5, pp. 1621–1626, 2017.
- [33] X. Feng, M. Pietikäinen, and A. Hadid, “Facial Expression Recognition Based on Local Binary Patterns 1,” Pattern Recognit. Image Anal., vol. 17, no. 4, pp. 592–598, 2007.
- [34] F. Ahmed, H. Bari, and E. Hossain, “Person-Independent Facial Expression Recognition Based on Compound Local Binary Pattern (CLBP),” Int. Arab J. Inf. Technol., vol. 11, no. 2, pp. 195–203, 2014.
- [35] D. Huang, C. Shan, M. Ardebilian, Y. Wang, and L. Chen, “Local Binary Patterns and Its Application to Facial Image Analysis: A Survey,” IEEE Trans. Syst. Man, Cybern. Part C, vol. 41, no. 6, pp. 765–781, 2011.
- [36] M. Dahmane and J. Meunier, “Emotion Recognition using Dynamic Grid-based HoG Features,” IEEE Xplore, pp. 884–888, 2011.

- [37] P. Kumar, "A Real-time Robust Facial Expression Recognition System using HOG Features," *Int. Conf. Comput. Anal. Secur. Trends*, pp. 289–293, 2016.
- [38] B. Martinez, M. F. Valstar, B. Jiang, and M. Pantic, "Automatic Analysis of Facial Actions: A Survey," *IEEE Trans. Affect. Comput.*, vol. 3045, no. c, 2017.
- [39] D. Ghimire and J. Lee, "Geometric Feature-Based Facial Expression Recognition in Image Sequences Using Multi-Class AdaBoost and Support Vector Machines," *Sensor*, vol. 13, pp. 7714–7734, 2013.
- [40] Y. Liu, Y. Li, X. Ma, and R. Song, "Facial Expression Recognition with Fusion Features," *Sensor*, vol. 712, no. 17, pp. 1–18, 2017.
- [41] R. Breuer and R. Kimmel, "A Deep Learning Perspective on the Origin of Facial Expressions," *arXiv*, vol. 5, no. 5, pp. 1–16, 2017.
- [42] G. Sandbach, S. Zafeiriou, M. Pantic, and D. Rueckert, "A Dynamic Approach to the Recognition of 3D Facial Expressions and Their Temporal Models," *Face Gesture*, pp. 406–413, 2011.
- [43] K. Sikka, A. Dhall, and M. Bartlett, "Exemplar Hidden Markov Models for classification of facial expressions in videos," *Comput. Vis. Pattern Recognit. Work. (CVPRW), 2015 IEEE Conf.*, pp. 18–25, 2015.
- [44] X. Feng, M. Pietikäinen, and A. Hadid, "Facial Expression Recognition Based on Local Binary Patterns 1," *Pattern Recognit. Image Anal.*, vol. 17, no. 4, pp. 592–598, 2007.
- [45] D. Huang, C. Shan, M. Ardebilian, Y. Wang, and L. Chen, "Local Binary Patterns and Its Application to Facial Image Analysis : A Survey," *IEEE Trans. Syst. Man, Cybern. Part C*, vol. 41, no. 6, pp. 765–781, 2011.
- [46] M. Abdulrahman, A. Eleyan, A. Kelimeler, İ. Yüz, and Y. İ. Örtüntü, "Facial Expression Recognition Using Support Vector Machines Destek Vektör Makineleri ile Yüz İfade Tanıma," pp. 14–17, 2015.
- [47] D. Anggraeni, A. Wulandari, T. Barasaruddin, and D. Yanti, "Enhancing CNN with Preprocessing Stage in Automatic EmotionEnhancing CNN with Preprocessing Stage in Automatic Emotion Recognition Recognition," in *Procedia Computer Science*, 2017, vol. 116, pp. 523–529.
- [48] P. Kumar, "A Real-time Robust Facial Expression Recognition System using HOG Features," *Int. Conf. Comput. Anal. Secur. Trends*, pp. 289–293, 2016.
- [49] R. Breuer and R. Kimmel, "A Deep Learning Perspective on the Origin of Facial Expressions," *arXiv*, vol. 5, no. 5, pp. 1–16, 2017.
- [50] B. Yang, J. Cao, R. Ni, and Y. Zhang, "Facial Expression Recognition Using Weighted Mixture Deep Neural Network Based on Double-Channel Facial Images," *IEEE Access*, vol. 6, pp. 4630–4640, 2018.
- [51] T. Zhang, W. Zheng, Z. Cui, Y. Zong, J. Yan, and K. Yan, "A DeepNeural Network-Driven Feature Learning Method for Multi-view Facial Expression Recognition," *IEEE Trans. Multimed.*, vol. 18, no. 12, pp. 2528–2536, Dec. 2016.