© February 2023 | IJIRT | Volume 9 Issue 9 | ISSN: 2349-6002

A Review of Advancements in Face Recognition: Methods and Approaches

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Abstract: **Face recognition technology is based on the identification of facial features of a person. People collect the face images, and the recognition equipment automatically processes the images. The paper introduces the related researches of face recognition from different perspectives. The paper describes the development stages and the related technologies of face recognition. Face recognition has become the future development direction and has many potential applications in the field of criminal Identification,, access verification, biometric based attendance tracking, health care etc.,.**

Index Terms **- face recognition, image processing, neural network, deep learning.**

I. INTRODUCTION

Face recognition is a part of the problem of pattern recognition. Eyes play a vital role in recognizing patterns, which is recognized by the brain and interpreted as meaningful concepts. For a computer, to recognize these patterns the images/ pictures/ videos are represented in form of matrices consisting of pixels. The machine should identify these concepts which are represented in the data. This problem may be thought roughly as a classification problem. For face recognition problems, it is necessary to make a distinction about who the face belongs to. This is a subdivision problem. Face recognition includes preprocessing of images, then detect the face in the image, with respect to the face position, etc. Face detection algorithms scan the image to determine the face area and its co-ordinates . The output of the face coordinate system can be square, rectangular, etc. The face position is the coordinate position of the face feature. The deep learning framework implements some current good positioning technologies. The face recognition started with the PCA,LDA based methods, later with the advent of AI, Machine learning, based classifiers were used, Deep Learning methods such as CNN enhanced the recognition accuracy and raised the usage of the methods based on Deep Learning in commercial auto detection based systems for face recognition.

The stages of development of Face Recognition and its technologies

Table 1: Lists the stages and the Technologies in Face Recognition

Stage	Technology
Early Stage	PCA,LDA Based on Geometric Structure of Face
Machine Learning Stage	SVM,ADABOOST, Neural Networks Based On Classifiers
Deep Learning Stage	Neural Networks , Deep Learning Based on

II. EARLY FEATURE-BASED METHODS

During the early stages,face recognition was performed on the basis of features. Principal Component Analysis (PCA), also known as Eigenfaces, was one of the earliest methods used to extract essential facial features. Linear Discriminant Analysis (LDA) and Local Binary Patterns (LBP) further improved feature extraction and classification. These methods, however, struggled with variations in lighting, pose, and occlusion.

PCA

PCA also known as Karhunen Loeve projection. PCA is a useful statistical technique that has found application in fields such as face recognition and image compression, and is a common technique for finding patterns in data of high dimension. PCA calculates the Eigen vectors of the covariance matrix, and projects the original data onto a lower dimensional feature space, which is defined by Eigen vectors with large Eigen values. The Eigen vectors calculated are referred to as Eigen faces. The dimensionality of the original data is very large compared to the size of the dataset, PCA as a first step in analysis performs dimensionality reduction.

Eigen faces use a principal component analysis approach to store a set of known patterns in a compact subspace representation of the image space. PCA is one of the more successful techniques of face recognition and easy to understand and describe using mathematics. This method involves using Eigen faces. The first step is to produce a feature detector (dimension reduction). Principal Components Analysis (PCA) is the most efficient technique, of dimension reduction, in terms of data compression. This allows the high dimension data, the images, to be represented by lower dimension data and so hopefully reducing the complexity of grouping the images.

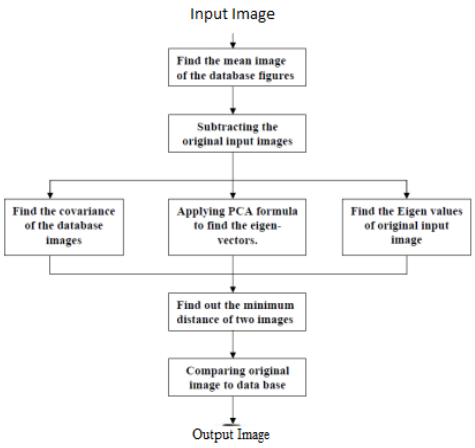

Fig 1: Flowchart of PCA

RECOGNITION PROCESS IN EIGEN FACES APPROACH

Step 1. Form a face database that consists of the face images of known individuals.
Step 2. Choose a training set that includes a number of images (M) for each person with some variation in pose and different faces.
Step 3. Calculate the M x M matrix L, find its Eigen vectors and Eigen values, and choose the M' Eigen vectors with the highest associated Eigen values.
Step 4. Combine the normalized training set of images to produce M' Eigen faces.
Step 5. Store these Eigen faces for later use.
Step 6. For each member in the face database, compute and store a feature vector.
Step 7. Choose a threshold value e that defines the maximum allowable distance from any face class. Optionally choose a threshold f that defines the maximum allowable distance from face space.
Step 8. For each new face image to be identified, calculate its feature vector and compare it with the stored feature vectors of the face library members.
Step 9. If the comparison satisfies the threshold for at least one member, then classify this face image as "known", otherwise a miss has occurred and classify it as "unknown" and add this member to the face library with its feature vector.

LDA

Linear Discriminant Analysis (LDA) is a dimensionality reduction technique which is used for classification problems. LDA is also known as Fisher's Discriminant Analysis and it searches for the vectors space for the best discriminate among classes. LDA creates a linear combination of independent features which produce the largest mean differences between the desired classes. The basic idea of LDA is to find a linear transformation such that feature clusters are most separable after the transformation which can be achieved through scatter matrix analysis . The goal of LDA is to maximize the between-class scatter matrix measure while minimizing the within-class scatter matrix measure.

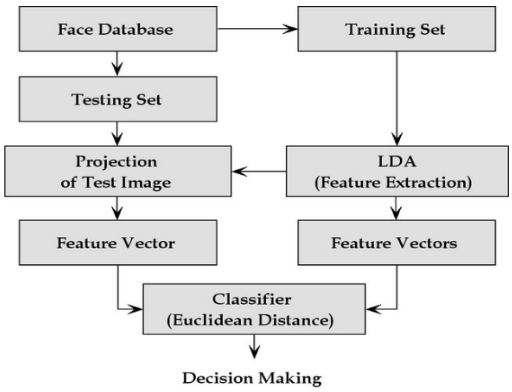

Fig 2: Flowchart for LDA

The basic steps in LDA are as follows: • Calculate within-class scatter matrix, Sw :

$$S_w = \sum_{j=1}^{C} \sum_{i=1}^{N_j} (x_i^j - \mu_j)(x_i^j - \mu_j)^T$$

where x_i^j is the ith sample of class j,
μ_j is the mean of class j,
C is the number of classes,
N_j is the number of samples in class j.

- Calculate between-class scatter matrix, S_b

$$S_b = \sum_{j=1}^{C} (\mu_j - \mu)(\mu_j - \mu)^T$$

where μ represents the mean of all classes.

- Calculate the eigenvectors of the projection matrix

$$W = \text{eig}(S_w^{-1} S_b)$$

The test image's projection matrix is compared with the projection matrix of each training image by using a similarity measure like Euclidean distance. The result is the training image which is the closest to the test image.

LBP

Local Binary Pattern (LBP) features have performed very well in various applications, including texture classification and segmentation, image retrieval and surface inspection. The original LBP operator labels the pixels of an image by thresholding the 3-by-3 neighborhood of each pixel with the center pixel value and considering the result as a binary number. The 256-bin histogram of the labels computed over an image can be used as a texture descriptor. Each bin of histogram (LBP code) can be regarded as a micro-texton. Local primitives which are codified by these bins include different types of curved edges, spots, flat areas, etc. The process is described in fig below.

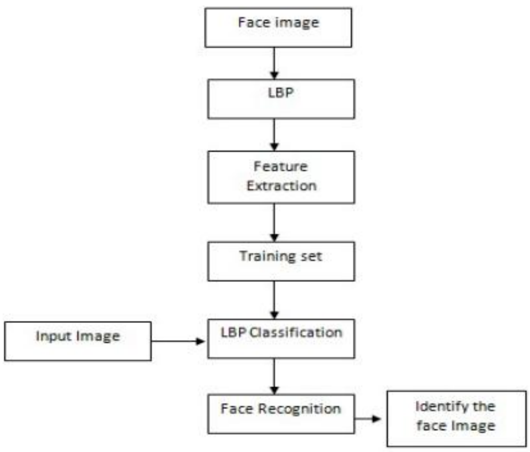

Fig 3: Flowchart for LBP

Each face image can be considered as a composition of micro-patterns which can be effectively detected by the LBP operator. Ahonen et al. introduced a LBP based face representation for face recognition. To consider the shape information of faces, they divided face images into M small non-overlapping regions R0, R1, ...,……… RM . The LBP histograms from each sub-region are then concatenated into a single, spatially enhanced feature histogram.

$$H_{i,j} = \sum_{x,y} I(f_l(x,y) = i) I((x,y) \in R_j)$$

where i = 0, ... , L-1, j = 0, ..., M-1. The extracted feature histogram describes the local texture and global shape of face images.

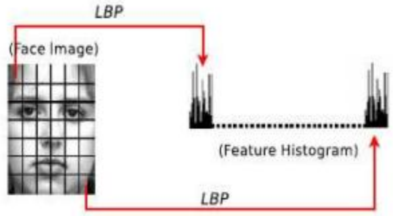

Fig 4: Histogram for Face Image

III. MACHINE LEARNING APPROACHES

The indroduction of machine learning, methods such as Support Vector Machines (SVM) and Hidden Markov Models (HMM) improved classification. The introduction of artificial neural networks (ANNs) in the late 1990s and early 2000s provided enhanced feature learning capabilities. However, traditional machine learning models still relied heavily on handcrafted features, limiting their ability to generalize effectively.

SVM is a classification procedure which was illustrated by Vapnik in 1992. The characterstics of SVM are high accuracy, ability to process the high dimensional data. It is associated to the regular category of kernel procedure. A kernel procedure implies the data obtained through dot-products. In this case, kernel function calculates a dot product in possibly high dimensional facial components space. The primary characteristics of SVM is the capacity to develop non-linear classifier utilizing systems connected on linear classifiers. Classification is acquired by understanding a linear or non-linear partition surface in the information space. It stacks the set with the closest combine of focuses from inverse classes like the Direct SVM calculation.The process is as illustrated in the diagram below:

SVM Algorithm

- Identify a violating point in the dataset.
- If there is a Violater point is identified in the dataset then it will be greedily added to the candidate set.
- It may take place if adjoining of the violating point as a Support Vector may be impeded by other candidate Support Vectors that are already present in the set.
- Steps Repeated if the Violating points are eliminated.

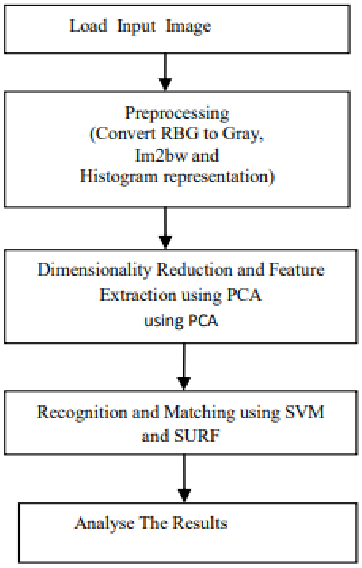

Fig 5 : Flow chart for SVM

ADABOOST

AdaBoost is used as a short form for Adaptive Boosting, which is a widely used machine learning algorithm It's a meta-algorithm, algorithm of algorithm, and is used in combination with other weak learning algorithms to improve their performance. Usage of AdaBoost creates a stronger learning algorithm. In our case AdaBoost is combined with Haar feature to improve the performance rate of face recognition. The algorithm, AdaBoost is an adaptive algorithm in the sense that the subsequent classifiers built is tweaked in favor of instances of those misclassified by the previous classifiers. But it is very sensitive to noise data and the outliers.

AdaBoost takes an input as a training set S = , ((x1,y1),…..(xm,ym)),where each instance of Sxi, belongs to a domain or instance space X, and similarly each label belongs to the finite label space, that is Y. The focus on the binary case when Y = {-1,+1}.The basic idea of boosting is actually to use the weak learner of the features calculated, to form a highly correct prediction rules by calling the weak learner repeatedly processed on the different-different distributions over the training examples. The AdaBoost learning procedure attempts only to minimize error and is not specifically designed to achieve high detection rates at the expense of large false positive rate.

IV. DEEP LEARNING AND CONVOLUTIONAL NEURAL NETWORKS (CNNS)

The deep learning, methods like Convolutional Neural Networks (CNNs), have brought a new revolution in face recognition. CNN-based models such as DeepFace, FaceNet, and VGG-Face significantly improved recognition accuracy by learning hierarchical feature representations directly from raw images. Unlike previous methods, CNNs reduced dependence on manual feature engineering, enabling more robust and scalable solutions. Deep Learning A large number of emerging works adopt the principle of "shallow to deep". This approach exploits something that a superficial model meets faster than a deeper model. Another approach does so implicitly by modifying the network architecture and objective functions for the network to allow input and flow through the network and gradually adapt to deep representation learning.However, everything that has been designed to optimize the loss function is based on the output obtained from the innermost layer. When batch convergence increases, the inferences made by the innermost layer take considerable time for convergence. The DNN consists of convection layer resolution, max-pooling and fully connected . A typical hierarchical characteristic extractor that maps the raw image intensity of the input image into the feature vector to be classified by multiple connected layers. DNN also has more maps per layer, and thus more connections and weights. After performing the 1st to the 4th stage on the convolutional layer and the union of multiple full layers connected further incorporates the output into the 1D vector feature. The output layer is always a fully connected layer with one neuron per class. The softmax activation function used for the last layer ensures that each activation of the neuron output can be interpreted as a certain probability the class image input is a general hierarchical characteristic extractor that maps the pixel default intensity of the input image to the feature vector to be classified. by several fully connected layers. All of these parameters can be adjusted optimized together with minimizing error classification error in the training set. Each convolutional layer performs a 2D convolution from its input map with a square filter. The output activation is obtained by summing the existing convolution response through the nonlinear activation function.

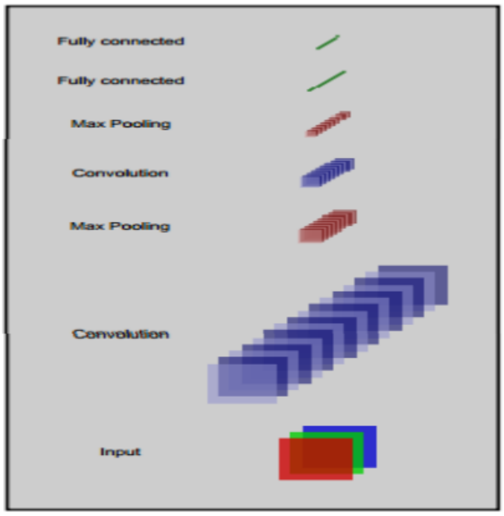

Fig 6: DNN Architecture.

CNN

CNN is a variation of Multilayer Perceptron that is inspired by human neural networks. Research conducted by Hubel and Wiesel , which became the basis of this discovery, has carried out a study of visual cortex in cat vision. Visual cortex in animals is very strong in the visual processing system that ever existed. Convolutional Neural Networks is a layer that has a 3D neuron arrangement (width, height, depth). The width and height are the sizes of the layer while the depth refers to the number of layers. In general, type of layer on CNN can be divided into two namely: The image feature extraction layer, located at the beginning of the architecture is composed of several layers and each layer is composed of neurons connected to the local region of the previous layer. The first type of layer is the convolution layer and the second layer is the layer pooling. Each layer is enforced by an activation function. Its position is intermittent between the first type and the second type. This layer accepts image inputs directly and processing. The process to produce vector output to be processed at the next layer. Layer classification, arranged on several layers and each layer is composed of neurons that are fully connected with other layers. This layer accepts input from the output layer of the feature extraction feature in the form of vector images and then transformed like Multi Neural Networks with the addition of several hidden layers. The output is a class scoring for classification. Thus CNN is a method for transforming the original image layer per layer from the image pixel value into the class scoring value for classification. And every layer has a hyperparameter and some have no parameters (weight and bias on neurons). The Convolutional Layer first receives direct image input on the architecture. Operation at this layer is the same as convolution operation that is doing combination operation of the linear filter to the local area. The filter is a representation of the receptive plane of neurons connected into the local connectivity of the image input.Fig below shows the flowchart for CNN.

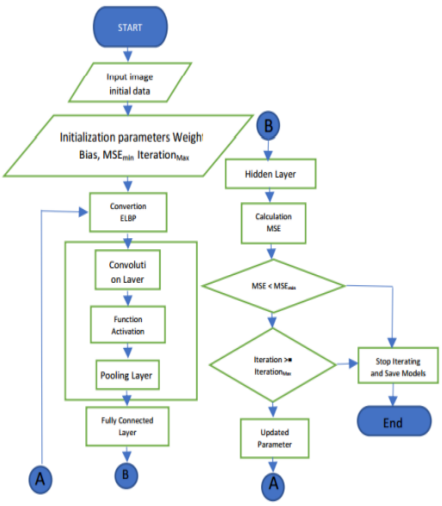

Fig 7: Flowchart for CNN

V. COMPARISON OF FACE RECOGNITION METHODS

Table 2: Lists the various methods, their key features and limitations

Method	Key Features	Limitations
PCA/LDA/LBP	Handcrafted features, simple classifiers	Sensitive to lighting and pose variations
ML-Based (SVM, ANN)	Improved classification, learns patterns	Requires feature extraction, limited scalability
CNN-Based (DeepFace, FaceNet)	Hierarchical feature learning, high accuracy	Requires large datasets, computationally expensive
Transformer-Based	Self-attention mechanism, robust to occlusion	High resource demand, ongoing research

VI. CONCLUSION

Face recognition has progressed from simple feature extraction techniques to complex deep learning models, significantly improving accuracy and robustness. Future research will focus on addressing ethical concerns, enhancing model interpretability, and developing more efficient architectures for real-world deployment.

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