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Human Face Recognition System Based on Deep Learning

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***Abstract*: For the past few decades, research on human face recognition has been ongoing. Face recognition has grown significantly in popularity as a result of its usage in the processing of biometric information. Its applicability is simpler and its working range is wider than that of other biometric technologies, such as fingerprint, iris scanning, signature, etc. Facial unlocking for mobile devices, criminal identification, and an automatic attendance system are just a few of the many uses for face recognition technology. Due to different face occlusions, different lighting conditions, shifting expressions and the effects of age, face recognition often becomes difficult. To deal these issues, a Deep learning-based face recognition approach has been presented in this paper. The proposed method operates in two phases, face detection and face identification, to provide solution to these issues. Deep learning and OpenCV are used in our suggested VGGFace2 model. Due to its great accuracy, deep learning is an effective and suitable way to do face recognition. To show the efficiency of our suggested facial recognition system, the outcome of experiments has been compared with existing papers.**

***Keywords*: Face recognition, Deep Learning, VGGFace2, OpenCV, Feature selection, Feature detection, Classification.**

1. Introduction

Face recognition is a technique for recognizing individuals based on their facial traits. In recent years, face identification and surveillance systems have both made extensive use of face recognition technology. Facial recognition systems are classified as biometrics since they involve measuring human facial traits. Due to its contact less procedure, it is highly regarded even though its accuracy is lower than some of the previously employed methods, such as fingerprint scanning or iris recognition. It is frequently utilized in video surveillance, automatic image indexing, and cutting-edge human computer interface.

Face recognition became increasingly popular in the early 1990s after the historical Eigenface method was introduced. Holistic strategies dominated the face recognition community throughout the 1990s and 2000s. Certain distribution assumptions, including linear subspace, manifold, and sparse representation, are used by holistic techniques to determine the low-dimensional representation. The issue with holistic approaches is that they ignore uncontrollable facial changes that differ from their presumptions. As a result, in the early 2000s, local feature-based face recognition was created [1]. Local-feature-based face recognition and learning-based local descriptors were first introduced in the early 2000s and 2010s. Learning-based local descriptors, which improve face recognition by learning local filters for improved distinctiveness and the encoding codebook for better compactness, were first developed in the early 2010s. Local-feature-based face recognition and learning-based local descriptors were first introduced in the early 2000s and 2010s. Through the use of Gabor filters and Local Binary Patterns (LBP), as well as their multilevel and high-dimensional extensions, face recognition algorithms have attained reliable performance. Unfortunately, the originality and compactness of handcrafted features were lacking. In the early 2010s, Learning-based local descriptors were first developed to improve face recognition by learning local filters for improved distinctiveness and the encoding codebook for better compactness. In 2014, Facebook's DeepFace and DeepID outperformed human performance in the unrestricted situation for the first time by achieving cutting-edge accuracy on the renowned Labeled Faces in the Wild (LFW) benchmark. Since then, deep learning-based techniques have become the main focus of study. To enable deep face identification, bigger face databases and more sophisticated face processing methods have been created. As a result, the LFW (Labeled Face in-the-Wild) performance continuously increased from roughly 60% to above 97 % due to representation pipelines.

Since the innovations of the DeepFace and DeepID approaches in 2014, deep learning technology has changed the face of facial recognition research. Deep face recognition algorithms, which use the hierarchical design to learn discriminative face representation, have since significantly improved state-of-the-art performance and spawned a large number of fruitful real-world applications. Deep learning employs numerous processing layers to learn representations of data with various levels of feature extraction. Classify different face recognition techniques starting from the type of data which can be used for its analysis to the point where we can differentiate among different deep learning models which are actually used for it as shown in Figure 1.

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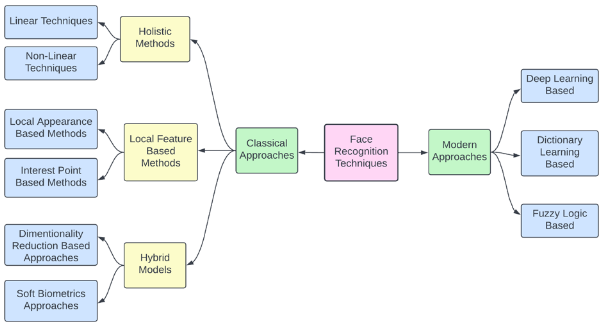

Fig. 1. Classification of various face recognition models

This paper proposes a novel model for face detection and face recognition. Face detection is used to locate the facial region and then face recognition is used to identify the person's identity. A custom database is created which comprises of the images of well-known celebrities and when a particular person matches with one of the faces stored in our database recognition is said to be successful.

The review of the literature is found in Section 2. The Proposed process is described in Section 3. In section 4, an algorithm is discussed. The comparison of the experimental results with existing works is covered in Section 5. Section 6 puts an emphasis on the conclusion and future application.

2. Literature Review

This section provides a summary of the different facial recognition studies that have been conducted. Additionally, emphasize the numerous conclusions that can be drawn from the research papers examined.

[1] In this paper, progressing PC system has been presented that can discover and follow a subject's head, and after that see the person by differentiating characteristics of the face with those of known individuals. Their investigations show that the eigenface framework can be made to perform at high precision, regardless of the way that with a liberal "cloud "rejection rate and in like manner 3 perhaps fitting to these applications.

[2] In this paper, authors have suggested a two-dimensional issue. Working on the face is done by PCA technique. Faces are encoded in this paper and are made using eigenface systems which are eigenvectors. PCA technique is used by the Eigen Face system for affirmation of the photos. This structure works by ramping up to many facial spaces that show the fundamental differences between the recognized facial images, for pre-vacuum facial images. [3] This paper is a phase towards structure up a face affirmation system which can see static pictures. Everything considered the dynamic pictures got from the camera would initially have the option to be changed over in to the static ones and a short time later a comparable strategy can be associated on them.

[4] This paper presents a strategy for facial identification that relies on an information-theoretic approach of encoding and unraveling facial images. The proposed framework is a two-step relationship. Feature extraction using the rule part test and confirmation using the feedforward stimulus neural network. Numbering started with 400 images (40 classes). The confirmation score for the test part is determined by considering virtually all types of feature extractions.

[5] This paper has adopted generic Masked Face Recognition and has contributed in improving the accuracy of Masked Face Recognition methods. Important aspects that directly affect Masked Face Recognition systems like image pre-processing, face detection, feature extraction; face restoration and unmasking; and verification and identity matching has been reported in this paper.

[6] System in this paper is used to confirm attendance in the class. Face recognition accuracy in a class of 35 students is approximately 97% when consistently similar conditions (illumination, occlusion, etc.) are used for image capture.

[7] This article outlines the requirements of the latest facial recognition pipelines and focuses on the pipeline stages for building a framework from scratch. Its hybrid capabilities allow you to switch models between the latest facial recognition models. This allows programmers to customize human-level facial recognition tasks with just a few lines of code.

[8] This paper presents a fast face recognition model which utilized the concept of local binary pattern. In this, authors test this model on three databases.

[9] This Paper has introduced a new deep learning technique, called the Local Binary Network. Accuracy achieved by them is 96% on the FERET dataset and 97% accuracy on the Labelled Faces in the Wild dataset with the same topology as the convolutional neural network.

[10] This paper has implemented a method that helps to solve recognition problems with different parameters like illumination, and expressions. This method is based on two methods, Local Binary Pattern and Artificial Neural Network. LBP is used for face recognition because it is invariant to the rotation of the target image. Authors achieved an accuracy of 87% on the LFW and 98.56% on the CMU Pie dataset.

[11] Authors has proposed a new facial recognition method based on the Laplace filter and the Gradient descriptor by Pyramid Histogram. In addition, support vector machines are used with various kernel features to study face recognition issues. He has applied this dataset on LFW and achieved an accuracy of 88.50%.

[12] Authors has proposed a variant of the Local Binary Pattern method called Multiscale Local Binary Pattern (MLBP) for feature extraction. Other type of extension is the Local Ternary Pattern technique. He has applied this technique on AR And FERET Dataset and achieved an accuracy of 86% and 95% respectively.

[13] Authors considered existing face recognition methods with occluded faces only. Approach created is divided into three features i.e., occlusion feature detection, occlusion feature extraction.

[14] To support face spoofing research, the author of this article presents a multimodal face spoofing dataset called CASIASURF. Their dataset contains 23,000 videos recorded by 1,500 subjects in red, green, blue, depth, and Interventional Radiology modality.

[15] This paper introduces an old system of face recognition model i.e FaceNet. This system uses a deep convolutional

neural network that optimizes the model. The team trained the model using convolutional neural network in a CPU cluster for 1,500 to 3,000 hours. Next, Evaluation was done using 4 datasets. FaceNet achieved 99.33% accuracy on Labeled Faces in the Wild (LFW) dataset and 97.45% accuracy on the faces provided by YouTube database.

[16] This paper contains embedding methods used for recognition to achieve high accuracy. These methods work by taking an image at a time of the face and stores the face data in a potential space. This is due to missing or ambiguous facial features in the image.

[17] This paper presents new VGGFace2 dataset which contains images which have a wide range of variations in the form of poses of person, age, ethnicity and illumination. Finally, there are 3.81 million images and 9,532 subjects.

[18] In this paper they have introduced the usage of support vector machine to recognize a Cambridge ORL face dataset that consists of 400 images of 40 people and has fairly high levels of variation in facial expressions, poses, and facial details. The accuracy of this algorithm was 92.69% and the minimum error rate for SVM was 9.19%.

[19] Galea and Farrugia present a deep neural network to compare the machine-generated sketch to facial images by using morphed faces along with transfer learning.

[20] Bashbaghi used a deep learning architecture based on triplet loss function for single face recognition in video surveillance dataset. The proposed model works well in the detection of a single image per person. The architecture is categorized into two parts- first triplet-loss function-based deep CNN model, and second, deep autoencoders. The results showed that CCM-CNN and CFR-CNN provide an impressive recognition performance over low computational cost.

[21] Ranjan provide a detailed overview of designing and implementing deep-learning frameworks for face recognition. Author talks about the dependencies present in large datasets, cost controlling and complexity handling of the algorithm and handling data degradation and bias training which may be present in the face recognition process.

[22] Peng developed a re-ranking based high-dimensional deep representation for face recognition. The presented model created a feature space by concatenating and extracting deep features from face patches through a convolutional neural network (CNN). A unique linear re-ranking framework is used to refine the ranking outcomes presented earlier, which analyze the important data from the initial ranking-based results.

[23] Galea and Farrugia present a deep neural network to compare the machine-generated sketch to facial images by using morphed faces along with transfer learning. First, a Deep CCN is trained with the help of transfer learning, further it is used to identify the identity of sketch with facial photos. Second, a 3D morphed model is devoted to incorporating both machine-generated face sketches with identified facial photos generated earlier.

[24] This paper proposes a new method called the Multi Degradation Face Restoration model. It restores a formalized high quality facial image from a specific facial image with odd poses and low elements. The model shows that an image with a tilt angle of 30-45 degrees has a face recognition rate of 98%. Among the findings from the studies cited above are: According to [1], the majority of previously developed models are only trained on celebrity face data like LFW, VGGFace, and Facebook Dataset; as a result, they can only identify celebrities on that dataset.

From [25],[26],[27],[17] it can infer that most of the previous works on the LFW dataset provide more than 90% accuracy, these models are based on the latest techniques such as ImageNet but they have setbacks as they are very complex models. These models are usually made of more than 30 sequential layers due to which they cannot be operated in a regular system and need very high specifications in terms of graphic Card and RAM, which is generally not present in our systems.

In this paper authors have created a Customized Lightweight model using Hybrid techniques. The proposed model is not dependent on the size and extensions of the image. Being the lightweight model can be run on regular systems and provide an accuracy that is close to these models and can be successfully deployed in real-world applications such as Attendance systems and security systems. Proposed customized dataset allows to recognize any person whether they are celebrity or not.

3. Proposed Face Recognition Process

Face recognition is a technology which can match a digital image or face with the database of a system and can easily help in identification of the person. Its applications include surveillance, security systems and attendance systems in universities. Generally, Deep Learning model select features from a person image which can distinctly classify a face from among others. The proposed model is presented through Figure 2 and explained in three mentioned below phases.

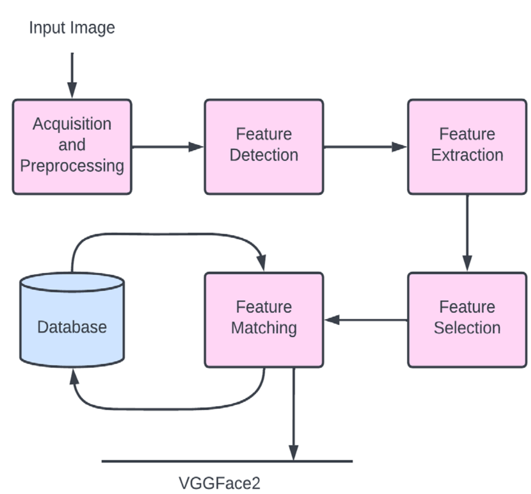

Fig. 2. Deep learning-based face recognition model

1. Preprocessing and face detection: First the image will be loaded into the system and converted into grayscale so that it could be fed into a DNN face detector. The detector gives the coordinates of the face in the image. After that, image is cropped according to these coordinates and then the cropped image is downloaded into our system. This process is done for each image present in dataset.

2. Feature Extraction and Feature selection: This Phase is implemented through VGG face model. It is a 16-layer model which is pre-trained on the VGGFace2 dataset which contains 3 million images. The VGG model converts an image into image embedding's using different facial features. These embeddings are then fed to customized model for further classification.

3. Feature Matching: In this Phase, the image will be classified using a customized deep learning model. This model takes inputs in the form of embedding's which were given by the VGG model and are further classified according to the training dataset on which the customized model was trained. The output of this model will be the image with the highest matching features.

4. Proposed Algorithm

The proposed model in consists of 5 distinct steps which were used to create and evaluate our model are mentioned below:

1. Dataset Creation: VGG Face is a dataset that contains 2.6 million photos of faces from 2,622 individuals and is used to develop face recognition system. Majorly, the images Celebrities, public figures, actors, and politicians make up the database collection. Their names were selected "by extracting males and females, ranked by popularity, from the Internet Movie Data Base (IMDB) celebrity list."

For custom face detection, A dataset of 5 public figures namely our prime minister Narendra Modi, Vladmir Putin, Neeraj Chopra, Angela Merkel and Xi Jinping has been created.

2. Preprocessing: Images which are fed into the model needs preprocessing to improve its accuracy and also to remove some noise from these images. The main steps of preprocessing are conversion of images into gray scale, getting face coordinates using MMOD face detector, Cropping the image according to the face coordinates and downloading the image in our system using cv2.

3. Model Creation: Model is created having input image of size as 224 x 224 and with 16 layers. The proposed model in image detection contains an 8-layer model having same activation function as VGG model.

4. Data Preparation: For each training and testing image fed that image to vgg166 model that have made earlier, the output of the model is image embedding that can stored in the python list. Then created two different list one for training and one for testing data and finally store the embedding on training list. This Python list has been transformed into a NumPy array so that it may be used as an input for our classifier model.

5. Model Training: Train the classifier model with test data as validation data.

Custom Face Recognition: For checking the model, random images of celebrities are provided to detector to extract the faces of celebrities. Then, extracted faces are fed to the classification model which successfully recognizes faces.

5. Results and Discussions

In this paper, approach is implemented on python with a system having 8 GB RAM, NVIDIA GeForce 1050 ,Intel i5 Processor, windows 10 operating system and VGGFACE2 dataset which contains 2.5 million images The performance of project is evaluated on 3 parameters namely: Accuracy , True positive rate, False Positive rate. The Visual results of proposed model are also presented in this section.

1. Accuracy Results: It is the ratio of number of correctly recognized images to the total number of input samples.

$$\text{Accuracy} = \frac{\text{M}}{\text{N}} = \frac{\text{Correct Recognized Images}}{\text{Total Test Images}} \tag{1}$$

Using equation 1, accuracy of proposed model which comes out to be 98.7%.

2. True Positive Rate (TPR) Results: TPR is the ratio of correctly identified cases to the total number of true cases determined.

$$\text{TPR} = \frac{\text{True Positive(TP)}}{\text{Actual Positive}} = \frac{\text{TP}}{\text{TP+FN}} \tag{2}$$

Using equation 2, True Positive Rate of proposed model which comes out to be 0.623.

3. False Positive Rate (FPR) Results: The FPR, or fall-out, is the ratio of falsely identified cases to the total number of false cases determined.

$$\text{FPR} = \frac{\text{False Positive(FP)}}{\text{Actual Negative}} = \frac{\text{FP}}{\text{TN+FP}} \tag{3}$$

Using equation 3, False Positive Rate of proposed model which comes out to be 0.05.

Table 1
Results of proposed model

Evaluation Parameters	Experimental Results
Accuracy	98.7%
True Positive Rate	0.623
False Positive Rate	0.05

The results of proposed method are presented in Table 1. It can be seen in table 1 that proposed VGGFACE2 model was able to achieve 97% accuracy on Labeled Faces in the Wild Dataset. Custom Deep learning model was successfully able to recognize and classify faces in single as well as multi faced images.

4. Visual results: The visual results of proposes model has been extracted and shown in three different scenarios – namely-single face recognition, Double face recognition, Multi face recognition.

The training results of proposed model by recognizing faces in single face, double face and multiple face scenarios in Figure 3, Figure 4, Figure 5 and Figure 6 respectively.

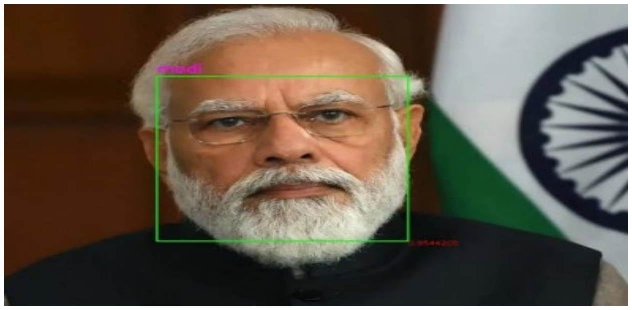

Fig. 3. Single faced Recognition - Scenario 1

The visual results under single face recognition scenario are displayed in Figure 3. It shows that proposed model successfully recognizes single faced images with high accuracy.

Fig. 4. Double Face Recognition - Scenario 2

The visual results under double face recognition scenario are displayed in Figure 4. It proves that proposed model achieved double face recognition with high accuracy.

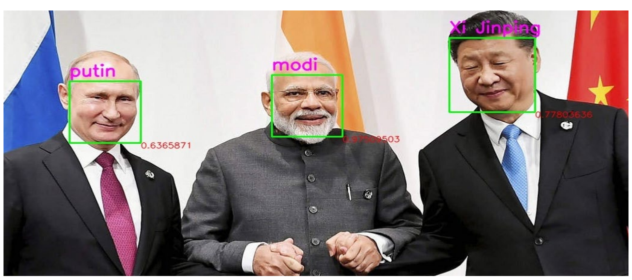

Fig. 5. Multi-Faced Detection - Scenario 3

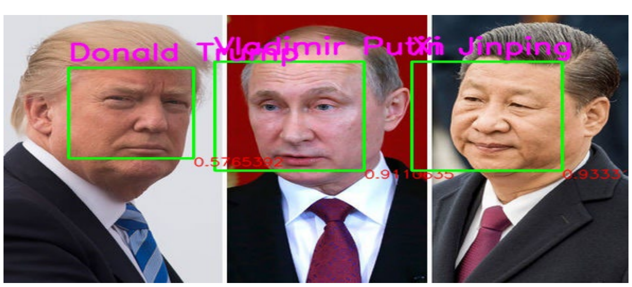

Fig. 6. Multi-Faced Recognition - Scenario 3

The visual results under single face recognition scenario are displayed in Figure 5 and Figure 6. Proposed model can successfully recognize more than two faces in the image with high accuracy. The evaluation results of proposed Deep Learning based Face Recognition model has been discussed in Table 1. For a model to be viable its accuracy should be greater than 90%. From the Table 1 and visual results, it can be said that proposed model perform efficiently and successfully recognizes single as well as multiple faces from the images.

6. Comparative Accuracy Results: Accuracy results of proposed model have been compared with three existing methods [35], [36], [37]. The comparison results are shown in Table 2.

Table 2
Accuracy result comparison of proposed model with existing schemes

References	**Method**	Architecture	**Accuracy**
[28]	DSPGM	ISRM	95.2%
[29]	AFW	CNN	75.29%
[30]	CCL	ResNet 27	98%
-	Proposed Model	**VGG16**	**98.7%**

The proposed model has better accuracy than existing method [28], [29], [30] are shown in Table 2.

It can be concluded that accuracy results are seems to be good and are acceptable and can be used in a number of different applications.

6. Conclusion

Firstly, the present paper investigates the work done in the field of human face recognition. With this, an effort is presented in the form of proposed face recognition model that is efficient. The performance of proposed model has been evaluated and discussed in results and discussion section. The accuracy results of proposed has been compared with existing work and found better than several benchmark models. It can be seen from visual results that proposed model was able to successfully recognize single faces as well as multiple faces from images. In other words, proposed model performs efficiently and can be used in variety of applications.

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