A Comprehensive Review of Machine Learning Algorithms and Datasets for Robust Face Recognition

Syed Muhammad Daniyal[1*], Mohsin Mubeen Abbasi[1], Sarmad Saud[2], Noman Bin Zahid[1], Sahar Abbas[1], Usama Amjad[1]

[1]Faculty of Engineering Science & Technology, Iqra University, Karachi, Pakistan
syed.daniyal@iqra.edu.pk, mohsin.abbasi@iqra.edu.pk, noman.zahid@iqra.edu.pk,
sahar.abbas@iqra.edu.pk, usama.amjad@iqra.edu.pk

[2] Global Technical Services & Support, USA
saud@rapidai.com

Corresponding Author: syed.daniyal@iqra.edu.pk

Abstract: Face recognition has been established as an essential biometric technology in security, surveillance, and human-computer interaction systems for verifying identities. Despite blistering development, the current literature is frequently unable to provide a cohesive comparative study that integrates classical machine learning approaches, recent deep learning models, benchmark datasets, and evaluation procedures within a unified framework. This paper shows a qualitative and analytical review of the face recognition methods, including the entire pipeline, such as face detector and alignment, feature extraction, feature classification, and recognition with deep learning. The gap of the research covered by the present study consists in the fact that a unified assessment, quantitatively comparing the traditional algorithms (PCA, LDA, LBP, SVM) to the deep learning models (CNN-based methods) under the influence of different real-world factors, is missing. The originality of this work is threefold: (i) the single taxonomy of face recognition development phases, (ii) the comparative performance analysis of the databases on a dataset basis using normalized measures of accuracy, and (iii) the detailed discussion of practical problems that include illumination variation, occlusion, age effects, and image resolution. Measured contributions can be made as a quantitative comparison across 4 benchmark datasets (AR, AT&T, Yale, FERET), showing that CNN-based models consistently achieve higher recognition accuracy (up to 99.79) than classical methods. The review presents researchers and practitioners with practical information on the choice of face recognition models that can be used in the real-world context.

Keywords: Machine Learning, Image Processing, Face Recognition, Face Detection

I. INTRODUCTION

Development has impacted every industry from manual driving cars to self-driving cars, doctors identifying cancers to machines identifying cancer, to the web-based buying pattern in most recent years, to today's internet of things, computer systems and technology have hastily integrated with everyday human lifestyle. We observe that the digital and real-world converge more, and an important research field has emerged around how to accurately and efficiently identify individuals while enhancing information security.

Not merely in public areas, since the terrorist attacks from last many years, governments worldwide have placed serious demands on this matter, spurring the creation of novel identification techniques [1]. Suppose we shed light on the traditional method of recognizing any specific person, which would be based on their memory in the form of password, username, etc. Unfortunately, there are significant security vulnerabilities because of their memory. In addition to being challenged to locate the original identity material if the identification items that serve as proof of identity are lost or stolen, identifying information is also easily accessible to others. If anyone uses the identity, there will be serious consequences.

Other than the traditional techniques, the use of biological features such as iris recognition, fingerprint, and face recognition is much more in the limelight in today's research [2]. If we compare traditional techniques of recognition with biological features recognition, biological features recognition provides several benefits, including the following: Replication of Biological features is impossible because they are natural and cannot be modified, biological features as a component of the human body which are easily accessible. In the light of above benefits, biometrics have gained the attention of many researchers and started to replace traditional recognition techniques.

However, the significant benefits of a face recognition system are its accuracy and efficiency. Since they can perfectly identify humans in real time, they are perfect for applications like security checks and authentication protocols [3]. Face recognition systems are much less intrusive than other biometric techniques like iris and fingerprint recognition, as they can be used at a distance and without physical contact.

A. Face Detection and Tracking

Among several papers by Viola, the paper [4] received a lot of citations and made realistic face detection possible. It contains information on various face detection techniques and algorithms. In the paper [5], the use of real Adaboost was first implemented, and a highly robust multiple face detection algorithm was proposed. Also, the paper made changes to the cascade structure using the nest structure, which was effective. Further, the paper [6] successfully combines offline and online face detection and tracking models, and it won the 2007 CVPR Best Student paper prize.

The three publications discussed above addressed the problem of face detection and tracking. The results of their research allow the development of real-time face detection methods. The major objective was to identify the location and dimensions of everyone in an image or video. Yet, it's important for tracking to find a relationship among individuals in the frames.

B. Face Positioning and Alignment

Early techniques for locating facial features only target a few important locations, for instance, the eyes or mouth. Further techniques improved the reliability and accuracy of facial feature positions by adding additional points and incorporating mutual constraints. It was proposed in the study [7] to use models with several facial feature points and textures. Whereas the ASM model still has the potential for improvement, the AMM model is notable, as it enhances the original model by including edge texture information. The paper [8] suggested a study based on regression that performed better than the categorization appearance mod el. Another paper [9] concentrated on enhancing the structure model itself. It uses a weighted average of training samples to control shapes and obtain the optimum sequence results.

C. Face Feature Extraction

A well-known face feature extraction approach is Principal Component Analysis (PCA), which is now mainly used in real-world applications for dimension reduction [10]. Now PCA and Linear Discriminant Analysis (LDA) are frequently used in many systems to extract authentic information [11]. PCA is used to minimize the matrix and avoid matrix singularities issues while addressing LDA, then LDA is subsequently applied to extract features useful for classification, proceeding to recognize the different unique features extracted after decision-level fusing. Another paper [12] presents a multi-scale description of the face utilizing exact position points as a baseline, which itself is valuable to understand and can be incorporated with numerous other representation techniques.

II. DEVELOPMENT STAGES OF FACE RECOGNITION

The evolution of the face recognition technique has gone through several phases, with each stage making a distinctive contribution as shown in Table I. Feature extraction, which uses basic algorithms like Principal Component Analysis (PCA) to determine facial characteristics like the distance between the eyes or the shape of the mouth, was the main focus of early face recognition research. To differentiate between faces, these characteristics were hand-picked. The next step, called the classification stage, had more sophisticated algorithms applied to it to improve accuracy. These classification techniques, such as SVM, more precisely match and classify faces by using extracted features. Deep learning ultimately made it to the third level, revolutionizing facial recognition. Convolutional Neural Networks (CNN) and other deep learning models have made it feasible to automatically learn from large datasets and extract features. This significantly increased the ability of the system to accurately and consistently recognize faces in a range of environments [13].

TABLE I: Stages Of Facial Recognition Development

Development Stage	Related Technologies	Characterization
Early Stages	PCA, LDA	Face Recognition is initially treated as a pattern recognition problem, focusing on facial geometric structures.
Classifier Stage	SVM, Adaboost	This stage sees the emergence of practical applications using classifiers for recognition.
Deep Learning Stage	Neural Networks, Deep Learning	Emphasis is placed on real-time recognition and handling complex scenarios.

A. Principal Component Analysis (PCA)

In face recognition, PCA has its importance and it is a widely used method for dimension reduction. It can reduce large numbers of data into smaller while retaining the most important information. Turk and Pentland were the first to solve the issues of two-dimensional facial recognition using PCA [14].

The fundamental concept to use PCA for facial recognition is that first facial images must be represented as vectors, with each pixel serving as a feature. After that, a variance matrix of these vectors was evaluated, and eigenvectors and eigenvalues of the variance values were calculated. The eigenvectors with the maximum eigenvalues (also referred to as principal components) are chosen as the base vector for the reduced dimensional space. The facial images are projected into this two-dimensional space to create a compact representation [15].

PCA has been commonly used in face recognition because of its simplicity, efficiency, and ability to identify the most significant differences in the data [16]. PCA uses Eigen-faces for dimension reduction as shown in Fig 1.

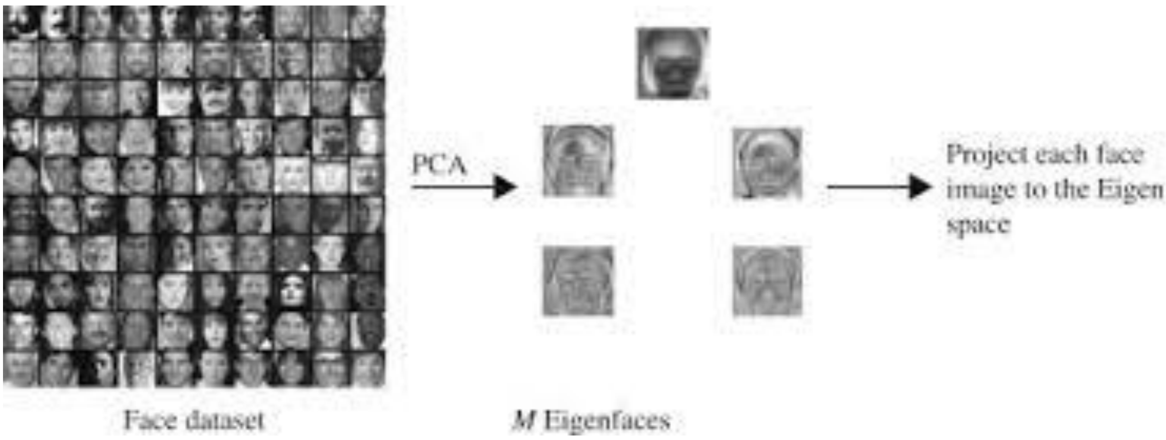

Fig. 1. Processing Eigen-faces for Face Recognition Using PCA [17]

The steps of the Face recognition technique using Eigen-faces are described below:

- All of the faces in S are transformed as a vector and are put in the dataset.

$$S = \{T1, \ldots.., Tn\} \quad (1)$$

- The dimensional size of the image is N^2 (2)
- Calculating the mean face:

$$x\text{-}bar = (1/n) * Sum(xn) \quad (3)$$

- After subtracting the mean from the initial face it is stored in a variable:

$$phi\_i = Ti - x\text{-}bar \quad (4)$$

- Calculating the Covariance matrix:

$$C = S = Sum(Ti - x\text{-}bar)^\wedge T / n \quad (5)$$

- Weight vector: Omega_t = {w1, w2, ..., wn} (6)

B. Linear Discriminant Analysis (LDA)

The LDA is an effective technique for facial feature extraction and dimension reduction [18]. The main purpose of LDA is to determine a feature space prediction that optimizes the distance between classes and minimizes the variation within each class [19]. To do this, the scatter matrices of data are computed and utilized to define a criterion function that assesses the separability of the classes as shown in Fig 2.

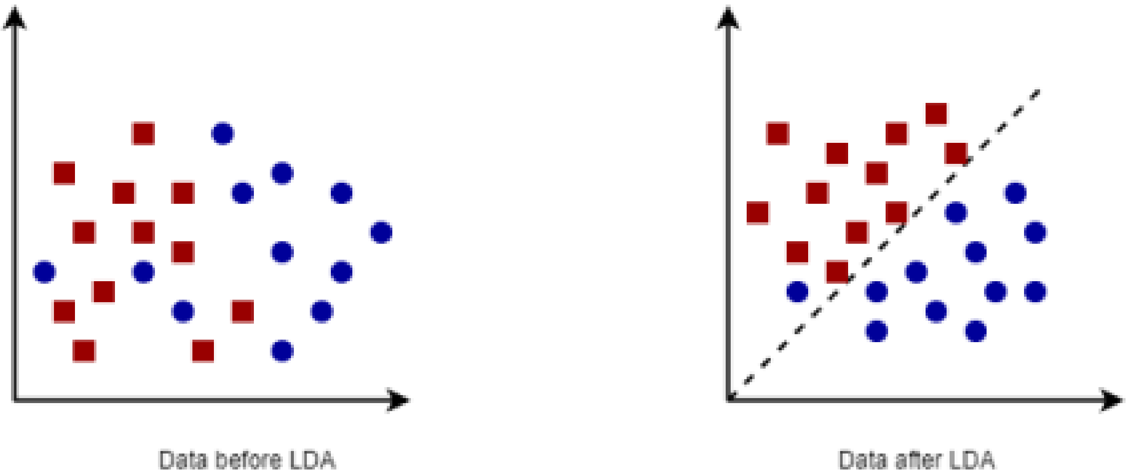

Fig. 2. Processed Data Visualization After Applying LDA Algorithm [21].

The steps of LDA calculation are:

- Create a dimensional mean vector of every class.
- Calculate within and between class scatter matrices:

$$SB = Sum\ Mi(xi - mu)(xi - mu)^\wedge T \quad (7)$$

$$SW = Sum\ Sum\ Mi(xi - mu)(xi - mu)^\wedge T \quad (8)$$

- Calculate eigenvalues and eigenvectors: (e1, e2, ..., ed) (9), (lambda1, lambda2, ..., lambdad) (10)
- Transform a sample into the new subspace:

$$y = W x^T \quad (11)$$

C. Local Binary Pattern (LBP)

The LBP is commonly utilized in face recognition due to its efficiency and simplicity. LBP is the structure of a total of 9 pixels which has a center pixel called threshold and 8 neighborhood pixels. Values that are higher than or comparable to the threshold are considered as 1 and values lesser than the threshold are considered as 0. The calculation of LBP is shown in Fig 3.

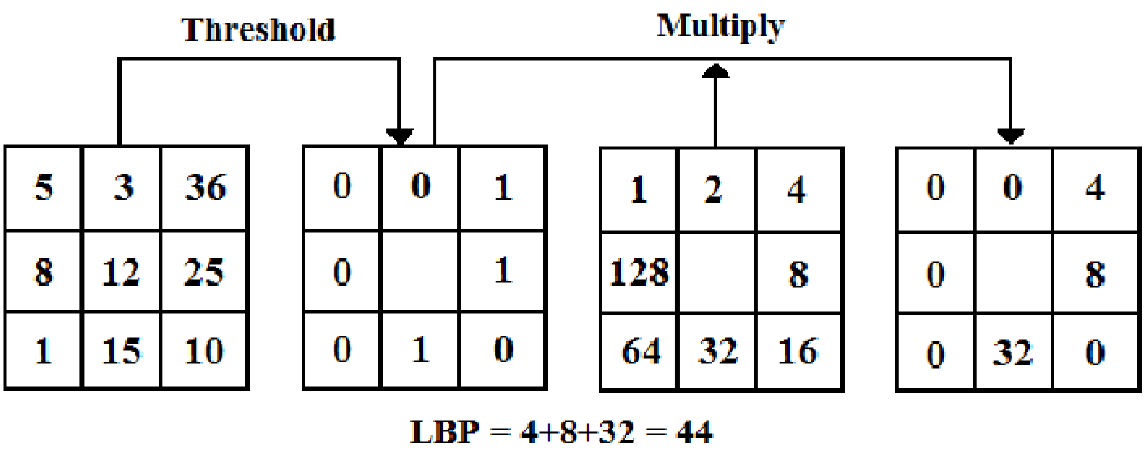

Fig. 3. Calculation of LBP For Text Feature Extraction [24].

The mathematical expression of LBP is given as:

$$LBP\_P,R(xc, yc) = \text{Sum } s(gp - gc) * 2^p, \; p=0 \text{ to } P-1 \quad (12)$$

Many researchers have made advancements in LBP: Elongated LBP (ELBP) [26], Improved LBP (ILBP) [27], Local line binary pattern (LLBP) [28], Local ternary pattern (LTP) [29], Multi-scale block local binary pattern (MB-LBP) [30], Three-patch LBP (TP-LBP) [31], LBP-histogram (LBPH) [32].

D. Support Vector Machine (SVM)

SVM is a popular machine learning method used in numerous face recognition systems. SVM is a supervised learning technique that operates under a maximization of the margin between two classes [33]. SVM divides data into two groups by locating a hyperplane as shown in Fig 4. The hyperplane is selected to optimize the difference between each class's closest point. Moreover, SVM could operate on non-linearly separable data as well by applying kernel function to map data into higher dimensional space [34].

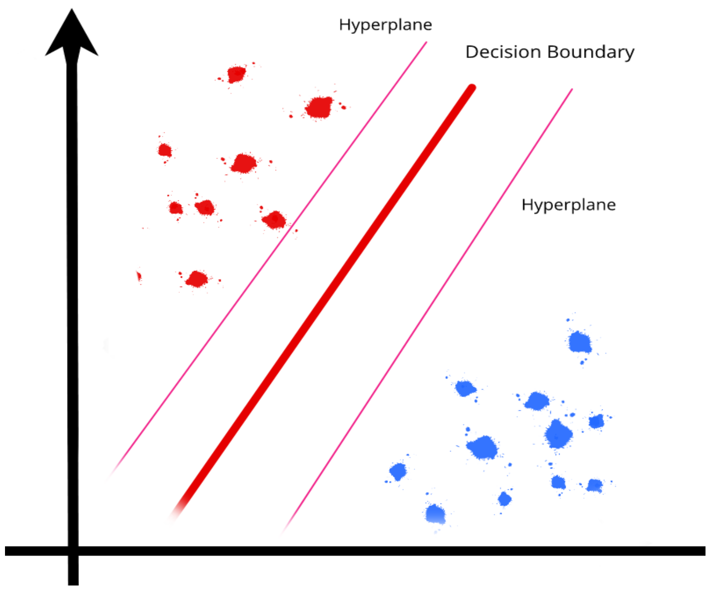

Fig. 4. Optimal Decision Boundary Representation Using SVM Hyperplane [35].

The calculation of SVM involves considering N points from two distant classes: (xi, yi) yi = +1, -1 (13,14). SVM divides two classes by a hyper-plane: w^T z + b = 0 (15). The operational margin hyper-planes are: w'xi + b' >= +1 (yi=1) (16) and w'xi + b' >= -1 (yi=-1) (17). The distance from a point x to the hyperplane is:

$$d(w0, b0, x) = |w0*x + b0| / ||w0|| \quad (18)$$

SVM maximizes the geometrical margin:

$$phi(w) = (1/2)||w||^2 \quad (19)$$

$$phi(alpha) = Sum(alpha\_i) - (1/2) Sum Sum(alpha\_i * alpha\_j * yi * yj * (xi.xj)) \quad (20)$$

$$fl(x) = Sum\ yi * alpha\_j * k(x, xsi) + b \quad (23)$$

E. Deep Learning

Deep learning is included in a crucial branch of machine learning. This technique employs a range of machine learning algorithms within a multi-layer neural network to address a range of problems, including those involving images and texts. The deep learning framework comprises several crucial algorithms to achieve the best results for various applications such as images, text, and voice.

F. Artificial Neural Network (ANN)

ANN has been on the top list of researchers for the past many years. This is the kind of machine learning algorithm that simulates the composition and operations of the human brain. They are made up of linked neurons that work together to process and interpret information [37]. Neural networks are capable of pattern recognition, relationship identification, and prediction based on input data as shown in Fig 5.

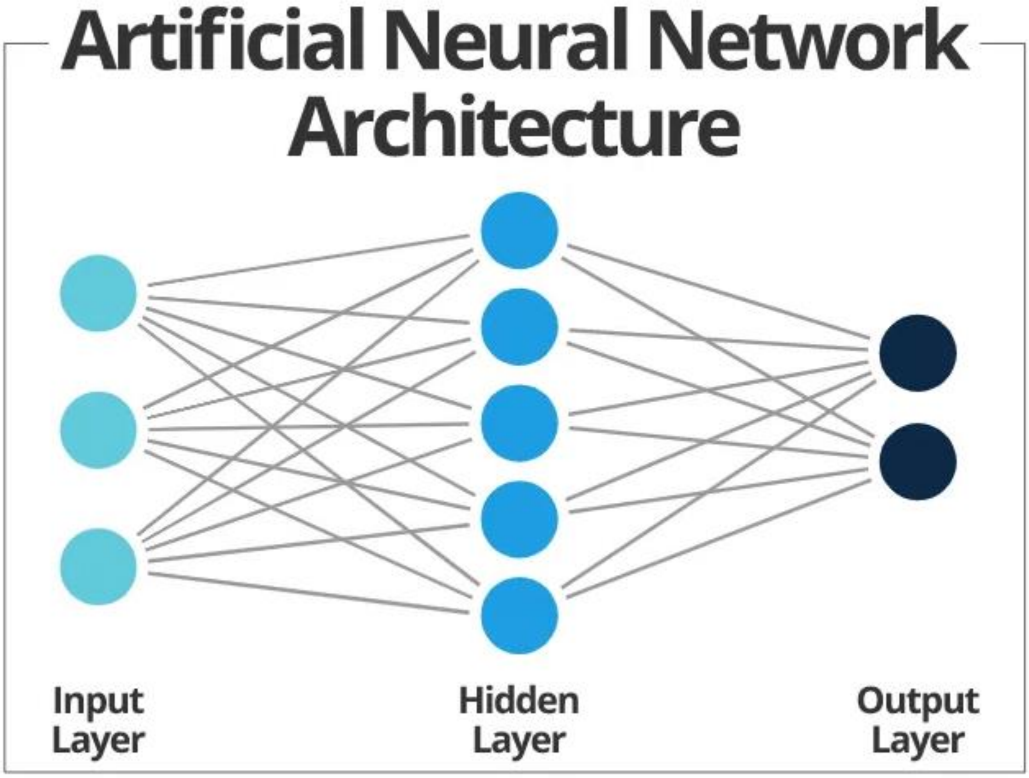

Fig. 5. ANN Architecture [38]

A neural network is trained using a process called back-propagation, where this network adjusts its weights and biases in response to errors in its predictions. Artificial neural network models can be divided into feedforward and feedback types.

In the feedforward neural network, the flow of data is in a single direction, from the input layers to many hidden layers to the output layer [40]. Feedback neural networks permit loops since the output is sent back to the input, making them effective at processing sequential data [41].

1) Input Layer:

The weighted sum of the input feature of every neuron is computed after a bias term is added:

$$zj = Sum(wij * xi * bj) \quad (24)$$

2) Hidden Layers:

Non-linearity is added to the model by passing the weighted sum via an activation function:

$$aj = phi(zj) \quad (25)$$

3) Output Layer:
This layer specifies the network's output:

$$yk = Sum(vjk * aj * ck) \quad (26)$$

4) Loss Function:
This layer measures the loss function and observes the discrepancy between expected and actual outputs:

$$L = (1/2) * Sum(yk - y\text{-}hat\_k)^2 \quad (27)$$

I. Convolutional Neural Network (CNN)

The convolutional neural network has completely transformed the domain of face recognition. CNN is developed to comprehend complicated patterns in an image by applying many layers of convolutional and pooling techniques. CNN can be divided into four layers as shown in Fig 6.

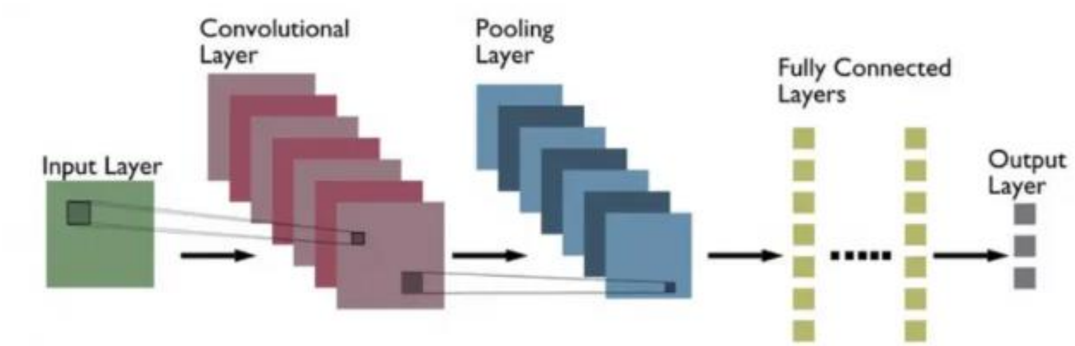

Fig. 6. CNN Architecture [42]

1) Input Layer:
The input layer is in charge of processing raw facial photos. Normalization, image scaling, and other standard pre-processing steps are included in this procedure. Data augmentation can also be applied to give additional variations of input photos.

2) Convolutional Layer:
A vital component of CNN is the convolutional layer, which applies several filters to an input image to extract valuable properties. These kernels are continuously applied over each receptive field of the entire area, and the resulting convolutional output creates a feature map of the input image as shown in Fig 7.

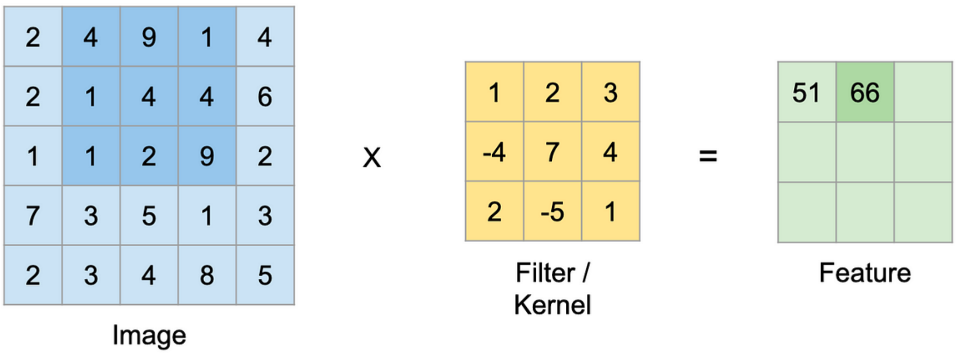

Fig. 7. Feature Extraction Through CNN Layer [44].

The mathematical expression of this layer is:

$$x^l\_i = f(Sum(x^{(l-1)}\_i * k^l\_ij + b^l\_j)) \quad (28)$$

3) Pooling Layer:

The pooling layer performs downsampling of the output of the convolutional layer to minimize the number of parameters. There are two types of pooling: average pooling and max pooling as shown in Fig 8. In face recognition, the max pooling technique is widely used.

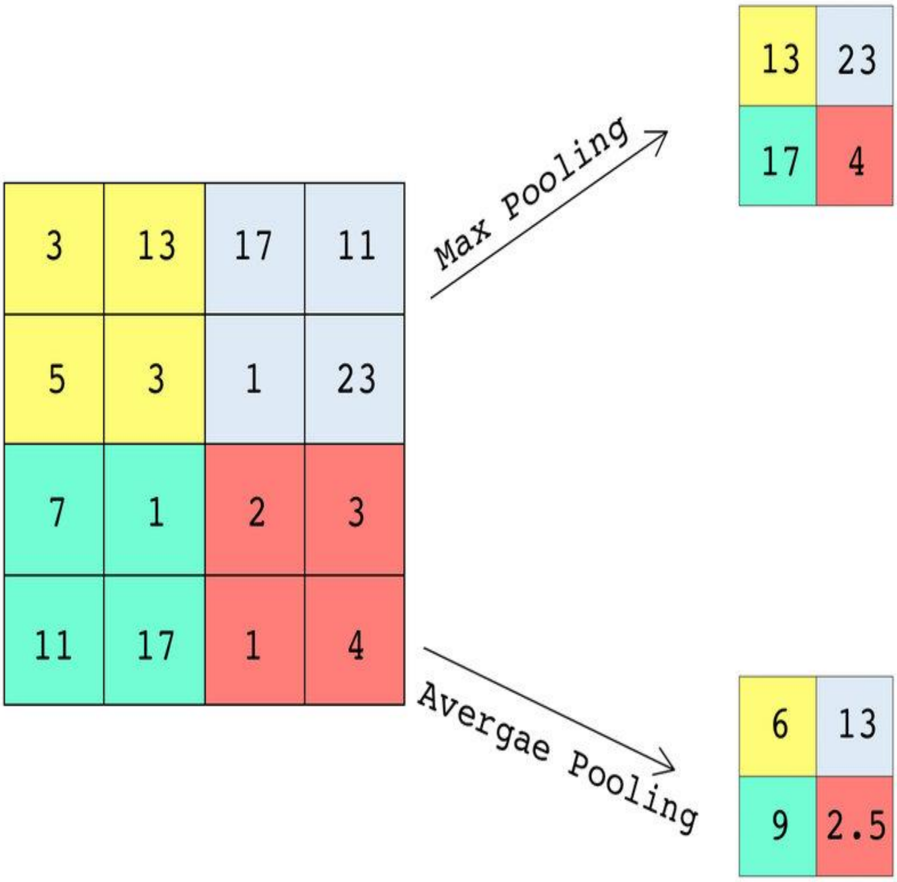

Fig. 8. Comparison on Average Pooling and Max Pooling Technique [45].

4) Fully Connected Layer:

The fully connected layer is the final phase of CNN in face recognition. It takes the output from the previous layers and flattens it into a single vector. The fully connected layer consists of several neurons which are connected to every neuron of the previous layers as shown in Fig 9.

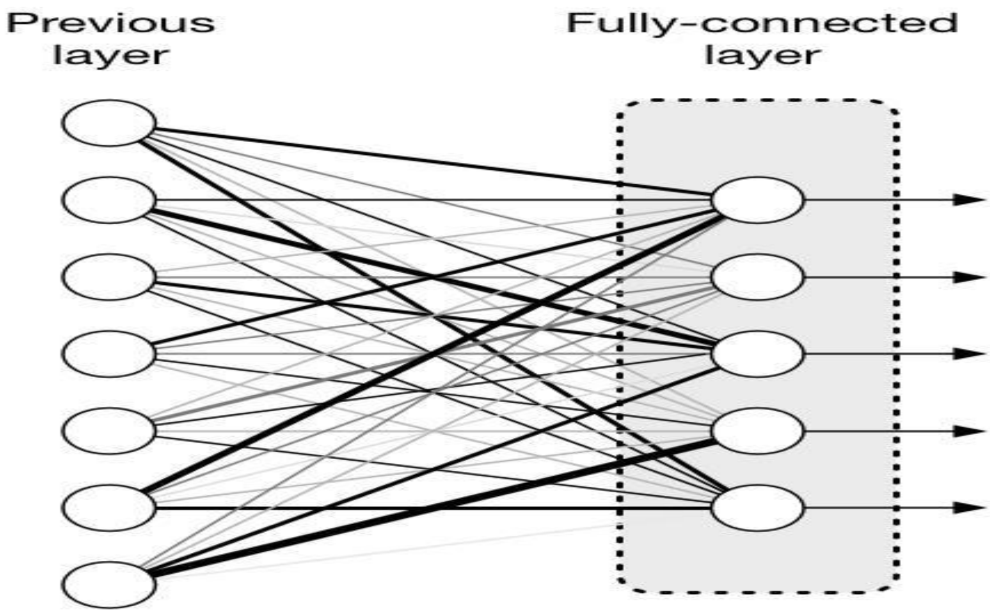

Fig. 9. Fully Connected Layer: Connecting To Each Neuron of Previous Layer [46].

The mathematical expression of this layer is:

$$yp\_j = f(Sum(x^\wedge(l-1)\_i * w^\wedge l\_ji + b^\wedge l\_j)) \quad (29)$$

III. FACTORS AFFECTING FACE RECOGNITION

While face recognition technology is becoming more common and accurate, several things can have a substantial impact on how well it works. The main factors influencing face recognition include: image resolution, aging effects, occlusions, differences in facial expressions, environmental variables, and the underlying computational method.

A. Environmental Condition

Face photo taking environment is one of the most significant factors of face recognition. It's important to consider the lighting. Poor or uneven lighting can cause incorrect identification due to shadows, highlighting of certain facial features, or hiding of important facial features.

B. Variations in Facial Expressions

Facial expressions can dramatically change a face's appearance, which in turn affects how a face is recognized. The muscles in human faces may be moved to create a wide range of expressions, such as squinting, frowning, and smiling. For instance, smiling can make the mouth and cheeks enlarge, which can cause the system to interpret the features of the face inaccurately.

C. Occlusions

Occlusions are when specific areas of the face are blocked off by hair, glasses, masks, scarves or other objects. These obstructions can conceal very important facial characteristics, providing the recognition system with inadequate data to operate on. For example, sunglasses can obstruct the eyes which are necessary for identification

D. Aging Effects

The natural process of aging causes a person's physical appearance to change over time. Accurate face recognition can be severely impacted by changes in an individual's skin tone, facial structure, and feature proportions as they age. Some systems use aging models to predict these changes and make necessary adjustments.

E. Image Resolution

The resolution and quality of the obtained image are crucial for successful face identification. The algorithm can retrieve finer features from high-resolution photographs, like skin texture or subtle variations in facial contours. Low-resolution images may lose crucial information required for precise identification.

F. Algorithm Approach and Model Training

A face recognition system's effectiveness is mostly determined by the caliber of the underlying algorithm and model training procedure. While traditional approaches like LBP and PCA may have trouble handling complex variations, deep learning techniques like CNNs can automatically learn and adapt by training on enormous datasets.

IV. EVALUATION CRITERIA OF FACE RECOGNITION

Accuracy is the most crucial consideration when evaluating facial recognition software. It refers to the system's ability to correctly identify or verify a person's identity. Accuracy is typically measured using metrics such as the True Positive Rate (TPR), False Positive Rate (FPR), and total recognition rate.

The mathematical expressions are:

$$TPR = TP / (TP + FN) \; (28)$$

where TP is the number of True Positives, and FN is the number of False Negatives.

$$FPR = FP / (FP + TN) \; (29)$$

Here TN represents the number of True Negatives and FP stands for the number of False Positives.

V. COMMONLY USED DATASETS

As shown in Table II there are different datasets used in face recognition.

TABLE II COMMONLY USED FACE RECOGNITION DATASETS

Dataset	Subjects	Images	Variations
AR Dataset	126	4,000+	Expressions, lighting, occlusions
AT&T Dataset	40	400	Lighting, expressions, head orientation
Yale Dataset	15 / 38	165 / 2,400+	Lighting, expressions, accessories
FERET Dataset	1,199	14,051	Expressions, illumination, head poses

AR Face Dataset is counted among the most favorite datasets for face recognition. The Autonomous University of Barcelona's Computer Vision Centre (CVC) produced it. More than 4,000 color photos of 126 people, 70 males, and 56 women, can be found in the dataset as shown in Fig 10.

Fig. 10. AR Face Dataset [46].

Another well-known dataset is the AT&T Dataset of Faces, sometimes referred to as the ORL Dataset. There are 400 greyscale photos in total, with 10 pictures for each of the 40 subjects as shown in Fig 11. These pictures are taken in different lighting and face expressions.

Fig. 11. AT&T Face Dataset [46].

Yale Face Dataset includes greyscale photos of fifteen people, eleven for every subject. The images show a range of emotions and circumstances, such as happiness, despair, sleep, surprise, and winking as shown in Fig 12.

Fig. 12. YALE Face Dataset [47].

The FERET Dataset was created to advance face recognition algorithms and offer a common dataset for evaluation. The 14,051 photos of 1,199 people in the FERET dataset were taken in a variety of settings as shown in Fig 13.

Fig. 13. FERET Face Dataset [48].

A. Comparison of Models on Different Datasets

TABLE III
ACCURACY OF DIFFERENT MODELS USING AR DATASET

Model	Accuracy
LBP [49]	90%
SVM+PCA [50]	92.67%
Deep Learning [51]	98.50%
LDA+CNN [52]	99.12%

TABLE IV
ACCURACY OF DIFFERENT MODELS USING AT&T DATASET

Model	Accuracy
LBP [53]	95%
PCA+SVM [54]	99.4%
LDA [55]	97.9%
CNN [56]	99.17%

TABLE V
ACCURACY OF DIFFERENT MODELS USING YALE DATASET

Model	Accuracy
LDA [57]	88%
LBP [58]	93.25%
PCA+ANN [59]	97.49%
CNN [60]	99.79%

TABLE VI

ACCURACY OF DIFFERENT MODELS USING FERET DATASET

Model	Accuracy
LBP [61]	94.1%
PCA [62]	97.15%
SVM [63]	98.75%
CNN [64]	99%

CNN has continuously shown itself to be the most efficient model for face recognition tasks because of its great accuracy over a wide range of datasets as shown in Tables III, IV, V, and VI. CNNs can effectively learn elements like edges, textures, and intricate patterns found in face structures, as well as spatial hierarchies in images because of their special architecture. This research indicates that CNNs perform significantly better than conventional machine learning models, particularly when trained on large-scale datasets with a variety of facial variants. The face recognition model is the best option due to its versatility in recognizing faces under various lighting, expression, and occlusion scenarios.

VI. CONCLUSION

The comparison of different machine learning algorithms highlights how well CNN performs in face recognition. Our analysis shows that CNN is consistently more accurate on a variety of datasets, which can be attributed to its sophisticated feature extraction and hierarchical learning capabilities. This resilience to changing environments such as shifting illumination, expressions on faces, and occlusions shows CNN's effectiveness and dependability in practical settings. CNN continues to be an essential tool in the ongoing evolution of machine learning, solidifying its status as the top method for tasks requiring in-depth picture analysis and recognition. To further improve CNN architecture's performance and applicability, future research should concentrate on improving them and investigating their potential in new fields.

REFERENCES

[1] M. Smith, S. Miller, M. Smith, and S. Miller, "Facial recognition and privacy rights," Biometric Identification, Law and Ethics, pp. 21-38, 2021.

[2] S. Ashraf, S. Saleem, T. Ahmed, Z. Aslam, and M. Shuaeeb, "Iris and foot based sustainable biometric identification approach," in 2020 International Conference on Software, Telecommunications and Computer Networks (SoftCOM). IEEE, 2020, pp. 1-6.

[3] Y. Kortli, M. Jridi, A. Al Falou, and M. Atri, "Face recognition systems: A survey," Sensors, vol. 20, no. 2, p. 342, 2020.

[4] P. Viola and M. J. Jones, "Robust real-time face detection," International journal of computer vision, vol. 57, pp. 137-154, 2004.

[5] B. Wu, H. Ai, C. Huang, and S. Lao, "Fast rotation invariant multi-view face detection based on real adaboost," in Sixth IEEE International Conference on Automatic Face and Gesture Recognition, 2004. IEEE, pp. 79-84.

[6] Y. Li, H. Ai, T. Yamashita, S. Lao, and M. Kawade, "Tracking in low frame rate video: A cascade particle filter with discriminative observers," IEEE Trans. Pattern Anal. Mach. Intell., vol. 30, no. 10, pp. 1728-1740, 2008.

[7] T. F. Cootes, C. J. Taylor, D. H. Cooper, and J. Graham, "Active shape models-their training and application," Computer vision and image understanding, vol. 61, no. 1, pp. 38-59, 1995.

[8] D. Cristinacce and T. F. Cootes, "Boosted regression active shape models," in BMVC, vol. 2, 2007, pp. 880-889.

[9] X. Cao, Y. Wei, F. Wen, and J. Sun, "Face alignment by explicit shape regression," International journal of computer vision, vol. 107, pp. 177-190, 2014.

[10] W. Zhang et al., "Local gabor binary pattern histogram sequence (lgbphs): a novel non-statistical model," in Tenth IEEE ICCV, vol. 1. IEEE, 2005, pp. 786-791.

[11] D. Chen, X. Cao, F. Wen, and J. Sun, "Blessing of dimensionality: High-dimensional feature and its efficient compression for face verification," in CVPR, 2013, pp. 3025-3032.

[12] M. Turk and A. Pentland, "Eigenfaces for recognition," Journal of cognitive neuroscience, vol. 3, no. 1, pp. 71-86, 1991.

[13] M. O. Oloyede, G. P. Hancke, and H. C. Myburgh, "A review on face recognition systems: recent approaches and challenges," Multimedia Tools and Applications, vol. 79, no. 37, pp. 27891-27922, 2020.

[14] M. A. Turk and A. P. Pentland, "Face recognition using eigenfaces," in Proc. 1991 IEEE CVPR. IEEE, 1991, pp. 586-587.

[15] K. Huang, "Principal component analysis in the eigenface technique for facial recognition," 2012.

[16] I. Dagher, "Incremental pca-lda algorithm," in 2010 IEEE Int. Conf. Computational Intelligence. IEEE, 2010, pp. 97-101.

[17] H. R. Yazdani and A. R. Shojaeifard, "Facial recognition system using eigenfaces and pca," Mathematics and Computational Sciences, vol. 4, no. 1, pp. 29-35, 2023.

[18] S. Wang, J. Lu, X. Gu, H. Du, and J. Yang, "Semi-supervised linear discriminant analysis for dimension reduction and classification," Pattern Recognition, vol. 57, pp. 179-189, 2016.

[19] X. Wang and K. K. Paliwal, "Feature extraction and dimensionality reduction algorithms and their applications in vowel recognition," Pattern recognition, vol. 36, no. 10, pp. 2429-2439, 2003.

[20] A. Kaur and T. Sarabjit Singh, "Face recognition using pca and lda techniques," Int. Journal of Advanced Research in Computer and Communication Engineering, vol. 4, no. 3, pp. 308-310, 2015.
[21] N. Tyagi, "Introduction to linear discriminant analysis in supervised learning," analyticssteps.com, Mar 2021.
[22] D. Huang et al., "Local binary patterns and its application to facial image analysis: a survey," IEEE Trans. Syst. Man Cybern., vol. 41, no. 6, pp. 765-781, 2011.
[23] T. Ojala, M. Pietikainen, and D. Harwood, "A comparative study of texture measures with classification based on featured distributions," Pattern Recognit., vol. 29, pp. 51-59, 1996.
[24] C. Zhu, C.-E. Bichot, and L. Chen, "Multi-scale color local binary patterns for visual object classes recognition," in 20th ICPR. IEEE, 2010, pp. 3065-3068.
[25] T. Ojala, M. Pietikainen, and T. Maenpaa, "Multiresolution gray-scale and rotation invariant texture classification with local binary patterns," IEEE Trans. PAMI, vol. 24, no. 7, pp. 971-987, 2002.
[26] S. Liao and A. C. Chung, "Face recognition by using elongated local binary patterns," in ACCV 2007. Springer, 2007, pp. 672-679.
[27] H. Jin, Q. Liu, H. Lu, and X. Tong, "Face detection using improved lbp under bayesian framework," in Third ICIG. IEEE, 2004, pp. 306-309.
[28] A. Petpon and S. Srisuk, "Face recognition with local line binary pattern," in 2009 Fifth ICIG. IEEE, 2009, pp. 533-539.
[29] X. Tan and B. Triggs, "Enhanced local texture feature sets for face recognition under difficult lighting conditions," in AMFG 2007. Springer, 2007, pp. 168-182.
[30] S. Liao et al., "Learning multi-scale block local binary patterns for face recognition," in ICB 2007. Springer, 2007, pp. 828-837.
[31] L. Wolf, T. Hassner, and Y. Taigman, "Descriptor based methods in the wild," in Workshop on faces in real-life images, 2008.
[32] C. Shan and T. Gritti, "Learning discriminative lbp-histogram bins for facial expression recognition," in BMVC, 2008, pp. 1-10.
[33] S. Ghosh, A. Dasgupta, and A. Swetapadma, "A study on support vector machine based linear and non-linear pattern classification," in 2019 ICISS. IEEE, 2019, pp. 24-28.
[34] F. Peter and S. John, "Support vector machine with radial basis function for facial emotion valence recognition," European Journal of Molecular & Clinical Medicine, vol. 9, no. 4, pp. 1960-1969, 2022.
[35] S. Mishra, "Breaking down the support vector machine (svm) algorithm," towardsdatascience.com, Oct 2020.
[36] Z. Li and X. Tang, "Bayesian face recognition using support vector machine and face clustering," in CVPR 2004, vol. 2. IEEE, 2004.
[37] M. I. Razzak, S. Naz, and A. Zaib, "Deep learning for medical image processing: Overview, challenges and the future," Classification in BioApps, pp. 323-350, 2018.
[38] N. Mahat et al., "Artificial neural network (ann) to predict mathematics students' performance," Journal of Computing Research and Innovation, vol. 7, pp. 29-38, 2022.
[39] H. Wang, R. Czerminski, and A. C. Jamieson, "Neural networks and deep learning," in The machine age of customer insight. Emerald, 2021.
[40] D. Svozil, V. Kvasnicka, and J. Pospichal, "Introduction to multi-layer feed-forward neural networks," Chemometrics and intelligent laboratory systems, vol. 39, no. 1, pp. 43-62, 1997.
[41] C. Wang and L. Wang, "Artificial neural network and its application in image recognition," Journal of Engineering Research and Reports, vol. 24, no. 2, pp. 50-57, 2023.
[42] A. Kumar, "Different types of cnn architectures explained: Examples," vitalflux.com, Apr 2022.
[43] B. R. Ilyas et al., "Facial expression recognition based on dwt feature for deep cnn," in 2019 CoDIT. IEEE, 2019, pp. 344-348.
[44] K. Patel, "Convolutional neural networks: a beginner's guide," towardsdatascience.com, Sep 2019.
[45] N. Aljaafari, "Ichthyoplankton classification tool using generative adversarial networks and transfer learning," Ph.D. dissertation, 2018.
[46] T. KIDS, "Convolutional neural networks: a beginner's guide," medium.com, Jul 2019.
[47] J. Gao, L. Li, and B. Guo, "A new extendface representation method for face recognition," Neural Processing Letters, vol. 51, no. 1, pp. 473-486, 2020.
[48] E. Khoshnevisan, H. Hassanpour, and M. M. AlyanNezhadi, "Face recognition based on general structure and angular face elements," Multimedia Tools and Applications, pp. 1-19, 2024.
[49] Y. Zhu and Y. Jiang, "Optimization of face recognition algorithm based on deep learning multi feature fusion," Image and Vision Computing, vol. 104, p. 104023, 2020.
[50] M. Norouzi et al., "A survey on face recognition based on deep neural networks," 2022.
[51] F. Liu et al., "Deep learning based single sample face recognition: a survey," Artificial Intelligence Review, vol. 56, no. 3, pp. 2723-2748, 2023.
[52] A. Ouyang et al., "A hybrid improved kernel lda and pnn algorithm for efficient face recognition," Neurocomputing, vol. 393, pp. 214-222, 2020.
[53] M. M. Ahsan et al., "Evaluating the performance of eigenface, fisherface, and lbph-based facial recognition methods," Technologies, vol. 9, no. 2, p. 31, 2021.
[54] T. Tuncer et al., "A novel facial image recognition method based on perceptual hash using quintet triple binary pattern," Multimedia Tools and Applications, vol. 79, no. 39, pp. 29573-29593, 2020.

[55] F. L. Abbasi et al., "Cnn-based face detection focusing on diverse visual variations," in Navigating Challenges of Object Detection. IGI Global, 2025, pp. 63-96.
[56] S. M. Daniyal et al., "An improved face recognition method based on convolutional neural network," Journal of Independent Studies and Research Computing, vol. 22, no. 1, pp. 103-110, 2024.
[57] J. Huang et al., "An mpca/lda based dimensionality reduction algorithm for face recognition."
[58] L. Zhou, M. Gao, and C. He, "Study on face recognition under unconstrained conditions based on lbp and deep learning," Journal of computational methods, vol. 21, no. 2, pp. 497-508, 2021.
[59] A. Aggarwal et al., "Principal component analysis, hidden markov model, and ann inspired techniques to recognize faces," Concurrency and Computation, vol. 33, no. 9, p. e6157, 2021.
[60] A. Hattab and A. Behloul, "An illumination-robust face recognition approach based on cnn," in Int. Symposium on Modelling. Springer, 2022, pp. 135-149.
[61] T. Chen et al., "A novel face recognition method based on fusion of lbp and hog," IET Image Processing, vol. 15, no. 14, pp. 3559-3572, 2021.
[62] Z. Wang et al., "Mmpcanet: An improved pcanet for occluded face recognition," Applied Sciences, vol. 12, no. 6, p. 3144, 2022.
[63] M. A. Yaman, F. Rattay, and A. Subasi, "Comparison of bagging and boosting ensemble machine learning methods for face recognition," Procedia Computer Science, vol. 194, pp. 202-209, 2021.
[64] M. A. BERBAR, "Faces recognition and facial gender classification using convolutional neural network," Menoufia Journal of Electronic Engineering Research, vol. 31, no. 2, pp. 1-10, 2022.

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