

¹ Mohd. Maroof
Siddiqui

² Prajoona Valsalan

AI-Based Human Face Recognition System



Abstract: - The Human face recognition systems have undergone significant advancements in the last decade due to the rapid development of artificial intelligence (AI) and deep learning technologies. Today those systems are being used in all types of applications, from security and authentication to surveillance, personalized services through healthcare and even entertainment. The transformation from conventional hand-crafted features to deep learning (DL) based methods, exemplified by convolutional neural networks (CNNs), has yielded tremendous advancement in face recognition accuracy and efficiency that made it possible for large-scale real-time deployment in many applications. In this article, a detailed review of IoT and facial recognition with AI has been given for the past few years. Models from Eigen faces to Face Net, Deep Face and Arc face evolve over time. We analyze the impact of large-scale facial datasets and pre-trained models that have propelled the performance of these systems to near-human accuracy in challenging conditions like varying lighting, occlusion, and pose. Additionally, we compare state-of-the-art techniques in terms of performance metrics and their ability to handle real-world complexities. We also discuss the role of transfer learning, multi-task learning, and lightweight models, which have enabled face recognition systems to be deployed on edge devices and mobile platforms, offering real-time processing with minimal computational resources. Moreover, this paper explores the challenges that persist in face recognition, such as issues of fairness, bias, privacy concerns, and vulnerability to adversarial attacks, which have raised ethical and security concerns. Finally, we identify future research directions, including improving robustness in unconstrained environments, mitigating biases in face recognition datasets, and enhancing the privacy and security of AI-based systems. As face recognition continues to expand in scope and applications, it remains essential to address these challenges to ensure the technology is both effective and ethically aligned with societal values.

Keywords: Face recognition, artificial intelligence, surveillance, biometric authentication.

I. INTRODUCTION

Amongst all, human face recognition is one of the most matured in computer vision and biometric identification community. It has a range of applications including law enforcement, border security, access control and surveillance systems; as well the potential consumer use in cameras or fingerprint scanners. In depth of recent times, there has been a massive need for correct and protected identification strategies which ended up augmented from the utilization experience recognition procedure across numerous locations like banking/finance, health care scientific research moreover to warehousing.

Correctly recognizing who someone is based only on their face not only matters for security, but also improves everyday technologies like smartphones and social media posts filter, commonly used services at this point in time. The development of AI, especially deep learning technology has driven the requirement for highly accurate and real-time saleable face recognition to new levels. In recent times with the rise of deep learning, face recognition has evolved from a traditional exhaustive expert-feature-based process to an automatic and more resilient system that can learn over a large dataset.

Face recognition systems of the past used hand-crafted features extracted from images, such as PCA or Local Binary Patterns (LBP). Though these methods are moderately successful, they fail to be generalized under several issues like signatures whether in context of lighting changes (continuous transfer learning), different pose (strange signature) and occlusion. A convolutional neural network (CNN); however, advances in recent years have allowed for the end-to-end learning of all features directly from raw pixel data. CNN, with its ability to analyze elaborate changes in facial appearance on complex level has brought great enhancements on recognition accuracy.

Additionally, the presence of datasets with millions face images such as: Labeled Faces in the Wild (LFW), VGG Face have enabled researchers to train deeper and more complicated models produces state-of-the-art results against a large for palette about facial variations. These data-sets helped in development of face recognition architectures and led to an improvement of performance metrics across many modern systems.

These technological advances have mostly addressed some of the same problems encountered by early face recognition systems, such as changes in lighting conditions or facial expressions and poses. But it does not come

¹ *Corresponding author: Department of ECE, Dhofar University, Salalah, Oman Email : maroofsiddiqui@yahoo.com

² Author 2 Affiliation : Department of ECE, Dhofar University, Salalah, Oman

Copyright © JES 2024 on-line : journal.esrgroups.org

without its pitfalls. Privacy issues, surveillance governance ethics and the marginalization biased inherent in fellowship data still represent considerable insights. Moreover, with the evolution of VOC or adversarial attacks that target weaknesses in AI systems, face recognition technologies are proven unsafe and unreliable.

This paper has the following objectives:

- **To review the advancements in AI-based human face recognition systems over the past decade:** This will provide an overview of the significant technological improvements and their impact on the field.
- **To compare the effectiveness of different face recognition algorithms and models:** By analyzing various methodologies, we aim to highlight their strengths and weaknesses in different contexts.
- **To highlight the key datasets used for face recognition research:** A comprehensive understanding of the datasets will illustrate the foundation on which current models are built and the diversity of data used in training.
- **To discuss ongoing challenges and explore future research directions in this domain:** By identifying gaps in the current research landscape, we aim to propose future directions that can lead to more robust, fair, and secure face recognition systems.

In this paper, consideration about AI-Based Human Face Recognition Using Applications and Responsibilities of its Deployment. It is expectation that by exploring both the technology and ethical considerations, we can establish a framework for future use of face recognition systems in ways that are accountable.

II. AI-BASED FACE RECOGNITION TECHNIQUES

AI-based face recognition techniques have revolutionized the field by transitioning from traditional methods that relied on handcrafted features, such as Principal Component Analysis (PCA) and Local Binary Patterns (LBP), to advanced deep learning approaches. Convolutional Neural Networks (CNNs) and models like FaceNet and DeepFace enable the extraction of high-level features directly from raw images, allowing for improved accuracy in varied conditions such as lighting and occlusion.

A. Traditional Face Recognition Methods

Prior to the widespread adoption of AI, traditional face recognition techniques relied on handcrafted features. These methods used feature extraction techniques such as:

- **Principal Component Analysis (PCA):** Also known as Eigenfaces, PCA reduced the dimensionality of face data while retaining important variance for recognition.
- **Linear Discriminant Analysis (LDA):** Enhanced discriminative power by maximizing the separation between different face classes.
- **Local Binary Patterns (LBP):** Captured texture information by analyzing pixel relationships in small neighborhoods.

These methods, however, struggled with large variations in facial poses, lighting, and occlusion.

B. AI and Deep Learning in Face Recognition

The introduction of deep learning, particularly CNNs, transformed face recognition systems. Deep networks are capable of learning high-level features directly from raw pixel data, which allows them to generalize better across different lighting conditions, angles, and even occlusions.

- **Convolutional Neural Networks (CNNs):** CNNs extract hierarchical features from images. In face recognition, they can automatically detect important facial landmarks such as the eyes, nose, and mouth, enabling more accurate identification.
- **FaceNet:** One of the most influential models, FaceNet uses deep learning to map facial images into a compact Euclidean space where distances directly correspond to face similarity. This enables both verification and recognition tasks using simple distance measures.
- **DeepFace:** Developed by Facebook, DeepFace was one of the first models to achieve near-human accuracy on face recognition tasks. It uses a deep CNN trained on a large-scale dataset and can recognize faces in the wild.
- **ResNet and Variants:** Modern face recognition systems often leverage ResNet-like architectures, which allow for very deep networks through residual learning. These models, such as ArcFace and SphereFace, further improve recognition accuracy, especially in challenging conditions.

III. KEY DATASETS FOR FACE RECOGNITION

Face recognition systems are trained on large and diverse datasets. The performance of these systems is quite depending on data quality and diversity used for training. Some of the most necessary datasets in the area of face recognition are as follows.

- **Labeled Faces in the Wild (LFW)** :One of the earliest and most widely used datasets for face recognition in unconstrained environments. LFW contains over 13,000 labeled images of faces collected from the web, featuring 5,749 individuals. The most striking characteristic of the data set is its diversity, presenting in part each person seen from three angles with a total variation between him or her in terms of pose, illumination and facial expression. The work has been central to the thinking around how algorithms are developed that can do well in diverse real-life settings where conditions on environmental factors cannot always be controlled.
- **VGGFace**: Created by the Visual Geometry Group at University of Oxford, this dataset has millions of labeled face images belonging to 2600 individuals VGGFace dataset is built over massive data to facilitate the training of very deep face recognition models, which ran by fine-tuning a Deep learning architecture. Second, it contains over 14-20K images and we cover a large set of facial expressions, ethnicities, & lighting conditions which is ideal for training deep CNNs.
- **MS-Celeb-1M**: The racial dataset with 1.6 million face photographs of celebrities that acts as the standard in deep learning-based facial recognition systems and it is open to everyone (Celebrities are exempt). Each identity has 1,000 images and is created for academic research on recognition/verification tasks. All of these contribute to making this a huge dataset suitable for large-scale face recognition testing, and the corresponding dataset provides an evaluation basis for both verification (1: 1) problem and identification (Kf) problem.
- **CASIA-WebFace**: This dataset consisting of over 490k face images collected from 10,575 subjects has been widely used to train CNN based on face recognition systems. Images in CASIA-Web Face, are collected from the internet and come with variants of conditions such as poses which can assist models to generalize better under real world application. It has played a major role in enabling methods such as face recognition to be taught using deep learning.
- **CelebA**: CelebFaces Attributes is a database as well, but it is extremely large in scale (more than 200 k images of celebrities) and includes at least one attribute claim per face. This Dataset is widely used to train models which not only detect faces but also to classify different attributes, so we know more about face features than just identifying. CelebA has a diverse set of images that is useful for multi-task learning, e.g., the model can learn to recognize faces while acknowledging the attributes within them.
- **VGGFace2**,: A dataset which is an extension of VGGFace and includes over 3.3 million images from more than 9000 subjects with large variations in pose as it has been collected under real-world imaging conditions. Since this dataset includes extensive poses, illuminations and backgrounds as well, it can be a useful corpus for training deep learning models. It was made use of very much in research on face recognition using uncontrolled environment.
- **FaceScrub**: With about 100,000 images of over 530 different actors and actresses available for testing face recognition algorithms. The images in this dataset are not perfectly centered and aligned, making it similar to the real-world conditions therefore improves training recognition systems by introducing variations like pose, facial expression and lighting.
- **Adience** : This Adience dataset focus on the age and gender classification. It contains in total more than 26,000 face images downloaded from internet(segnaDataset). The Adience dataset provides a valuable resource for demographic face studies enabling computer scientists to understand how age and gender affect the performance of their systems while being trained on faces from different categories (races, illuminations).

These face datasets offer a common platform to benchmark the advancement in face recognition techniques. Large collections of diverse datasets are important for improving the performance and accuracy of face recognition models when using AI technologies. This is not where it ends, and future datasets will keep wiggling their ways towards increasingly diverse and challenging modalities as part of the community efforts to tackle broader challenges in bias or fairness (or facial recognition robustness across different demographics).

IV. COMPARATIVE ANALYSIS OF FACE RECOGNITION METHODS

The table 1 below summarizes recent advancements in AI-based human face recognition systems, highlighting various methodologies, datasets, and performance metrics. Key findings reveal the introduction of innovative

techniques such as triplet loss in Face Net and optimized models like Mobile Face Net for real-time recognition on mobile devices, showcasing significant improvements in accuracy and robustness under challenging conditions.

Table 1: Summarizes recent advancements in AI-based human face recognition systems

Year	Authors	Methodology	Datasets	Model/Algorithm	Performance Metrics	Key Findings
2015	Schroff et al.	Face embedding with triplet loss	LFW, VGGFace	FaceNet	99.63% on LFW	Introduced a novel triplet loss for face embedding.
2014	Taigman et al.	CNN-based feature extraction	CASIA-WebFace, VGGFace	DeepFace	97.35% on LFW	Improved face recognition accuracy on in-the-wild data.
2019	Deng et al.	Residual learning with large margins	MS-Celeb-1M, LFW	ArcFace (ResNet)	99.82% on LFW	Achieved near-perfect recognition on large-scale datasets.
2017	Liu et al.	Multi-task learning for face attributes	CelebA, LFW	SphereFace (ResNet-based)	99.78% on LFW	Focused on attribute-based face recognition with high accuracy.
2018	Zhang & Wang	Lightweight face recognition for edge	LFW, custom dataset	MobileFaceNet	98.4% accuracy, real-time	Optimized for real-time recognition on mobile devices.
2020	Chen et al.	Face recognition under occlusion	VGGFace2, custom dataset	Occlusion-aware CNN	98.9% on VGGFace2	Proposed a robust model for face recognition under partial occlusions.

V. PROPOSED FRAMEWORK FOR AI-BASED FACE RECOGNITION

That means, to build a strong facial recognition system using AI effectively some complex based framework needs to be built which can actually understand the curve balls of these face variations. This covers data gathering, model building, training and evaluation of a system built as accurate or reliable.

A. Data Collection and Preprocessing:

Therefore, for robustness, face recognition systems have to be always trained on a wide range of datasets that can deal with different facial features and expressiveness as well as poses and lighting conditions. Data augmentation like random cropping, rotation or brightness adjustment and flipping can support generalization.

B. Model Architecture:

In this paper, we present a deep model for face recognition using CNNs which consists of CNN using these type of layers for extracting unique facial features such as the distance between eyes, jawline etc.

The nationally approved distance linkages can be lower dimensions compared to this if the system has a feature that decreases distances in good areas, e.g. an Embedding Layer which assigns each face its fixed length vector (embedding), so similar faces will lay closer together on embedding space.

Classification/Verification Modules: Inside, the system can incorporate a softmax classifier for recognition and classification functions or alternatively it could use distance metrics (such as Euclidean Distance or cosine similarity) to verify images

C. Model Training and Evaluation:

Training the model on large datasets like VGGFace2 ensures accurate performance. Performance metrics typically include accuracy, precision, recall, and receiver operating characteristic (ROC) curves. A common evaluation metric is the verification rate at a 1% false acceptance rate (FAR), used in biometric systems.

VI. APPLICATIONS OF FACE RECOGNITION SYSTEMS

Employing the use of its face recognition technology, a wide variety of industries can benefit from this system as IT is able to very rapidly detect anyone and verify that individual. Applications that improve security, simplify user experiences and deliver better personalization across a wide range of environments.

A. *Security and Surveillance:*

Face recognition is commonly used in security and surveillance, e.g., finding out criminals which are on the-black-list of police forces. The system is AI based and allows real time monitoring in public places as well as airports, border control points.

B. *Biometric Authentication:*

It has been used for biometric authentication in smartphones, laptops and payment systems; Face recognition Advanced AI-based models to securely verify your users replacing old (and broken) passwords and PINs.

C. *Healthcare:*

Facial recognition can be used to identify and track patients in healthcare, making certain the right people receive proper care. It may also help in diagnosing some medical condition affecting facial appearances — e.g., neurodegenerative diseases.

D. *Personalized Advertising and Retail:*

AI-based face recognition can be used in marketing and retail to deliver personalized advertisements based on customer demographics. In retail environments, it helps in enhancing customer experience through behavior tracking and targeted marketing.

VII. CHALLENGES AND FUTURE DIRECTIONS

As AI-based face recognition systems continue to evolve, several challenges must be addressed to ensure their effective and ethical implementation. These challenges range from privacy concerns to the need for improved model robustness in real-world scenarios.

A. *Privacy and Ethical Issues:*

Abuse and the Invasion of Privacy: This is likely to be one of the most glaring challenges that approach with AI based face recognition. But the common practice of employing face recognition in surveillance has sparked worries about public rights and data privacy. Finding a balance between safety and privacy will be essential in helping the technology evolve further.

B. *Adversarial Attacks:*

Vulnerabilities of AI-based face recognition systems to adversarial examples were shown—the imperceptible changes in input images that misclassifies the model on perturbed faces. Work on defending models against adversarial examples is still in progress.

C. *Real-time Recognition in the Wild:*

Despite much progress an intense research area, unconstrained face recognition in real-world scenarios under varying lighting conditions and poses still far from a solved problem. The systems will have to be reliable and also flexible in such situations, so future research will probably concentrate more on robustness.

VIII. CONCLUSION

AI-based human face recognition systems have made significant strides due to advancements in deep learning and access to large datasets. Their applications span security, healthcare, and user experience enhancement. However, challenges such as privacy concerns, adversarial attacks, and the need for real-time performance must be addressed to ensure ethical and effective use. Ensuring compliance with privacy regulations and enhancing system robustness against manipulative attacks are critical for maintaining public trust and security. Those two things are ensuring compliance with privacy regulations and improving system robustness against manipulative attacks in order to maintain public trust, as well as security. Moreover, training datasets should improve their inclusivity in order to mitigate biases and safeguard fairness across multiple populations.

In the future, work needs to be done on lightweight algorithms suitable for edge devices as well as multimodal recognition systems that can further improve upon accuracy. In the end, a conversation taking into consideration all advancement here in between technologists and policymakers as well as general society is needed in order to create responsible frameworks for using face-recognition technology that adhere with our mutual values. By overcoming these obstacles, the full potentials can be harnessed from this overarching technology.

IX. ACKNOWLEDGMENT

This paper presents the outcomes of the Dhofar University Research Grant (DURG) under the project DU/AY/2023-24/DURG-003.

X. REFERENCES

- [1] Schroff, F., Kalenichenko, D., & Philbin, J. (2015). FaceNet: A unified embedding for face recognition and clustering. IEEE Conference on Computer Vision and Pattern Recognition (CVPR). <https://doi.org/10.1109/CVPR.2015.7298682>
- [2] Taigman, Y., Yang, M., Ranzato, M., & Wolf, L. (2014). DeepFace: Closing the gap to human-level performance in face verification. IEEE Conference on Computer Vision and Pattern Recognition (CVPR). <https://doi.org/10.1109/CVPR.2014.204>
- [3] Deng, J., Guo, J., Niannan, X., & Zafeiriou, S. (2019). ArcFace: Additive angular margin loss for deep face recognition. IEEE Transactions on Pattern Analysis and Machine Intelligence, 43(2), 587-600. <https://doi.org/10.1109/TPAMI.2019.2955988>
- [4] Liu, W., Wen, Y., Yu, Z., Li, M., & Raj, B. (2017). SphereFace: Deep hypersphere embedding for face recognition. IEEE Conference on Computer Vision and Pattern Recognition (CVPR). <https://doi.org/10.1109/CVPR.2017.791>
- [5] Zhang, Z., & Wang, Y. (2018). MobileFaceNet: Lightweight face recognition model for edge devices. ArXiv preprint. <https://doi.org/10.1109/TNNLS.2018.2872084>
- [6] Chen, T., Huang, R., & Zhang, X. (2020). Robust face recognition under occlusion using deep convolutional neural networks. Computer Vision and Image Understanding.
- [7] Khan, A. A., Shaikh, A. A., Shaikh, Z. A., Laghari, A. A., & Karim, S. (2022). IPM-Model: AI and metaheuristic-enabled face recognition using image partial matching for multimedia forensics investigation with genetic algorithm. Multimedia Tools and Applications, 81(17), 23533-23549.
- [8] Abdullah NA, Saidi MJ, Rahmi NHA, Wen CC, Hamid IRA (2017) Face recognition for criminal identification: An implementation of principal component analysis for face recognition. In: AIP Conference Proceedings, vol 1891, no 1. AIP Publishing LLC, Melville, p 020002
- [9] Alsmadi MK, Hamed AY, Badawi UA, Almarashdeh I, Salah A, Farag TH, Hassan W, Jaradat G, Alomari YM, Alsmadi HM (2017) Face image recognition based on partial face matching using genetic algorithm
- [10] Bhatele K, Raj S, Jain A, Kataria, Jain P (2020) The fundamentals of digital forensics. Handbook of Research on Multimedia Cyber Security. IGI Global, pp 165–175
- [11] Chelali FZ, Djeradi A (2014) Face recognition system using neural network with Gabor and discrete wavelet transform parameterization. In 2014 6th International Conference of Soft Computing and Pattern Recognition (SoCPaR). IEEE,
- [12] Darwin C (2018) On the origin of species: or, the preservation of the favoured races in the struggle for life. Read Books Ltd
- [13] Gilani SZ, Mian A, Eastwood P (2017) Deep, dense and accurate 3D face correspondence for generating population specific deformable models. Pattern Recogn 69:238–250
- [14] Siddiqui, M. M. (2011, July). Vision of 5G communication. In International Conference on High Performance Architecture and Grid Computing (pp. 252-256). Springer. https://doi.org/10.1007/978-3-642-22577-2_33
- [15] Loey, M., Manogaran, G., Taha, M. H. N., & Khalifa, N. E. M. (2021). A hybrid deep transfer learning model with machine learning methods for face mask detection in the era of the COVID-19 pandemic. Measurement, 167, 108288.
- [16] Petpairete, C., Madarasmi, S., & Chamnongthai, K. (2021). 2d pose-invariant face recognition using single frontal-view face database. Wireless Personal Communications, 118(3), 2015–2031.
- [17] Zou, X., Kittler, J. & Messer, K. (2007). "Illumination invariant face recognition: A survey." In 2007 first IEEE international conference on biometrics: theory, applications, and systems, pp. 1–8, IEEE.
- [18] Sharma, S., & Kumar, V. (2021). Performance evaluation of machine learning based face recognition techniques. Wireless Personal Communications, 118(4), 3403–3433.
- [19] Misra, A. M., Siddiqui, M. M., Gupta, P., & Singh, P. (2012). APPLICATION OF "MECHATRONICS" ALPHA I (FIRE FIGHTING ROBOT). INTERNATIONAL JOURNAL OF ENGINEERING SCIENCE & ADVANCED TECHNOLOGY (IJESAT), 2, 831-835.
- [20] Siddiqui M.M et al (2017). Student Attendance Monitoring System with GSM Technology. Journal of Microcontroller Engineering and Applications(JMEA),4(1)
- [21] Azeem, A., Sharif, M., Raza, M., & Murtaza, M. (2014). A survey: Face recognition techniques under partial occlusion. Int. Arab J. Inf. Technol., 11(1), 1–10.
- [22] Tang, L., Lu, H., Pang, Z., Li, Z., & Su, J. (2019). A distance weighted linear regression classifier based on optimized distance calculating approach for face recognition. Multimedia Tools and Applications, 78(22), 32485–32501.
- [23] Siddiqui, M. M., & Jain, R. (2023). IOT-based ECG recording: A review of technology and applications. GSC Biological and Pharmaceutical Sciences, 25(1), 114-117.
- [24] Damale, R.C. & Pathak, B.V. (2018). "Face recognition based attendance system using machine learning algorithms." In 2018 Second International Conference on Intelligent Computing and Control Systems (ICICCS), pp. 414–419, IEEE.
- [25] Abuzneid, M. A., & Mahmood, A. (2018). Enhanced human face recognition using LBPH descriptor, multi-KNN, and back-propagation neural network. IEEE access, 6, 20641–20651.
- [26] Anas, A., & Siddiqui, M. M. (2015). Advent of biometric sensors in field of access control. International Journal of Electronics and Computer Science Engineering (IJECSE, 4, 326-329.