

FACIAL RECOGNITION SYSTEM USING A DEEP LEARNING APPROACH: A REVIEW

¹Nurudeen Bolaji Idrees, ²Adama Asmau Sani, ³Aliu Maryam Oriyomi, ⁴Ilyas Olamilekan Towobola

¹Kwara State University, Malette, Ilorin, Kwara State, Nigeria.

^{2,4}Department of Computer Science, Al-Hikmah University Ilotin, Kwara State, Nigeria

³ICT Department, Federal Medical Centre, Abeokuta, Ogun State, Nigeria.

⁴Alhikmah University, Ilorin, Kwara State, Nigeria

Corresponding Author: towobolailyasolamilekan@gmail.com

ABSTRACT

Facial recognition has emerged as a leading biometric technology, with deep learning driving significant improvements in accuracy, robustness, and applicability. This study reviews the progression from early handcrafted feature extraction methods to advanced neural architectures such as convolutional neural networks (CNNs), deep metric learning, attention mechanisms, and hybrid CNN–Transformer models. It highlights how deep learning enables automatic hierarchical feature learning, improving resilience against variations in pose, illumination, occlusion, and facial expressions. The review also explores diverse applications, including identity verification, emotion recognition, healthcare diagnostics, attendance monitoring, surveillance, and DeepFake detection, underscoring the interdisciplinary relevance of facial recognition systems. Despite these advances, challenges such as dataset bias, privacy concerns, computational demands, and vulnerability to adversarial attacks persist. Emerging solutions which includes multimodal biometric integration, liveness detection, federated learning, and lightweight architectures for mobile and edge devices are discussed as pathways toward more secure and efficient systems. The study concludes that while deep learning has elevated facial recognition to unprecedented levels of performance, sustainable adoption requires balancing technical innovation with ethical governance, fairness, and privacy preservation.

KEYWORDS: Facial Recognition, Biometric Systems, Deep Learning, Convolutional Neural Networks (CNNs), Deep Metric Learning

I. INTRODUCTION

Facial recognition has emerged as one of the most widely adopted biometric technologies, powering applications in security, authentication, and human–computer interaction (Fadel, 2025; Sipulova et al., 2025). Its appeal lies in the non-intrusive nature of facial features, which can be captured and analyzed without physical contact. Over the years, research has transitioned from handcrafted feature engineering to deep learning methods that exploit large-scale datasets and advanced neural architectures (Murtaza et al., 2026). This shift has revolutionized facial recognition by enabling end-to-end learning of discriminative features directly from raw images (Ede et al., 2025). Key innovations such as Convolutional Neural Networks (CNNs), deep metric learning, and attention-based models have significantly improved recognition accuracy and robustness, particularly in unconstrained environments with variations in pose, lighting, and occlusion (Zhang et al., 2023).

These advances have helped overcome many of the limitations that previously restricted real-world performance.

Nonetheless, challenges persist. Issues including algorithmic bias, privacy concerns, high computational requirements, and susceptibility to adversarial attacks underscore the importance of responsible deployment (Ajibola et al., 2025). At the same time, emerging directions such as lightweight architectures for mobile devices, multimodal biometric integration, and ethically aware system design are shaping the next phase of facial recognition research. This review provides a comprehensive examination of deep learning–based facial recognition systems. It traces the evolution of methodologies, highlights key architectural breakthroughs, and evaluates benchmark performance across widely used datasets. In addition, it critically addresses current limitations and explores emerging trends, offering insights for both academic research and practical implementation.

II. RELATED WORKS

A. Deep Learning Algorithm

Deep learning is a branch of machine learning that employs multi-layered artificial neural networks to automatically learn complex patterns from data. Unlike traditional methods that depend on manually crafted features, deep learning extracts hierarchical representations directly from raw inputs, making it highly effective for tasks such as image processing, language understanding, and speech recognition. The learning process is based on forward propagation to generate outputs and backpropagation to update network weights and reduce errors. Nonlinear activation functions and optimization techniques enable these models to capture complex relationships and improve accuracy over time. Various deep learning architectures have been developed to address different data types and problems. Convolutional neural networks specialize in spatial data and dominate computer vision tasks, while recurrent neural networks and long short-term memory models are suited for sequential data like text and speech. Transformer architectures have further advanced natural language processing through attention mechanisms that model long-range dependencies. Generative adversarial networks represent another major development, producing realistic synthetic data through competitive learning. Deep learning has transformed many sectors. In healthcare, it supports medical imaging and drug discovery; in finance, it enables fraud detection and automated trading; in transportation, it powers autonomous systems; and in cybersecurity, it aids intrusion and anomaly detection. Entertainment platforms also rely on deep learning for recommendation systems and content generation. Despite these achievements, challenges persist. Deep learning models often require large labeled datasets and significant computational power, are difficult to interpret, and may inherit biases from training data. To address these issues, ongoing research focuses on explainable AI, federated learning, and energy-efficient model design. Future developments are expected to integrate deep learning with edge computing, IoT, robotics, and Industry 4.0 technologies, with increased emphasis on fairness, transparency, and trustworthiness.

B. Convolutional Neural Network (CNN) for Facial Recognition

Convolutional Neural Networks (CNNs) are a class of deep learning models specifically designed for processing structured grid data such as images. In facial recognition, CNNs have become the dominant approach because of their ability to automatically learn and extract meaningful facial features without the need for manual feature engineering. Facial recognition itself involves identifying or verifying an individual based on facial images, and CNNs significantly enhance the accuracy and efficiency of this process (Nemavhola et al., 2025). A CNN processes facial images by applying a series of convolutional operations that detect low-level features such as edges and

textures in the initial layers. As the data moves deeper into the network, more complex and abstract features such as facial shapes and unique identity characteristics are captured. This hierarchical learning process allows CNNs to build a comprehensive representation of a face, making them highly effective for recognition tasks (Zhang et al., 2024). The architecture of a CNN for facial recognition typically consists of an input layer that receives the facial image, followed by multiple convolutional layers that extract features through filters. These are usually combined with activation functions such as the Rectified Linear Unit (ReLU) to introduce non-linearity. Pooling layers are then used to reduce the spatial dimensions of the data while retaining essential information, which helps improve computational efficiency and prevent overfitting. The extracted features are then passed to fully connected layers, where classification or identity matching is performed, leading to the final output of the system (Chen, 2023).

In practice, CNN-based facial recognition systems operate by training on large datasets of labeled facial images. During training, the network adjusts its internal parameters using backpropagation to minimize prediction errors. Once trained, the CNN converts a facial image into a numerical representation known as an embedding. This embedding is then compared with stored representations in a database using similarity measures to determine identity. This approach enables accurate recognition even when there are variations in pose, lighting, or facial expression (Baareh, 2024). Recent advancements in CNN-based facial recognition between 2023 and 2025 have focused on improving accuracy, robustness, and adaptability in real-world conditions. Studies have shown that modern deep CNN architectures can achieve very high recognition accuracy, often exceeding 97% under controlled conditions (Baareh, 2024). Furthermore, the integration of techniques such as data augmentation and transfer learning has improved performance on smaller datasets and enhanced generalization. Hybrid approaches that combine CNNs with other models, including Long Short-Term Memory (LSTM) networks and transformer-based architectures, have also been introduced to handle more complex scenarios such as video-based recognition and deepfake detection (Tipper et al., 2024).

Despite these advancements, CNN-based facial recognition systems still face several challenges. They require substantial computational resources and large volumes of data for effective training. Additionally, issues related to bias in training datasets can affect fairness and accuracy across different demographic groups. Privacy and ethical concerns also remain significant, particularly in surveillance and security applications. Moreover, extreme variations such as occlusion or poor lighting conditions can still impact system performance (Nemavhola et al., 2025). In conclusion, CNNs have revolutionized facial recognition by providing a powerful framework for automatic feature extraction and accurate identity classification. Their ability to learn complex patterns from large datasets has made them the backbone of modern biometric systems. Ongoing research continues to address their limitations, focusing on improving efficiency, fairness, and robustness to ensure reliable deployment in real-world applications.

III. RELATED WORKS

The early research on facial recognition focused on handcrafted feature extraction and statistical learning approaches. One of the foundational works was by Matthew Turk and Alex Pentland (1991), who introduced the Eigenfaces technique, applying Principal Component Analysis (PCA) for face representation. Although effective in controlled environments, this approach was sensitive to variations in lighting and pose. Furthermore, several researchers have used deep learning in a face recognition system. These include Chandrsekhar et al. (2026) proposed a deep learning-based face recognition model leveraging the Deep Face architecture with transfer learning and deep residual layers to extract robust facial features. It was discovered that the improved recognition performance under varying lighting and pose

conditions outperforms traditional feature-based methods. This study confirms that deep residual and transfer learning techniques can enhance accuracy and robustness in face recognition tasks across diverse real-world conditions. Sharzizi et al. (2026) compared four prominent deep learning frameworks (FaceNet, SFace, OpenFace, DeepFace) in a web-based environment, assessing accuracy, latency, and robustness under pose, lighting, and occlusion variations. The output showed that no single model consistently excels across all metrics; performance varies depending on application requirements for speed versus accuracy. The evaluation highlighted the trade-off between recognition accuracy and computational performance in real-time applications, underscoring the need to tailor model choice to specific deployment scenarios.

Zhou (2026) examined the integration of Transformer architectures with deep reinforcement learning to address limitations of traditional CNN-based models, such as sample efficiency and unstable training. The result showed early promising results and identified the potential of Transformer-based models to capture long-range dependencies in face features. The emerging approach suggests that combining deep reinforcement learning with Transformer models could be a future-oriented direction in deep learning facial recognition research. Ren and Zhang (2026) designed a deep learning face recognition system that detects facial emotions in real time to provide teacher feedback on student engagement. There was an improvement in classroom engagement metrics by giving educators objective data from emotional feedback. Although *application-specific*, this work highlights how deep learning face recognition systems can extend beyond identity verification to broader contexts like emotion analysis in education. Dede et al. (2025) provided a systematic review of deep learning techniques for improving the efficiency of high-resolution image processing. The study investigated techniques like lightweight neural networks, vision transformers adapted for high-resolution inputs, and models using frequency-domain inputs based on 96 studies from 2018 to 2023. These techniques have many applications, from environmental monitoring and urban planning to disease diagnosis. We emphasize the advancements in efficient high-resolution deep learning models, discussing their performance in terms of accuracy, speed, and resource requirements. Key challenges, including the trade-off between processing efficiency and model accuracy, are analysed, and potential future research directions are proposed to address these issues.

Zhalgas and Amirgaliye (2025) surveyed face recognition models that are based on deep learning, specifically security and surveillance. Existing systems are susceptible to pose variation, occlusion, low resolution, and even aging, even though they perform quite well under controlled conditions. The systematic review of four state-of-the-art architectures—FaceNet, ArcFace, OpenFace, and SFace—through the use of five benchmark datasets, namely LFW, CPLFW, CALFW, AgeDB-30, and QMUL-SurvFace. The measures of performance are evaluated as the area under the receiver operating characteristic (ROC-AUC), accuracy, precision, and F1-score. The results reflect that FaceNet and ArcFace achieve the highest accuracy under well-lit and frontal settings; when comparing SFace, this proved to have better robustness to degraded and low-resolution surveillance images. This revealed the weaknesses of traditional embedding methods because bigger data sizes reduce the performance of OpenFace with all of the datasets. These results underscore the main point of this study: a comparative study of the models in difficult real-life conditions and the observation of the trade-off between generalization and specialization inherent to any model. Specifically, the ArcFace and FaceNet models are optimized to perform well in constrained settings, and SFace in the wild ones. This means that the selection of models must be closely monitored with respect to deployment contexts, and future studies should focus on the study of architectures that maintain performance even with fluctuating conditions in the form of hybrid architectures. Fadel (2025) emphasized the recent development in deep learning techniques, especially CNNs, which greatly improved the accuracy and efficiency of facial recognition systems. The findings revealed that there has been a noticeable evolution in facial recognition technology, especially with the current use of deep learning techniques. Nevertheless,

it highlighted important challenges, including privacy concerns, ethical dilemmas, and biases in the systems. These factors highlighted the necessity of using facial recognition technology in an ethical and regulated manner. In conclusion, the study proposes several future research directions to establish the reliability of facial recognition systems and reduce biases while building user confidence. These considerations are key to responsibly advancing facial recognition technology by ensuring ethical practices and safeguarding privacy.

El Boudouri (2025) proposed EmoNeXt, a deep learning model adapted from the ConvNeXt architecture. The study integrated a spatial Transformer Network (STN) to focus on discriminative face regions. Used Squeeze-and-Excitation blocks and a self-attention regularization term for more compact and discriminative features. Evaluated on the FER2013 dataset for facial emotion recognition. Results demonstrated improved emotion classification accuracy compared to existing state-of-the-art models. Ramanaharan et al. (2025) purposed of systematic review to explore state-of-the-art frameworks for DeepFake detection and provided readers with an understanding of the strengths and weaknesses of current approaches, as well as the generalisability of existing detection techniques. The study indicated that generalising DeepFake detection remains a challenge that requires further research. Moreover, 46.3% of the selected publications agreed that DeepFake detection techniques could be generalised to identify various types of DeepFakes. A key limitation in achieving generalisation is the tendency of models to overfit to available data datasets, reducing their effectiveness in adapting to new or unseen types of DeepFakes. This review emphasises the need for the development of extensive and diverse datasets that more accurately reflect the wide range of DeepFake manipulations encountered in real-world applications. Lastly, the paper explored potential advancements that could pave the way to the next generation of solutions against Deep fakes.

Kilany and Mahfouz (2025) conducted a systematic review on deep face verification systems, including adversarial attack vulnerabilities and defense techniques. The study examined various network architectures and threat mitigation methods. The result identified that standard deep face recognition systems are susceptible to adversarial manipulation. Reviewed effective defense strategies that enhance model robustness. Nazar (2025) performed a systematic literature analysis of recent facial recognition technologies and their algorithmic foundations. The work covered both classic and deep learning approaches, emphasizing performance metrics, challenges, and applications. Identification of major trends in algorithm design and common performance benchmarks. It was highlighted that cutting-edge deep learning models consistently outperform traditional algorithms under controlled datasets, but real-world robustness remains an open challenge. Hayder (2025) explored various GAN-based models, each designed to tackle specific face recognition challenges. These models demonstrate significant improvements in enhancement ratios, ranging from 75% to 97%, by leveraging advanced generative techniques to reconstruct and augment facial images. Beyond face recognition, the methodologies discussed in this research have broader implications for enhancing image datasets in other domains, such as medical imaging, surveillance, and autonomous driving, where poor data quality is a common issue. By improving dataset quality through generative AI, this research paves the way for more robust and accurate machine learning applications across diverse fields.

Saoud et al. (2025) provided an extensive review and comparative analysis of state-of-the-art MFR techniques. We focus on DL-based methods due to their superior performance in real-world scenarios, discussing key architectures, feature extraction strategies, datasets, and evaluation metrics. Also, introduced a structured methodology for selecting and reviewing relevant works, ensuring transparency and reproducibility. As a contribution, the work gave a detailed taxonomy of MFR approaches, highlighted current challenges, and suggested potential future research

directions. This survey serves as a valuable resource for researchers and practitioners seeking to advance the field of robust facial recognition in masked hyperparameter-tuned and parametric setting convolution neural network model for facial palsy classification. Using the proposed multi-model facial palsy framework, we presented results on a dataset of YouTube videos featuring patients with palsy. The results indicate that the proposed framework can detect facial palsy efficiently. Furthermore, the achieved accuracy, precision, recall, and F1-score values of the proposed framework for facial palsy detection are 97%, 94%, 90%, and 97%, respectively, for the training dataset. For the validation dataset, the accuracy achieved is 95%, the precision is 90%, the recall is 75.6%, and the F-score is 76%. As a result, this framework can easily be used for facial palsy detection. Deng (2024) conducted a survey covering core stages of face recognition: detection, alignment, representation, and matching, focusing on the contributions of Convolutional Neural Networks and deep feature learning. Identified that deep learning methods significantly enhance feature richness and stability, making them superior to classic machine learning approaches, particularly in real-world and unconstrained environments. The review emphasises the central role of CNN-based representations in achieving accurate and stable face recognition performance in diverse scenarios.

Abdel (2024) designed a lightweight CNN with 16 layers for facial recognition using the FEI face image dataset; the model performs both face detection and classification through deep feature extraction. Achieved a training accuracy of 97.73% and a testing accuracy of 83.33% on 280 FEI images of 20 individuals. The study showed that compact CNN architectures can offer competitive recognition performance while being suitable for real-world applications. Dakhil and Abdulazeez (2024) performed a survey of major deep learning techniques applied in face recognition systems, discussing architectures such as CNNs and autoencoders, and the challenges of illumination, occlusion, and expression. It was concluded that deep learning models significantly improve accuracy and robustness compared with traditional techniques, with key advancements in feature extraction and preprocessing. The comprehensive review showed the trajectory and limitations of current deep learning-based face recognition methods, guiding future research. Yu et al. (2024) introduced domain-adaptive training strategies that improved performance across different sensors, resolutions, and environmental conditions. Hybrid CNN–Transformer models were further refined to balance local feature extraction and global contextual understanding.

Anujar et al (2024) designed a multi-model facial palsy framework that combined two convolutional models: a multi-task cascaded convolutional network (MTCNN) for face and landmark detection, and an improved occluded face recognition performance using a family of autoencoders (AE) architectures. The proposed structures include four stages: image preprocessing, feature extraction using autoencoder derivatives, classification via a convolutional neural network (CNN), and evaluation on occluded, non-occluded, and unseen datasets. Three deep autoencoder variants with combinatorial loss terms have been introduced to extract features from images: Convolutional Autoencoder (CAE), Self-Supervised Convolutional Autoencoder (SSCAE), and Smooth Convolutional Autoencoder (SCAE). A Masked Convolutional Autoencoder (MCAE) is also introduced to evaluate the capability of the convolutional autoencoder model in reconstructing images from masked inputs. Seven public datasets have been utilized to evaluate the performance of the proposed methods: the Extended Yale Dataset B, FERET, CMU Multi-PIE, Occluded ORL, Masked LFW (MLFW), AR, and RMFRD. Occluded ORL is used to analyze the performance of the proposed autoencoder derivatives on severely occluded images. MLFW is used to test the generalization of the proposed methods as an unseen dataset for the encoder part of the autoencoder variants. The recognition accuracies of 100% for

FERET, 99.89% for the Extended Yale B, 99.45% for the CMU Multi-PIE, and 94.2% for unseen MLFW, and the ability to reconstruct masked ORL with 90% of masking, demonstrate that the proposed methods achieve significant improvement in accuracy for face recognition with acceptable computational cost in comparison to the state-of-the-art. To the best of our knowledge, this study is the first work where convolutional autoencoder architectures achieve such performance on occluded datasets without incorporating any occlusion-specific design.

Al-Juboori (2024) combined deep facial feature extraction with traditional machine learning classifiers to build a robust face recognition framework; employed CNN-based embeddings followed by a classification stage. Results revealed that integrating deep features with machine learning classifiers improved recognition accuracy and generalization compared to classic end-to-end CNN models. The study showed that hybrid approaches leveraging deep feature extraction and traditional classifiers can yield strong face recognition performance. Beldi (2023) proposed a deep learning-based facial recognition system using Convolutional Neural Networks (CNNs) implemented in TensorFlow; the system pipeline included face detection, feature extraction, and classification using models like MTCNN and FaceNet. Experimental evaluation showed near-perfect accuracy ($\approx 100\%$) on static test images and high recognition rates ($\sim 95\text{--}96\%$) even when faces were tilted up to 30° from the frontal pose. This work demonstrated that integrating deep learning models with practical feature extraction methods yields highly accurate face recognition under controlled conditions, highlighting deep learning's effectiveness for biometric applications. Li et al. (2023) developed an approach combining 3D facial modeling with deep learning (ResNet architecture) to extract richer geometric features from faces; the framework used multi-view 2D inputs and 3D Morphable Models for feature enhancement. The system achieved 100% individual classification accuracy, 95.4% gender classification, and 83.5% expression classification, outperforming standard 2D-only approaches on benchmark tasks. Integrating 3D structural information with deep CNNs significantly improves face recognition and attribute classification performance compared to traditional 2D models.

Zhao et al. (2023) investigated federated learning frameworks for facial recognition, enabling collaborative model training without sharing raw facial data. Adversarial robustness was also widely studied, with researchers proposing defense mechanisms against spoofing and adversarial attacks that threaten deep facial recognition systems. Banumalar et al. (2023) proposed an approach that involved the utilization of the Haar cascade techniques for face detection, followed by the following steps for face identification. To begin with, facial features are extracted through a combination of CNN methods and the linear binary pattern histogram (LBPH) algorithm. For attendance to be marked as "present," the check-in and check-out times of the detected face must be legitimate. If not, the face will be displayed as "unknown." Wang (2023) reviewed contemporary deep learning models such as DeepFace, FaceNet, and ResNet. applied to face recognition, analysing how hierarchical feature extraction and neural network depth impact performance and robustness. It was found that deep learning-based algorithms considerably outperform earlier handcrafted methods in both recognition accuracy and robustness to variations in pose, illumination, and occlusion. This analysis confirmed deep learning as the dominant paradigm in modern face recognition, with deeper architectures consistently yielding higher performance.

Yifan et al. (2022) proposed vision transformer (ViT)-based facial recognition frameworks capable of modeling global facial relationships, improving robustness to occlusion and pose variation. Meanwhile, Serengil and Ozdemir (2022) evaluated real-world facial recognition systems and emphasized challenges related to demographic bias, and face-preserving and secure facial recognition became major research themes. Saini and Kumari (2022) proposed a two-phase

deep learning approach using the VGGFace2 model for face detection and identification, leveraging OpenCV for feature extraction and classification. The system demonstrated effective recognition performance under varying conditions (e.g., occlusion and lighting) compared to existing deep learning methods. The work validates deep learning's suitability for robust face recognition in practical biometric applications.

Hummady and Ahmad (2022) conducted a comprehensive literature survey on face recognition techniques; compared deep learning-based CNN approaches with traditional handcrafted feature methods. It was ascertained that deep learning models such as CNNs significantly outperform classical feature extraction techniques on benchmark datasets. The review confirms the dominant role of deep learning approaches in enhancing face recognition accuracy over earlier methods.

Ismail and Allias (2022) explored deep learning for face recognition within an attendance Te output tracking context; employed CNN models to learn face features and assess recognition reliability. The output demonstrated that deep feature learning provides improved accuracy for attendance systems compared with traditional methods. The exploratory study clarified the deep learning's effectiveness in customized biometric solutions such as attendance systems. Musa and Yahya (2022) used deep learning models to detect biometric presentation attacks (e.g., spoofing) in face recognition systems, enhancing system security. Experimental results showed that deep learning-based detection can effectively identify presentation attacks, improving system reliability. The work underscored the importance of incorporating anti-spoofing deep learning components into face recognition systems. Singh and Sinha (2022) compared several deep CNN architectures (VGG16, AlexNet, GoogleNet) on a large face dataset to evaluate their recognition performance. The models achieved high test accuracy (up to ~97.7%), demonstrating the effectiveness of deep convolutional networks for face recognition tasks. The comparative analysis confirms that deeper CNN models generally yield superior performance on complex face recognition datasets.

Summary of the Findings for Related Work

The body of related research highlights deep learning as the dominant and most effective approach for facial recognition and broader facial analysis. Traditional methods relying on handcrafted features have been largely outperformed by convolutional neural networks (CNNs), which deliver superior feature extraction and discrimination. Advances such as deeper architectures, residual networks, and transfer learning consistently yield high recognition accuracy, especially in controlled or semi-controlled environments. A notable strength across these studies is the ongoing refinement of model architectures to tackle real-world challenges. Hybrid models that integrate CNNs with Transformers enhance global context understanding, while autoencoder- and GAN-based techniques improve recognition under conditions of occlusion, low resolution, and image degradation. Additional strategies such as domain adaptation, federated learning, and multi-task learning contribute to greater robustness, privacy protection, and adaptability across diverse applications. These innovations have expanded facial recognition beyond identity verification to include emotion detection, facial palsy diagnosis, attendance tracking, surveillance, and DeepFake identification.

Nevertheless, several limitations remain evident. Many systems achieve strong results on benchmark datasets but struggle in unconstrained environments due to overfitting and dataset bias. High computational demands hinder real-time use on resource-limited devices. Furthermore, deep

learning-based facial recognition remains susceptible to adversarial attacks, spoofing, and bias, while ethical and privacy concerns are often acknowledged but insufficiently addressed in practice. In comparison, CNN and residual-based models continue to deliver the highest accuracy and stability in controlled scenarios, whereas hybrid and generative approaches offer improved resilience to real-world variability. Transformer-based methods show promise in modeling long-range dependencies but introduce significant computational overhead. Overall, the literature underscores.

A. CHALLENGES AND SOLUTIONS OF DEEP LEARNING APPROACH FOR FACE RECOGNITION

Challenges of the Deep Learning Approach for nFace Recognition

Deep learning has significantly advanced face recognition, but recent studies highlight persistent challenges that complicate its deployment. A major issue is dataset bias: many training sets lack diversity across ethnicity, age, and gender, which leads to unequal performance and misidentification in underrepresented groups. This problem has been emphasized in reviews of deep learning methods for face recognition under challenging conditions, where bias and fairness remain unresolved concerns (Zhalgas et al., 2025). Another difficulty is robustness in uncontrolled environments. Variations in lighting, occlusion, and pose can drastically reduce accuracy. Even with sophisticated architectures, recognition performance drops when faces are partially covered or captured at extreme angles, making real-world reliability a continuing challenge (Mohmad, 2024). Security vulnerabilities also persist, as systems remain susceptible to spoofing attacks using photos, videos, or masks. Researchers stress the need for liveness detection and multimodal approaches to counter these threats (Zhalgas et al., 2025). On the technical side, deep learning models demand enormous computational resources for training and inference. Deploying them on edge devices such as smartphones or IoT systems requires compression and optimization, but this often comes at the cost of reduced accuracy. Finally, ethical and legal concerns are increasingly prominent. The widespread use of facial recognition raises privacy issues, especially in surveillance contexts, while regulatory frameworks remain fragmented across regions, complicating compliance (Mohmad, 2024; Zhalgas et al., 2025). In conclusion, despite outstanding progress, deep learning-based face recognition continues to face challenges of bias, robustness, security, computational demands, and ethical governance. Addressing these issues is central to ensuring fair, secure, and trustworthy applications of the technology.

Solutions to Challenges of Deep Learning Approach for nFace Recognition

Researchers have proposed several solutions to address the challenges of deep learning in face recognition, focusing on fairness, robustness, security, efficiency, and ethics. One of the most important strategies is improving dataset diversity. By curating large-scale datasets that include balanced representation across age, gender, and ethnicity, models can reduce bias and improve fairness. Independent bias testing and fairness audits are increasingly recommended to ensure systems perform equally well across demographic groups (Dilmegani, 2026). To improve robustness in real-world conditions, researchers are turning to advanced architectures such as 3D face models and generative adversarial networks (GANs). These approaches help systems handle occlusions, extreme poses, and poor lighting. Combining facial recognition with other biometric modalities—like voice or fingerprint recognition—also strengthens reliability (Mohmad, 2024). Security concerns, particularly spoofing attacks, are being addressed through liveness detection techniques. These include analyzing micro-movements, depth information, or thermal imaging to

distinguish real faces from photos or masks. Encryption and strict access controls are also recommended to protect biometric data from misuse (Dilmegani, 2026). On the computational side, model compression, pruning, and quantization are being applied to reduce resource demands without sacrificing accuracy. Edge optimization allows deployment on mobile and IoT devices, making systems more practical in everyday use (Zhalgas et al., 2025).

In summary, ethical and legal challenges are being tackled through clearer regulations and transparency. Consent-based data collection, strict limits on surveillance applications, and compliance with regional laws are emphasized as necessary safeguards. Researchers argue that aligning technical innovation with ethical governance is essential for trustworthy adoption (Mohmad, 2024; Dilmegani, 2026).

IV. RESEARCH METHODOLOGY

A. Research Design

This study adopted a systematic literature review approach to analyze and synthesize existing research on facial recognition systems based on deep learning techniques. The methodology follows established guidelines such as the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework to ensure transparency, reproducibility, and rigor.

B. Research Questions

The review is guided by the following research questions:

Q1: What are the most effective deep learning architectures used in facial recognition systems, and how do they compare in performance?

RQ2: Which datasets are commonly used for training and evaluating facial recognition models, and how do dataset characteristics influence model performance and bias?

RQ3: What evaluation metrics are used to measure the performance of deep learning-based facial recognition systems, and how do they reflect real-world reliability?

RQ4: What are the key technical, ethical, and security challenges associated with deep learning-based facial recognition systems?

RQ5: What emerging trends and future research directions are shaping the evolution of facial recognition technologies?

C. Search Strategy

Systematic and comprehensive search strategy was employed to identify relevant studies on deep learning-based facial recognition systems. The search process was designed to ensure coverage, relevance, and reproducibility of the selected literature. To achieve this, multiple reputable electronic databases were consulted, including IEEE Xplore, ScienceDirect, SpringerLink, ACM Digital Library, and Google Scholar. These databases were selected due to their extensive coverage of peer-reviewed publications in computer science, artificial intelligence, and biometric systems. The search was conducted using carefully constructed keyword combinations and Boolean operators to capture a wide range of relevant studies. The primary search terms included:

- (a). “facial recognition” AND “deep learning”
- (b). “face recognition” AND “convolutional neural network” OR “CNN”
- (c). “deep neural networks” AND “face identification”
- (d). “biometric authentication” AND “deep learning”
- (e). “face recognition” AND “transformer” OR “hybrid models”

To further refine the search results, filters were applied based on publication year, language, and relevance. Specifically, only studies published between 2015 and 2025 were considered, as this period reflects the most significant advancements in deep learning techniques. Additionally, only articles published in English and appearing in peer-reviewed journals or conference proceedings were included. The search process was iterative, with initial results reviewed and additional relevant studies identified through backward and forward citation tracking. Duplicate records were removed, and titles and abstracts were screened to ensure alignment with the study objectives.

D. Inclusion and Exclusion Criteria

To ensure the quality, relevance, and rigor of the selected studies, explicit inclusion and exclusion criteria were defined prior to the screening process. These criteria guided the selection of studies for the systematic literature review.

(a). Inclusion Criteria

Studies were included in the review if they met the following conditions:

- i. Published in peer-reviewed journals or conference proceedings
- ii. Focused on facial recognition systems using deep learning techniques
- iii. Reported experimental results, model performance, or empirical evaluation
- iv. Written in English language
- v. Published within the timeframe of 2015 to 2025, capturing recent advancements in deep learning
- vi. Addressed relevant aspects such as model architectures, datasets, evaluation metrics, applications, or challenges

(b). Exclusion Criteria

Studies were excluded from the review if they met any of the following conditions:

- i. Not related to facial recognition (e.g., general image processing without biometric focus)
- ii. Did not employ deep learning methods (e.g., purely traditional or handcrafted feature-based approaches)
- iii. Classified as editorials, opinion papers, tutorials, or non-peer-reviewed articles
- iv. Lacked sufficient experimental validation or technical detail
- v. Duplicate publications across multiple databases
- vi. Studies not accessible in full text

The inclusion and exclusion criteria were designed to ensure that only high-quality, relevant, and recent studies were considered. Emphasis was placed on deep learning–based approaches due to their dominance in modern facial recognition research. Excluding non-empirical and non-peer-reviewed works helped maintain the scientific credibility and reliability of the review findings.

E. SUMMARY AND DISCUSSION OF STUDY

(a). Summary of the Study

This study provides a comprehensive review of facial recognition systems with a strong emphasis on deep learning–based approaches. It traces the evolution of facial recognition from early handcrafted feature extraction techniques, such as Principal Component Analysis (Eigenfaces), to modern deep learning architectures including Convolutional Neural Networks (CNNs), deep metric learning, attention mechanisms, and hybrid CNN–Transformer models. The review establishes that deep learning has significantly improved facial recognition performance by

enabling automatic hierarchical feature extraction, thereby increasing robustness against real-world challenges such as variations in pose, illumination, facial expressions, occlusion, and image resolution. Across the reviewed literature, CNN-based architectures, particularly those enhanced with residual connections, transfer learning, and domain adaptation, consistently achieve superior recognition accuracy compared to traditional methods.

The study further highlights the expanding scope of facial recognition applications. Beyond identity verification and security, deep learning-driven systems are now applied in emotion recognition, attendance management, healthcare diagnostics (e.g., facial palsy detection), surveillance, and DeepFake detection. This demonstrates the versatility and interdisciplinary relevance of facial recognition technologies. However, the review also identifies persistent challenges. These include dataset bias, privacy and ethical concerns, high computational requirements, and vulnerability to spoofing and adversarial attacks. To address these limitations, the study discusses emerging solutions such as diverse dataset curation, liveness detection, multimodal biometric integration, federated learning, and lightweight models optimized for edge and mobile devices.

(b). Discussion of the Findings of Study

The findings of this study underscore that deep learning has become the dominant paradigm in facial recognition research and deployment. The consistent superiority of CNN-based and deep metric learning models confirms that data-driven feature learning is far more effective than handcrafted approaches, particularly in unconstrained environments. This aligns with the broader consensus in the literature that deeper and more expressive architectures yield better discriminative facial representations. A key strength revealed in the reviewed studies is the architectural innovation aimed at real-world robustness. Hybrid models combining CNNs with Transformers improve global contextual understanding, while autoencoder- and GAN-based methods enhance performance under occlusion, low resolution, and image degradation. These developments indicate a shift from purely accuracy-driven models toward systems that prioritize generalization and resilience. Nevertheless, the discussion reveals notable weaknesses. Many deep learning models demonstrate excellent results on benchmark datasets but experience performance degradation in real-world scenarios due to overfitting and dataset bias. This raises concerns about fairness, as underrepresented demographic groups may experience higher misidentification rates. Ethical issues related to surveillance, consent, and data misuse further complicate deployment, especially in sensitive applications such as law enforcement.

From a technical perspective, computational complexity remains a major barrier. While large-scale deep models achieve high accuracy, their resource demands limit real-time deployment on mobile, IoT, and edge devices. Although techniques such as pruning, quantization, and lightweight CNNs mitigate this issue, a trade-off between efficiency and accuracy often persists. Security vulnerabilities also remain a critical concern. The susceptibility of deep facial recognition systems to spoofing, presentation attacks, and adversarial manipulation highlights the necessity of incorporating liveness detection, multimodal biometrics, and robust defense mechanisms. Overall, the discussion emphasizes that future progress in facial recognition depends not only on architectural advancements but also on ethical governance, fairness-aware training, privacy-preserving learning frameworks, and deployment-context-aware model selection. The study, therefore, concludes that while deep learning has elevated facial recognition to unprecedented levels of performance and applicability, sustainable and responsible adoption requires balancing technical innovation with ethical, legal, and societal considerations.

V. CONCLUSION

This study underscores the transformative impact of deep learning on facial recognition systems. By moving beyond handcrafted feature extraction to advanced architectures such as CNNs, residual networks, attention mechanisms, and hybrid CNN–Transformer models, facial recognition has achieved unprecedented accuracy and robustness. These innovations have enabled applications that extend far beyond identity verification, including emotion analysis, healthcare diagnostics, attendance monitoring, surveillance, and DeepFake detection. Despite these advances, persistent challenges remain. Issues such as dataset bias, privacy concerns, high computational demands, and susceptibility to adversarial attacks continue to limit real-world deployment. While strategies like multimodal biometric integration, liveness detection, federated learning, and lightweight models offer promising solutions, they also highlight the need for balancing technical innovation with ethical governance. Overall, the findings confirm that deep learning has elevated facial recognition to new levels of performance and applicability. However, sustainable and responsible adoption requires addressing fairness, privacy, and security concerns while tailoring models to specific deployment contexts. Future progress will depend not only on architectural breakthroughs but also on ensuring transparency, inclusivity, and trustworthiness in the design and implementation of facial recognition technologies.

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