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A HIGHLY EFFICIENT FACIAL RECOGNITION FOR BIOMETRIC APPLICATIONS USING CONVOLUTIONAL NEURAL NETWORK

Dr.JAYANTHI SREE S[1], JAYA HARSHAN S[2], LINGAMOORTHY S[3], MOKAN RAAM E[4]

Associate Professor, Department of ECE, Sri Krishna College of Engineering and Technology, Coimbatore, India[1].

UG Scholar, Department of ECE, Sri Krishna College of Engineering and Technology, Coimbatore, India[2,3,4].

Abstract: The most common feature that people use to identify one other is their faces. In computer vision and image understanding, face recognition (FR) is a traditional problem that is still actively pursued. This function of biometrics, which is a component of deep learning, has long been met. Face recognition has grown in importance as a tool for safety and security in recent years. Measuring and examining each person's distinct physical or behavioral traits is the aim of biometric systems. Due to its ability to gather biometric data without invading personal space or requiring the agreement of the user, facial biometrics have become one of the most popular biometric data types in recent years. Face recognition has seen a recent surge in interest in deep learning, particularly in deep convolutional neural networks, and several deep learning techniques have been put forth. In the proposed work, a comparison is made between the holistic and fisher face approaches and the face recognition application using Convolutional Neural Networks (CNN) using Python. In contrast to traditional techniques, the suggested methodology normalizes the probability distribution by employing pooling layers, extra convolutional layers with ReLU layers, a fully connected layer, and a Softmax Loss Layer. 1500 photos with various facial expressions make up the dataset, and the CNN method is used to train and evaluate the model to achieve accuracy. Based on experimental data, the suggested Neural Network received a score of 98.96% accuracy.

Keywords: Facial Recognition, biometrics, deep Learning, convolutional neural networks, facial dataset, data security.

I. INTRODUCTION

Biometric systems are required for person identification and verification systems due to the growing importance of human elements in next generation technology. Biometric systems can be classified into two categories: those that rely on behavioral traits like walking, gait, voice, and facial dynamics, and those that use static physiological features like fingerprint, iris, and palm print. The latter type of technology is often referred to as soft biometrics. One of the most common biometric characteristics is the face, which finds use in a wide range of fields such as human-computer interaction, education, marketing, finance, education, security, and law enforcement. Face recognition is especially useful since, unlike a few other biometric characteristics, it doesn't always require the subject's agreement and can be done in an inconspicuous manner for surveillance applications. Furthermore, face recognition is appropriate for behavioral biometrics since it can be based on both the face's dynamic and physical (static) properties. Face identification in unconstrained contexts is a difficult challenge because of differences in head attitude, illumination, age, and facial expression. Additionally, changes in look could result from facial hair, makeup, or accessories like scarves or glasses. The similarity of faces among people presents another challenge to facial recognition. The idea of "Deep Learning" is used to achieve this goal. Neural networks are used to train the system [1,4], enabling it to evaluate the input and forecast future events based on its learning.

Convolutional Neural Networks (CNN), sometimes known as artificial neurons, are the building blocks of deep learning. They function similarly to the human brain, processing several inputs and producing a single output. There are numerous layers in CNN [12]. From the input image, each is in charge of extracting deterministic features. Accuracy can be improved by applying and include each new layer. Pattern Recognition is one of the key uses of neural networks that needs further research. In the realm of facial recognition, trained neural networks identify users or people from datasets by analyzing the geometrical pattern [10] of the face, which includes the eyes, nose, mouth, and every other facial component. The use of facial recognition technology is growing in as the most important factor for security purposes. The paper is ordered as follows. Related work has been described in Section II. Various methodologies related to face recognition is explained in section III. Proposed face recognition technique is described in section IV. Section V describes the evaluation results and section VI concludes the paper.

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II. RELATED WORK

Chakka Mounica and Venugopal P (2016) in the paper “Face Detection and Recognition using LBPH “, [12] due to an analysis of the rising crime rate in the ATM industry, the LBPH face recognition technique was tested. Haar-like features were used, and the process was carried out in three stages: feature extraction, matching, and classification. The system's efficiency was 76%, and it was also able to recognize images that were tilted at a 45-degree angle.

Shekhar Karanwal and Ravindra Kumar Purwar (2017) in the article “Performance Analysis of Local Binary Pattern Features with PCA for Face Recognition “ [13] examined various techniques for image recognition utilizing LBPH on two distinct datasets and found that, for both short and large sample training sizes, LBPH(3x3)-PCA on the ORL face database and LBPI-PCA on the extended Yale-B face database outperform other features.

Moreover, Poonam Tanwar, Divya Arora, Dhruv Anand (2016) in the paper “Facial Expression Detection using Hidden Markov mode “, [16] additionally addressed the issues with the face expressions. They proposed that the problem might be effectively addressed by combining the KNN and Hidden Markov Model.

Later, Hadi Santoso Agus Harjoko, Agfianto Eko Putra (2017) in the paper “Efficient K-Nearest Neighbor Searches for Multiple-Face Recognition In The Classroom Based On Three Levels Dwt-Pca “, [17] improved the KNN's efficiency because calculating distance takes a long time. In order to expedite the KNN classification process, they proposed using priority k-d tree search as a solution.

P. Jothi Thilaga,B. Arshath Khan,A.A. Jones and N. Krishna Kumar (2018) in the paper “Face recognition with deep learning” Hog descriptors can be used to offset stated flaws in face feature detection caused from occlusions, posture, and lighting shifts. Using deep learning techniques to measure a face is the most dependable method available. The last stage involves training a classifier to determine which known individual is the closest match based on measurements from a fresh test image. An application based on Python is being developed to identify faces under any circumstances.

Jegadeesan S,Monika M,Oviya P and Supriya M (2022) in the paper “Artificial intelligence based face recognition using deep learning”, uses OpenCV in Python to enable an attendance automation system for numerous users that processes continuously and without delay. The employee's existence in the database will only be noted once, even if he enters multiple times. Comparing this approach against the current one, it is more effective in terms of prompt attendance.

III. VARIOUS METHODOLOGIES RELATED TO FACE RECOGNITION

The state of face recognition technology today uses a wide variety of approaches, such as deep learning techniques, statistical methods like fisher face, and conventional holistic approaches. The novel use of holographic principles to the capture of three-dimensional facial features is drawing attention to holistic techniques. While deep learning uses neural networks to automatically build hierarchical representations, Fisher Face uses statistical models for discriminative feature selection. Nonetheless, current systems frequently struggle to strike a compromise between computational efficiency and accuracy, and worries about bias and privacy issues continue to prevail. Significant obstacles may include differences in performance between different datasets and real-world scenarios.

A. Holistic Matching Method

The holistic technique considers the entire face region as input data for the face-catching system. The most popular facial recognition technique, Eigenfaces [8], Principal Component Analysis, Linear Discriminant Analysis [7], and Independent Component Analysis, among others, are some of the best examples of holistic approaches. Turk and Pentland used eigenfaces to successfully demonstrate face recognition on a machine for the first time in 1991. They address face recognition as a two-dimensional recognition problem in their methodology. A series of photos is first inserted into a database; these images are referred to as the training set since we will use them for image comparison and to produce eigenfaces.

Making the eigenfaces is the second step. Eigenfaces are created by taking the faces' defining characteristics and extracting them. The eyes and mouths are aligned by normalizing the input photos. After that, they are scaled to match in size. Now, eigenfaces can be retrieved from the image data using Principal Component Analysis (PCA), a mathematical method. Following the creation of the eigenfaces, every image will be represented as a vector of weights. Queries can now be entered into the system. After determining the weight of the incoming unknown image, a comparison is made.

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B. Fisherface Method

Because Fisherface aims to increase the separation between classes throughout the training process, it is considered to be a superior face recognition algorithm compared to eigenface and other prominent methods. The Fisherface technique of image identification begins with the Principal Component Analysis (PCA) method's reduction of the face space dimension. Fisher's linear discriminant (FDL) approach, also called the linear discriminant Analysis (LDA) method, is then applied to extract the features of the image characteristic. Fisherfaces algorithm is used in the image recognition process, whereas minimal Euclidean is utilized in the face image identification or matching phase.

IV. PROPOSED FACE RECOGNITION TECHNIQUE USING CNN

The system receives a face image, processes face alignment and detection as depicted in Fig. 1. After that, features are extracted using a feature extractor. In order to do face matching, the system lastly checks the retrieved features with the gallery faces. Face verification (FV) and face identification (FI) are two distinct tasks in face matching.

The purpose of FV is to ascertain if a particular set of face photos or videos are related to one another. FI is a one-to-many matching system that identifies an individual from a collection of gallery face photos or videos featuring various subjects.

Face identification is a closed-set problem since it often assumes the query person has already enrolled in the gallery. Similar to face identification, watch lists have an open-set problem in that they do not ensure that every query subject is registered in the gallery. It is typical to approach FI as an open-set problem in the real world.

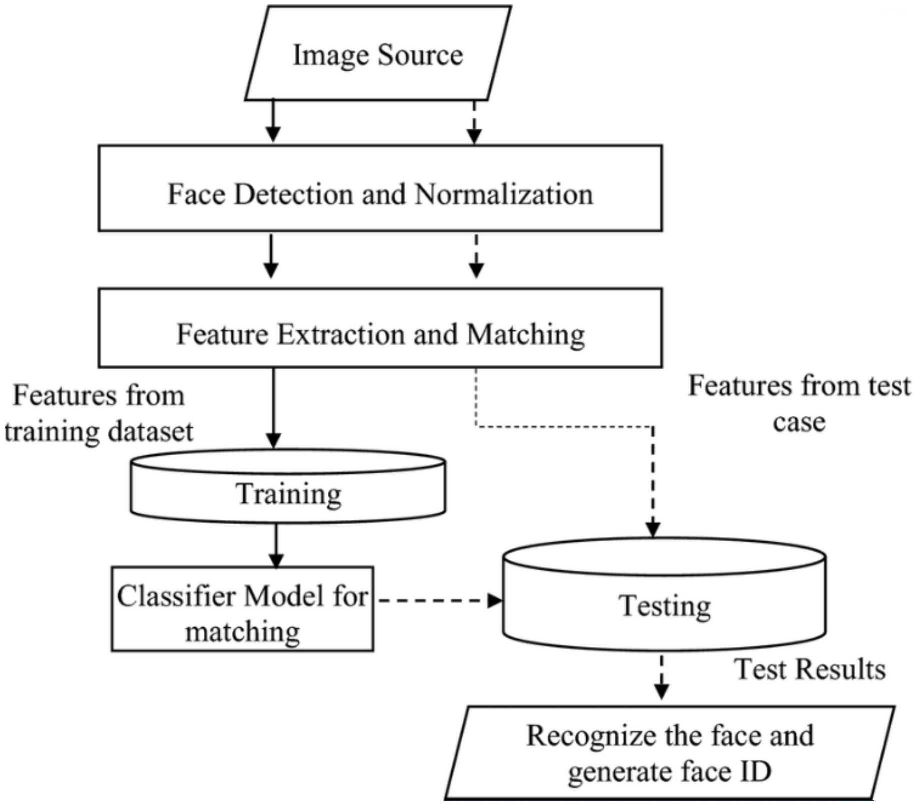

Fig. 1 Flow chart of the face recognition system

The suggested study develops a CNN model that includes input data, network width, and entire connection layer in order to increase the accuracy of face picture categorization. Two convolutional layers (C1 and C2) and two pooling layers (S1 and S2) make up the developed CNN. As illustrated in Figure 2, these layers are placed inversely in the configuration C1-S1-C2-S2.

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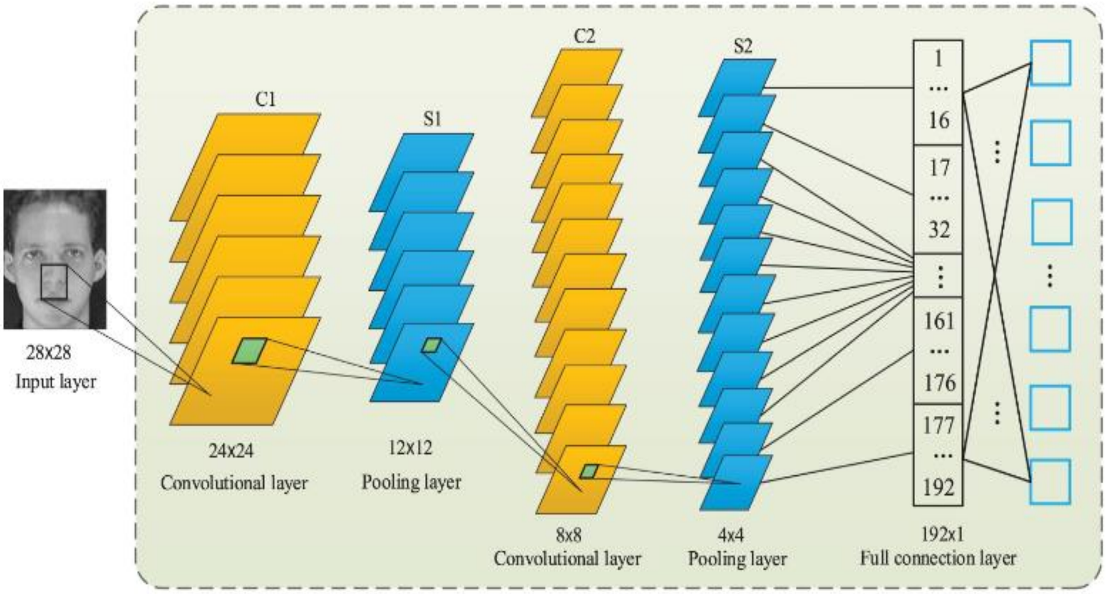

Fig.2 CNN layers used for face recognition

One type of mathematical procedure that is frequently utilized in image processing is convolution. The layer amount of the edge can be ascertained based on the size of the convolution kernel when the convolution process performs edge zeroing for the input picture. Edge zeroing is used to make sure that the output is rational, meaning that the convolution kernel and the input image's components may be weighted and added up in a sequential manner. Furthermore, it is necessary to rotate the convolution kernel 180 degrees around its center, flipping it up and down in the process. It is important to remember that convolution operations can accomplish parameter sharing and sparse multiplication, which can reduce the input data's dimension.

CNN does not need to supply connection weights for every neuron in the input data separately, in contrast to DNN. As with most neural networks used for feature extraction, CNN can actually be thought of as a standard feature extraction procedure. The local connection field of a neuron in the buried layer is referred to as the receptive field in CNN. The primary function of the pooling layers, which are often positioned behind the convolutional layers, is to compress the convolutional layers' output feature data. The enhanced output results after the pooling layer can lessen the chance that the neural network would over fit. Additionally, the image feature can be further extracted by pooling operations without affecting the image's information gathering. In actuality, pooling—which includes mean-pooling, max-pooling, overlapping-pooling, stochastic-pooling, and global average pooling—is a reduction processing of the image. As an example, mean-pooling preserves the relative backdrop by extracting the average value of the feature points, but max-pooling extracts the maximum value of the feature points and improves texture extraction.

The normalized facial image is fed into the CNN model using a single feature map in the input layer. The first convolutional layer, or C1, has six feature maps and convolves each neuron with a randomly generated, 5x5 convolution kernel. Six feature maps are produced by the first pooling layer (S1), which is based on the results of the layer before it. The mean convolution kernel of the matching feature map in the C1 layer connects each element in the feature map, ensuring that the elements' receptive fields do not overlap. The second convolutional layer (C2) and the pooling layer (S2) have 12 feature mappings and comparable computation processes to its predecessors. Moreover, between the S2 layer and the output layer is positioned a fully connected single-layer perceptron. The resultant output is a 40-dimensional vector that is utilized for multi-label classification using the sigmoid function in the facial recognition of 40 different people.

V. EVALUATION RESULTS

An analysis was conducted on the algorithms' comparability. CNN was effectively applied to the dataset, which included 1500 PNG images in 256 x 256 resolutions, with varying intensity and facial expressions, and 100 photographs of each of 15 distinct subjects. It was manually made by filming the subject for a minimum of ten seconds, after which the frames were taken out of the same video.

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It includes a variety of facial expressions, including straight and smiling faces, as well as open and closed eyes, allowing a thorough examination of the pictures. A changing angle from left to right is also used to capture the face position towards the camera. Python was used to implement the code.

Table I Comparison among different Facial Techniques

Technique	Size of Dataset	Accuracy Obtained	Time Elapsed (sec)
Holistic approaches	1500 images	92.4%	115.4
Fisher face	1500 images	93.7%	108.6
Propose CNN	1500 images	98.96%	63.5

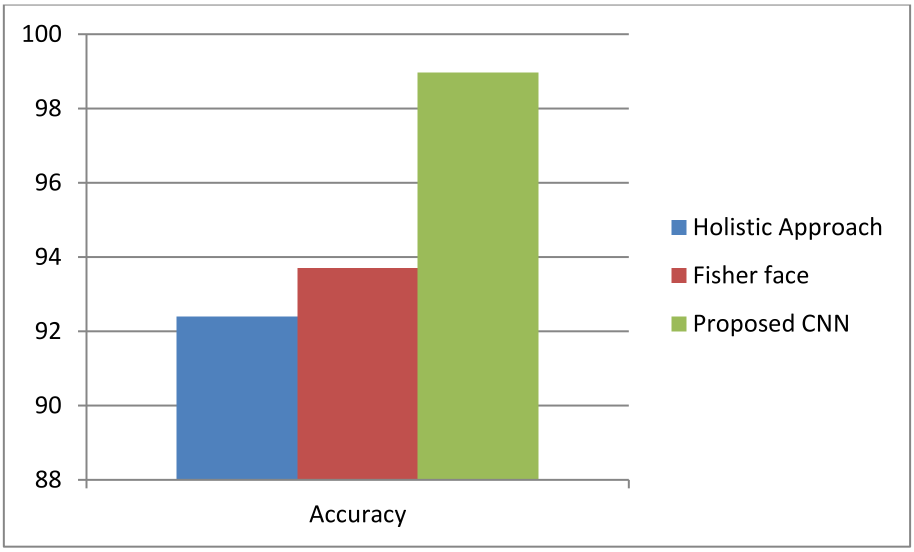

Fig. 3 Accuracy comparison

Even while CNN's accuracy is not perfect, it is nevertheless considered to be the greatest algorithm available for use with the facial recognition approach. Table I and Fig. 3 provide evidence of this. This table presents a comparative analysis of popular facial recognition algorithms, including features like recognition accuracy, time elapsed, and dataset size. It demonstrates unequivocally that CNNs have achieved the highest level of accuracy possible using this method.

VI. CONCLUSION AND FUTURE SCOPE

Convolutional neural networks are demonstrated in the proposed work. Fisher face and other facial procedures like holistic methods are compared. The pooling layer comes after each of the four convolutional layers used in the suggested network for feature extraction. Moreover, the probability distribution is normalized using the Softmax Loss layer. With the generated dataset, the method achieves 98.96% accuracy.

This method can be expanded to accommodate a sizable dataset for wider use. This study would be beneficial in concentrating on the diverse problems and obstacles of the near future. Future improvements to the current neural network-based work could lead to more accurate, realistic, and trustworthy results. Deep Learning is significant because of the comparison it makes to the way the human brain functions.

All three forms of neural networks have a lot of promise for use in their respective domains of application, including pattern recognition, feature extraction, estimation, prediction, learning disclosure, and more. They have a broad range of applications almost in any business where databases are present and forecasts on specific current trends are required. It is undoubtedly going to be very important in the field of artificial intelligence in the future.

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