# Face Recognition Using Convolutional Neural Networks: A Review

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**Abstract**

Face recognition is a crucial application of deep learning and computer vision, playing a significant role in security, authentication, and surveillance systems. Convolutional Neural Networks (CNNs) have significantly improved the accuracy and efficiency of face recognition by learning hierarchical feature representations. This paper comprehensively reviews CNN-based face recognition techniques, including widely used datasets, architectures, and performance evaluation metrics. The study highlights the advantages of deeper CNN architectures such as ResNet and GoogleNet while discussing the challenges posed by illumination variations, occlusions, and pose changes. Furthermore, we examine optimization techniques, such as pruning and quantization, to enhance computational efficiency. Finally, we outline key research challenges, including bias mitigation, adversarial robustness, and privacy concerns, to guide future advancements in this field.

**Keywords:** Face recognition, Deep Learning, CNN, ResNet, GoogleNet, Optimization Techniques

## 1. Introduction

Facial recognition has become essential in security, authentication, and surveillance applications. It has gained prominence due to its non-intrusive nature and wide applicability across various industries, including law enforcement, healthcare, banking, and border control [1]. Despite advancements in deep learning, challenges such as variations in illumination, facial expressions, pose, occlusions, and ageing continue to affect accuracy [2]. This paper provides a detailed analysis of CNN-based face recognition techniques, focusing on existing architectures, datasets, and challenges.

## 2. Face Recognition Systems

Automated face recognition involves three primary stages [3]: (1) Face detection, (2) Feature extraction, and (3) Face recognition. Figure 1 illustrates this process. Face detection involves locating a face within an image and extracting distinctive facial features. Finally, recognition is performed by matching the extracted features against a stored database.

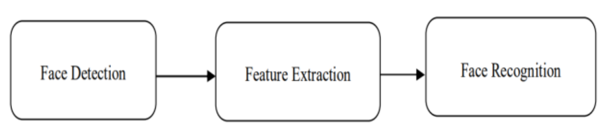


Figure 1. Face Recognition Process.

## 3. Overview of Available Face Recognition Datasets

This section provides a detailed discussion of publicly available datasets used in face recognition research, including:

### 3.1. AT&T (ORL) Dataset

The AT&T database, commonly known as the ORL database, contains 40 distinct people and 10 photos of each person, for a total of 400 photographs. The database contains 36 males and 4 females. The files are in PGM format, and each image is 92x112 pixels, for a total of 10,304 pixels [4].

### 3.2. FERET Dataset

The FERET (face Recognition Technology) database is one popular option for face recognition systems. DARPA (Defense Advanced Research Projects Agency) and the National Institute of Standards and Technology manage the FERET program. A database of face images was gathered between August 1996 and December 1993 [5].

### 3.3. FRGC Dataset

The University of Notre Dame created the Face Recognition Great Challenge (FRGC) [6] In 2004–2006, performance was improved by seeking algorithm advancement over all techniques suggested in the available literature. 50,000 images make the entire FRGC dataset divided into training and validation sets.

### 3.4. VGGFACE Dataset

A large-scale training database called VGGFACE (visual geometry group) was collected from the Internet by integrating humans and machines. It contains over 2.6 K identities and 2.6 M images. Parkhi et al. [7] Established by the University of Oxford in 2016.

### 3.5. VGGFACE2 Dataset

Oxford University researchers Cao et al. [8] Developed the large-scale face database VGGFace2 in 2017. A large variety of ages, positions, and ethnicities were found in the Google Images search that was gathered into the database. With an average of 362.6 images for each identification. Subdivided into two subclasses: 500 classes make up the evaluation set while 8631 classes make up the training set.

### 3.6. IARPA Janus Benchmark-B

The second version of the IJB-A database, published by Whitelam et al. in 2017, is known as the Benchmark-B (IJB-B) [9]. IJB-B has 21,798 still photos, comprising 10,044 non-face and 21,754 face shots, as well as 55,026 frames from 7011 face videos, which together represent a total of 1845 people.

### 3.7. DFW Dataset

To propel the field of disguised face detection to new heights, Kushwaha et al. [10] In 2018, a special masked face formed in the wild dataset, with 1000 individuals that were both impersonalized and obfuscated.

### 3.8. UMIST Face Database

The images in the UMIST database show different postures from the University of Manchester Institute of Science and Technology, which merged with Victoria University of Manchester. This database is primarily used for facial recognition. Twenty people in all, with 564 8-bit grayscale and 92x112 photos, are included in this database [11].

### 3.9. Yale Database

The Yale Face Database is used to evaluate emotion-invariant person recognition performance. This database consists of 165 grayscale images of 15 subjects showing 11 emotions, such as happy, sad, and shocked. This database aims to tackle the difficulty of recognizing faces with various emotional expressions [12].

### 3.10. Extended Yale B database

The Yale Face Database B is gathered to systematically evaluate face recognition techniques under wide posture and lighting changes. The individual's images were taken within a geodesic dome that contained 64 controlled xenon flashers. Ten images of individuals are taken in nine various poses in 64 various lighting scenarios [13].

These datasets vary in terms of the number of subjects, image quality, and environmental conditions, making them valuable for benchmarking face recognition models.

## 4. Factors Impacting Face Recognition

Face recognition performance is influenced by several intrinsic and extrinsic factors, including:

### 4.1. Aging

As shown in Figure 2, humans naturally change over time—ageing. The bones, muscles, and skin tissues that make up the face. These muscles tighten over time, twisting the features of the face and giving an individual's appearance [14].


Figure 2. Variations in Aging [15].

### 4.2. Facial expression

A person's facial expression alters as they express their feelings. The geometry of facial features such as the lips, nose, and eyebrows are altered as the muscles of the face contract during an expression change. Figure 3 shows the difficulty in face recognition results from variations in facial geometry [14].

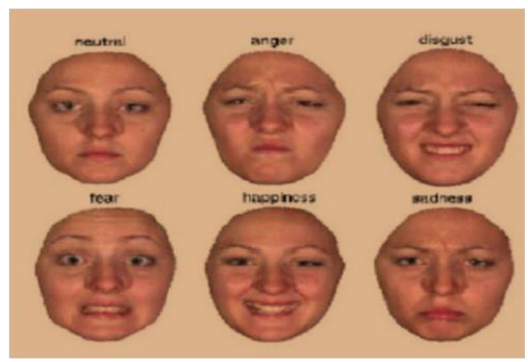


Figure 3. Expression Variations [15].

### 4.3. Occlusion

A visible portion of the face is what causes occlusion. It is put on by people hiding their eyes with sunglasses, as shown in Figure 4, their mouths with masks, half of their faces being hidden by scarves or boyish moustaches, and so on. These factors impact the system's performance [14].

Figure 4. Partially Delusion [15].

### 4.4. Low Resolution

The poor quality of the images obtained from video surveillance, as shown in Figure 5, makes it difficult to match the low-resolution image input with the high-resolution database image [14].


Figure 5. Frame from surveillance video. a) video, b) facial capture [15].

### 4.5. Noise

Noise is biased toward that specific image due to various factors that impact the generation of digital images. As shown in Figure 6, this noise reduces the accuracy of face recognition and facial detection [14].


Figure 6. Image of a face with noise [15].

### 4.6. Illumination

The lighting negatively impacts face recognition performance. There are some reasons for this lighting, including shadow and background light [14]. Figure 7 depicts the impact of illumination on facial appearance.

Figure 7. The impact of illumination on facial appearance [15].

### 4.7. Pose Variation

Figure 8 presents different pose variations. A frontal face is needed to match the profile face with the database face. As a result, posture changes lead to inaccurate findings that significantly impair system performance [14].

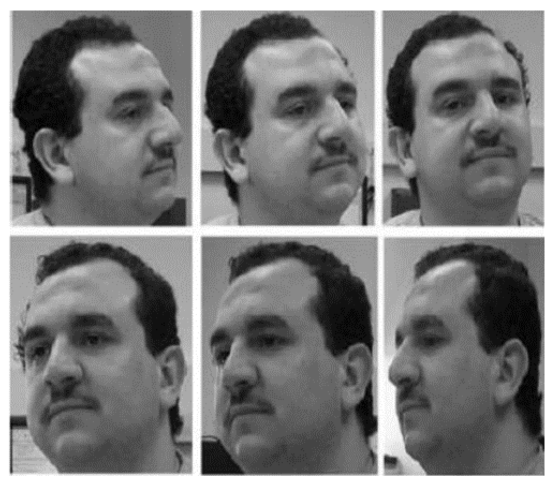

Figure 8. Pose variations [15].

### 4.8. Plastic Surgery

It plays an important role in facial recognition. Many people get plastic surgery for changing their face look as a result of various conditions, such as accidents. Many people, particularly criminals, alter their facial features to hide their identities. Thus, a system that can recognize faces even after plastic surgery is required [14], as shown in Figure 9.


Figure 9. Plastic Surgery [14].

## 5. Face Recognition Approaches

The problem of automated face recognition in engineering involves three crucial processes [3]

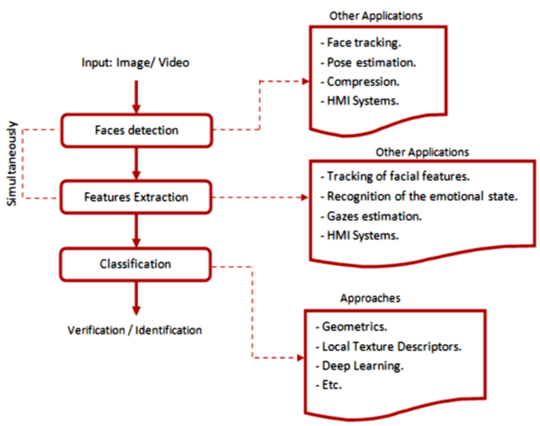


Figure 10. Basic steps of Face recognition [16].

(as seen in figure (10)): (1) feature extraction, precise face normalization, and classification (identification or verification). Extracting features from identifiable face details creates a signature feature vector, an essential component of accurate facial representation. Confirming the face's singularity and discriminatory power between two individuals is required. It is worth mentioning that the face detection step may finish this operation. Verification and identification are necessary for classification. Matching two faces is necessary for verification to get access to a desired identity. However, to identify a face, it is necessary to compare it against several other faces that have different alternatives presented to it.

### 5.1. Two-Dimensional Face Recognition Approaches

Figure 11 illustrates how different 2D face recognition methods can be classified into four subclasses based on the type of extraction and classification techniques used. These subclasses are: (1) holistic methods, (2) local (geometrical) methods, (3) local texture descriptors-based methods, and (4) deep learning-based methods.

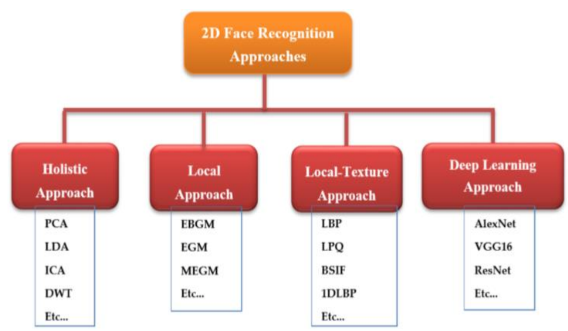


Figure 11. Face Recognition Method [16].

#### 5.1.1. Holistic Methods

Algorithms based on subspace or holistic approaches presume that redundancies in any M-collection of face photos can be eliminated by using the tensor's decomposition. These techniques preserve the unique set of images while producing conventional of-origin vectors that reflect a reduced space dimension. Every face in the subspace can be recreated using the collection of basis vectors [12]. To simplify the process, a vector is generated by supporting the image rows for every N × N face image. Decomposition of the consequence matrix (N × N) × M yields the non-singular basis vectors.

### 5.1.2. Geometric Approach

Human face recognition relies heavily on attention and fixations. Typically, landmark traits serve as guidance for sensitive processes. When compared to algorithms for recognition, the same landmarks might provide helpful information. Not all of the information is contained in the image's face regions. The forehead and cheeks have simpler features and fewer distinguishing patterns than the nose or eyes. Face landmarks are utilized for the registration of facial features, expression normalization, and defined position recognition based on the grey-level pattern and geometric distribution [17].

### 5.1.3. Local-Texture Approach

Techniques for extracting features that account for texture knowledge are crucial in computer vision and pattern recognition. The research has suggested two main types of texture extraction algorithms: statistical and structural approaches. After that, local texture descriptors attracted increased interest and were used in numerous applications, including face recognition, texture classification, and image indexing. They don't require segmentation because they are unique and resistant to monotonous grayscale shifts, poor illumination, and brightness variations [18].

### Principal Component Analysis

Analysis of Principal Components (PCA) is the most well-known facial recognition algorithm. PCA is an unsupervised approach employed in machine learning to reduce dimensionality. Facial recognition algorithms are created using PCA using feature face extraction. Face recognition and detection were first handled by Turk and Pentland using principal component analysis. Pandey, I.R., et al [19] different parameters are eliminated, called principal components, using mathematical functions.

### 5.1.4. Artificial Neural Networks for Face Detection

Over the last several years, many artificial neural network (ANN) models and architectures have been used for facial detection and recognition. Facial recognition and detection are two areas where artificial neural networks (ANN) models have shown promise. This mainly explains its role in face recognition. A neural network converts its input into a set of hidden layers. All of the neurons in one hidden layer are completely connected to all of the neurons in the layer following it. The last fully connected layer in a classification system that shows the class scores is called the output layer. [20].

### Deep Learning Approach

Because of its many benefits, particularly the ones related to speed and accuracy, deep learning has attracted a lot of attention lately and has found extensive applications across many academic fields [21]. As part of the machine learning class, deep learning employs a hierarchical structure with increasingly more buried layers of information processing levels to learn features, classify representations or patterns, and extract features.

Based on how the method and architecture are applied, deep learning falls into three primary types [21]:

Unsupervised, Boltzman machine (BM), recurrent neural network (RNN), and sum-product network (SPN).

Supervised (convolutional neural network (CNN)).

Hybrid (deep neural network (DNN) [22, 23].

## 6. Convolutional Neural Networks (CNNs)

Convolutional neural networks (CNNs) have achieved remarkable results in several domains, including image identification and classification. CNNs are built from a set of filters, kernels, and neurons trained using parameters, weights, and biases available for learning. A non-linearity is applied to each filter when it gets certain inputs, performs a convolution, and so on. Each convolutional neural network (CNN) has four layers: convolutional, pooling, rectified linear unit, and fully connected layers.

The fundamental component of a CNN, the convolutional layer tries to extract features from the input data. Convolution is used by each layer to produce a feature map. Subsequently, the feature maps or activation data are supplied as input data to the next layer [24]. As seen in Figure 12.

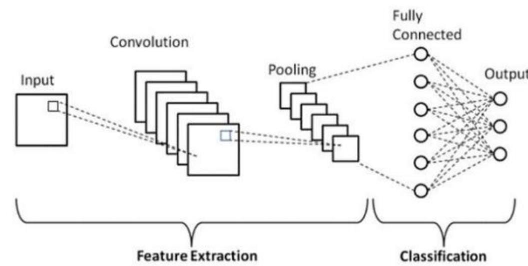


Figure 12. Convolutional neural network [24].

A convolutional neural network (CNN) has two types of layers: the primary and secondary. convolutional, Activation, pooling, flattening, and dense layers are the main components of convolutional neural networks (CNNs). Adding secondary layers to convolutional neural networks (CNNs) makes them more resistant to overfitting and makes them more generalizable. Among them are normalization, batch regularization, and dropout layers [25]. The pooling layer employs a non-linear downsampling method [26, 27] to decrease the feature map's dimensionality while retaining essential information. The best and most preferred non-linear pooling function, over sub-sampling, is max-pooling [28]. the rectifier is used in this non-linear process. Fully connected layer (FC): When applying different convolutional and max-pooling layers, fully connected layers perform high-level reasoning in neural networks [29].

Researchers have constructed several face recognition architectures by changing the CNN architecture, including VGGNet, GoogLeNet, ResNet, etc..

Popular Convolutional Neural Network Architectures

### 6.1. LeNet

LeNet stands for LeNet-5, which Lecun et al. proposed in 1998 [30]. It is a competent

CNN trained to recognize handwritten digits using the back-propagation algorithm. LeNet-5 comprises three fully linked, two pooling, two convolutional, and seven trainable layers. LeNet is thought to be the foundation of contemporary CNN.

### 6.2. AlexNet

As seen in Figure 13, AlexNet is made up of three fully connected layers that use 1000-way softmax, five convolutional layers, several of which are followed by max-pooling, and additional techniques including data augmentation, dropout, and rectified linear unit (ReLU) [31].

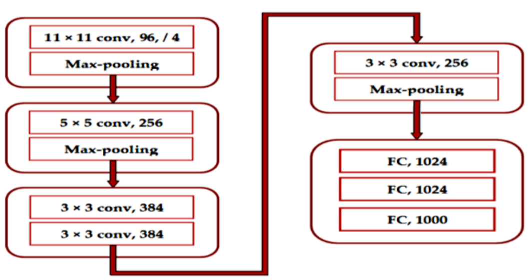


Figure 13. AlexNet architecture [32].

### 6.3. VGGNet

Using a VGGNet architecture with tiny (3 × 3) convolution filters and doubling the number of feature maps following the (2 × 2) pooling was their main contribution. As the network's depth was raised to 16–19 weight layers, Figure 8 illustrates the deep architecture's ability to acquire nonlinear maps [33]. As seen in Figure 14.

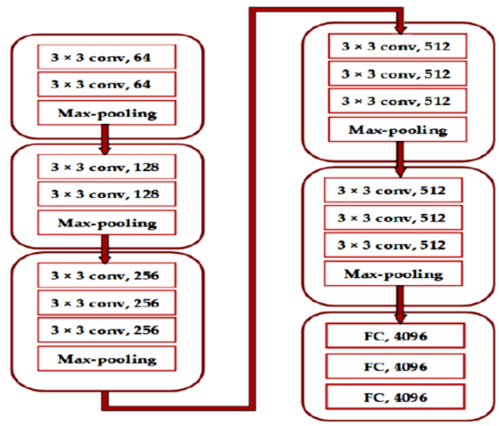


Figure 14. VGGNet architecture [33].

### 6.4. GoogleNet

To make GoogleNet's computations easier than the traditional CNN model [50]. An "inception module" was shown, which can be adjusted by changing the kernel size to provide receptive fields of varying sizes. Several convolutions (1 × 1, 3 × 3, and 5 × 5), together with (3 × 3) max-pooling, are used to evaluate the input and output from before all at once. Figure 15 shows that the following module also takes in all feature maps together [34].

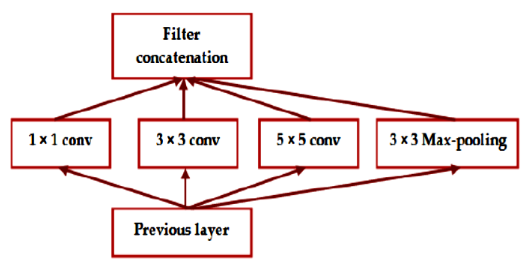


Figure 15. GoogleNet Architecture [34].

### 6.5. SENet

In contrast to existing networks, He et al.'s [35] innovative residual neural network (ResNet) architecture makes it easier to train ultra-deep networks. ResNet was the ILSVRC winner; it was created with batch normalization and "shortcut connections," and it could train a neural network with 34, 50, 101, 152, and even 1202 layers. The ResNet architecture is shown in Figure 14.

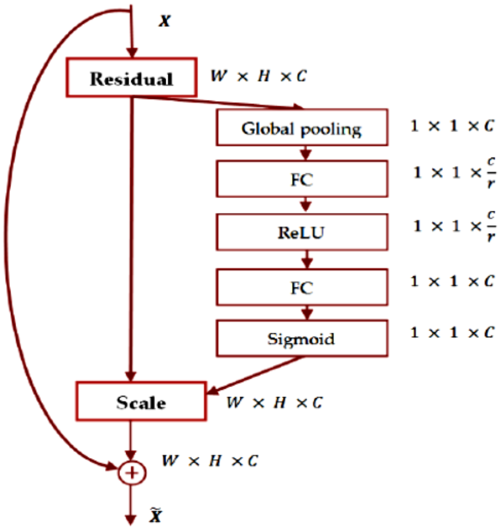


Figure 16. SENet architecture [35].

## 7. Performance Evaluation and Comparison

To assess the effectiveness of CNN-based face recognition models, researchers use several key evaluation metrics:

### 7.1. Recognition Accuracy:

is assessed using benchmark datasets such as LFW, VGGFace2, and IJB-B. Higher accuracy indicates a model's ability to identify individuals under various conditions correctly.

- A study comparing ResNet-50 and GoogleNet for face mask detection found that ResNet-50 achieved an accuracy of 96.40%, slightly higher than GoogleNet's 95.41% [36].
- Benchmarking deep learning techniques for face recognition indicated that Inception-v3 (a variant of GoogleNet) achieved 98.5% accuracy on the LFW dataset, outperforming other models. [37].

### 7.2. Computational Complexity:

CNN models vary in training time and inference speed. Lightweight models like MobileNet are optimized for real-time performance, whereas deeper architectures like ResNet require higher computational power but improve accuracy.

- MobileNet is designed for efficient inference on mobile devices, balancing accuracy and computational efficiency. Its architecture reduces model size and computational cost, making it suitable for real-time applications [38].
- An improved MobileNet algorithm demonstrated better recognition performance and efficiency than the original model, highlighting its practicality for face recognition systems [39].

### 7.3. Robustness to Variability:

Factors such as lighting conditions, occlusions (e.g., masks, sunglasses), and pose variations significantly impact face recognition performance. Models trained with diverse datasets tend to generalize better in real-world scenarios.

- The proposed Face-Inception-Net achieved an Accuracy of 95.9% at a Loss of 0.001 across various benchmarks, demonstrating effectiveness and generality in diverse scenarios [40].
- A lightweight FaceNet model based on MobileNet showed high accuracy (99.28% on LFW) with fewer parameters, making it suitable for environments with limited computational resources [41].

A comparative analysis of CNN architectures on standard benchmarks reveals that deeper architectures such as ResNet and GoogleNet consistently outperform shallower networks in accuracy while maintaining reasonable computational efficiency [42].However, these deep models may require optimization techniques like pruning and quantization to reduce their computational resources [43].

## 8. Challenges and Future Research Directions

Despite significant advancements in CNN-based face recognition, several challenges remain that require further exploration:

- **Bias and Fairness:**
  Face recognition models often exhibit biases due to unbalanced training datasets, leading to disparities in recognition accuracy across different demographic groups. Research suggests that adaptive CNN architectures, which adjust kernel representations based on demographic characteristics, can help mitigate these biases and improve fairness.
- **Adversarial Attacks:**
  CNN-based face recognition systems are vulnerable to adversarial attacks, where subtle image perturbations can deceive the model. Recent studies have explored passive and proactive defense mechanisms, including adversarial training, perturbation detection, and deepfake localization, to enhance system robustness.
- **Privacy Concerns:**
  The widespread deployment of facial recognition raises ethical and privacy concerns, particularly regarding data collection, storage, and unauthorized surveillance. Ongoing research investigates privacy-preserving techniques such as federated learning and differential privacy to minimize risks while maintaining recognition performance.
- **Lightweight Models:**
  High-performance CNN models often require significant computational resources, making real-time deployment challenging, especially on mobile and edge devices. Recent advancements in lightweight architectures, such as video-based face recognition models leveraging temporal dynamics, are helping to optimize performance while reducing computational overhead.

Future research should focus on developing explainable AI techniques, strengthening adversarial defense mechanisms, and ensuring ethical and privacy-conscious deployment of face recognition systems.

## 9. Conclusion

Face recognition using CNNs has demonstrated remarkable progress in recent years, offering improved accuracy and robustness in controlled environments. This review examined various CNN architectures, datasets, and performance evaluation criteria, emphasizing the advantages of deep networks such as ResNet and GoogleNet. Despite these advancements, challenges such as dataset bias, susceptibility to adversarial attacks, and computational limitations remain unresolved. Future research should focus on developing fair and unbiased models, enhancing adversarial defense mechanisms, and optimizing CNN architectures for real-time applications on edge devices. Additionally, ethical considerations, including data privacy and regulatory compliance, should be prioritized to ensure responsible deployment of face recognition technologies. Addressing these challenges will be crucial for achieving widespread and trustworthy adoption of face recognition in real-world applications.

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