



Face Recognition Using Transfer Learning by deep VGG16 model

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Abstract : In computer-aided detection (CAD) Face Recognition is a vital issue, this paper presents a novel and efficient face recognition technique using VGG16 working on the principle of Transfer Learning. JPEG, GIF, and PNG image forms are used to investigate these issues, and they require skill to discern facial activity. This paper essentially centers on designing a CAD model which performs face recognition of 15 subjects, each subject with 11 images per subject, the facial expression include images with glasses, without glasses, happy, sad, sleepy, surprised or wink. The classification problem, used to differentiate among all these different set of categories. The suggested Classification model is motivated by the concept of Transfer Learning, and it employs a deep pre-trained VGG-16 architecture to extract features from GIF images, as well as a deep learning method with a Softmax layer acting as a classifier. The experiment is carried out by comparing two configurations one with normal VGG architecture and other with Customized Fully Connected Layer in VGG architecture. The methodology recorded test accuracy of 83.11% using first customized configuration and 92.80% accuracy with second customized configuration.

Keywords - Transfer Learning, Face Recognition, FRS, VGG16, GIF, Computer-Aided Detection, Classification Model, Yale dataset.

1. INTRODUCTION

Face identification has since become a prominent research subject, because of a boom in interest in biometric security systems in general, but also because of recent advancements that have improved the state-of-the-art far beyond early attempts at employing direct photo comparison. The very first facial recognition technology has been in development since the early 1970s. Due to computational limitations, the system is unable to meet the users' need for real-time identification of passport photographs. Face recognition algorithms were proposed at the beginning of the 1990s, which increased the demand for face detection. Face recognition has gotten a great deal of focus, and not only engineers but also neuroscientists have been working on it, because it has a wide range of uses in computer vision communication and automated access control systems recognition [1]. It has always been a difficult topic in the field of image processing and computer vision, and as a result, it has gotten a lot of attention in recent years. On the one hand, its applications are quite valuable in a variety of fields. However, given to the large number of settings in which a human face could be found, it has always been challenging to apply. Because face detection is the initial stage in automatic face identification, it is a critical element of face recognition. Due to various factors in picture appearance, such as posture (front, non-1.1 Checking the PDF File front), Face identification is difficult due to image orientation, lighting conditions, occlusion and facial expression. Face detection [2] is a technique for identifying persons in pictures and movies. In a facial recognition system, as well as in our regular social interactions, the face, which plays such an important part in transmitting our identity and emotion, is our primary center of attention. Despite the many differences in look that a face might have depending on the situation, Face Recognition systems have been constructed based on a variety of ways to detect faces, however they do not equal human ability to recognise faces. Humans have a remarkable ability to recognise other people's faces. We can recognise thousands of faces learned throughout our lives and recognise familiar faces at a glance even after years of separation, despite large changes in the visual stimulus due to viewing conditions, expression, ageing, and distractions such as glasses or changes in hairstyles or facial hair. A face recognition system (FRS) is a computer programme that recognises or verifies a person based on a digital image or a video frame from a video source.. The Face Recognition System (FRS) uses proposed methods to match a face image or image sequence includes photos of people in the database[3].

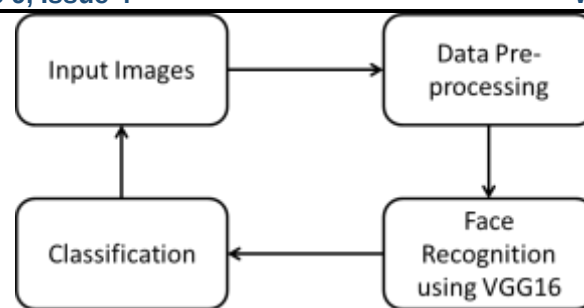


Figure 1: Represents the flow of Face Recognition System

To improve the accuracy of these technologies, face recognition is being utilised in concert with other biometrics such as speech, iris, fingerprint, ears, and gait recognition. The human brain, on the other hand, has a limit to how many people it can accurately "remember." A computer system's ability to manage vast amounts of face images is an important feature.

The invention of a powerful high-accuracy recognition system is the research's key contribution. Two alternative VGG16 configurations are employed in this study: one employs the normal pre-trained VGG16 architecture with the Softmax classifier, while the other uses the VGG16 architecture's fully connected layer.

In this study, the general framework of the face recognition process is separated into four sections. It starts with photograph input and moves on to pre-processing in the second stage: Stage 3 entails color space conversion and photo scaling, followed by feature extraction using the Deep Convolution Neural Network (CNN) VGG16 and face feature extraction, and finally categorization of the extracted feature set. Softmax Classifier is used in the final stage of our system to classify the various classes of images, which is classification based on face categorization using Transfer learning [4].

This paper is organised as follows: Section 1 contains background information on facial recognition, followed by Section 2 which contains state-of-the-art work done in the field of facial recognition in the past. Section 3 depicts the proposed technique, dataset description, and pre-processing used in this study. All of the experimental data and comparisons with relevant work are presented in Section 4. The conclusion is presented in Section 5.

2. RELATED WORKS

Various CAD approaches have been offered throughout the years, and a few researchers have used a variety of Machine Learning, Deep Learning, and Hybrid algorithms for Facial Recognition categorization. Listed below are a few of the papers:

Meena Prakash et al. describe a transfer learning-based Convolutional Neural Network-based automatic facial recognition algorithm (CNN). On the huge ImageNet database, the pictures from the face database are trained using a CNN with weights learned from a VGG-16 model that has already been trained. Yale and AT&T, two publicly available face image datasets, were used to evaluate the approach, with accuracy rates of 98.7% and 100%, respectively [5].

Saad Shakeel et al. developed an age-invariant face recognition system based on deep feature training and discriminative models. AlexNet is utilized as a transfer learning CNN model to learn high level deep features in this research. These characteristics are then stored into a higher-dimensional code word that can be visualized in a code book. Face images taken at different times of the same person have comparable code words thanks to the encoding method. For facial recognition, a linear regression-based classifier is utilized, and three datasets are used to test the system as well as the publicly accessible FGNET. The model's accuracy was 94% [6].

Wu et al. Max-Feature-Map (MFM) was offered as a unique activation function for use in their proposed light-CNN model. By reducing parameters and speeding up the computational process, the light CNN framework was able to construct a robust face representation on a noisy labelled dataset [7].

Perdana and Prahara describe a well-lit-Convolutional Neural Network for face recognition with a small dataset based on a modified VGG16 model. Despite the fact that the suggested light-CNN is modest, it performs admirably, with 94.4 percent accuracy[8].

Sun et al. were inspired to use deep neural networks to solve face recognition difficulties. This project modified VGGNet and GoogLeNet to make them suitable for facial recognition. On the LFW face recognition dataset, the result achieves 99.53 percent accuracy and 96.0 percent accuracy in LFW rank-1 face identification [9].

Parkhi et al. Construct a VGG network containing 2622 identities created from 2.6 million photographs retrieved from the internet, then fine-tune the model with a triple-based metric learning method like FaceNet, which achieves an LFW accuracy of 98.95 percent. [10].

Zheng and Zu offer a LFW implements a normalised light-CNN with 11 hidden layers that achieves a face verification accuracy of 98.46% [4].

A. Krizhevsky proposed AlexNet in 2012, and it won the first prize in the ILSVRC 2012 classification task. Deep learning was then gradually adopted in a variety of artificial intelligence applications, including facial recognition[11].

Sukhbaatar et al. To depict a class-dependent noise distribution, employ multi-class classification. They present a bottom-up noise model for altering back-propagation label probabilities, before feeding data, as well as a top-down approach for doing so given noisy labels [12].

Mnih and Hinton provide two strong loss techniques for noisy label aerial photos. However, their method is restricted to binary classification [13].

Li et al. suggested a two-stage hierarchical learning approach. Face recognition starts with the extraction of discriminative features from face image microstructures, which are then converted into integer codes[4].

In some variations of the random sampling LDA technique were developed to address the face ageing problem in face recognition. They've been shown to be significantly more robust than previous approaches, with fewer parameters and training data limits, and they've delivered superior results [14].

CNNs are frequently recognized as trustworthy feature extractors in modern face recognition systems. DeepFace [5] is a face verification system that uses CNN as a feature extractor and was trained on 4.4 million face photos. On LFW, it obtains 97.35 percent accuracy with a 4096-D feature vector [15].

Face recognition is a widely used method of verifying and identifying individuals. Face features can be utilized in a variety of ways to identify people. The goal of this study is to develop a deep CNN architecture that can be implemented with less data by changing an existing architecture, VGG16, and building a new face recognition architecture based on its design. The implementation of the proposed CNN model will be explained in the next section.

3. METHODOLOGY

We have chosen popular Deep Convolution Neural Network architecture that is VGG16. VGG16 is a pre-trained architecture used on the ImageNet dataset which constitutes of millions of images distributed among thousands of classes, the weights of the VGG16 are used and the architecture of VGG16 is customized to make a new architecture for performing classification in face recognition.

3.1. DATA COLLECTION

In the Yale Face Database, there are 165 grayscale GIF images of 15 distinct people. Each theme has 11 photographs, one for each expression or facial configuration: center-light, with glasses, happy, left-light, without glasses, normal, right-light, sad, sleeping, shocked, and wink. The 64MB collection contains 5760 single light source photos of 10 different topics shot under 576 different viewing situations [16]. The researcher stated this figure 2 in his study Face Recognition using Convolutional Neural Network and Simple Logistic Classifier, and this image was derived from it [29].



Figure 2: Represents the sample images of Yale Face dataset [29]

3.2. DATA PREPROCESSING

The images in the Yale dataset were 176x208 pixels, and the VGG-16 model was created with high-scale image recognition in mind, i.e. RGB colour images with a rectangle as the input shape (224, 224, 3). However, the dataset contained grayscale images, so the photos were preprocessed as described. With intensity values ranging from 0 to 1, the photos were standardized [17]. In this study, the intensity values were scaled using the Min-Max Normalization approach, followed by decreasing the photographs to one size for all of the images with 224x224. The Yale dataset has several classes with a small number of photos, resulting in unbalanced data and a model that didn't perform well. To address this, we employed image augmentation to boost the number of samples by reproducing the images in 90°, 180°, and 270° angles [18].

3.3. TRANSFER LEARNING

The term "transfer learning" refers to a method in which a model proposed for one job is utilized as a starting point for a different task. TL is a wonderful strategy in which models that have been transmitted on large data, models with similar weights, are used as a starting point for processing another problem with less data and improving the task's hypotheses [19]. In our study, an image dataset is utilised as input, with feature extraction based on the principle of transfer learning and a Softmax classifier employed to solve the classification or face recognition problems. VGG16 architecture is a widely perceived pre-trained model for image classification. The models were trained using the ImageNet dataset, which contains hundreds of thousands of photos with thousands of classifications. The models employ transfer learning, in which the pre-trained weights of the model architecture are used to categories other target datasets [20].

3.4. FEATURE EXTRACTION USING DEEP CNN ARCHITECTURE

It takes a long time and a lot of resources to develop Deep convolution neural networks over a huge dataset. Reusing the model weights from pre-trained models that have been constructed as benchmarks on large datasets, such as the ImageNet dataset [21], is the greatest option to decrease computational feasibility and time. Models for computer vision can be downloaded and used immediately, or they can be merged with classifiers to generate new models. The output of a model from a layer before to the output layer is utilised as an input to the new classifier models in this study, as is the output of a model from a layer prior to the output layer. The pre-trained models are used to extract features from new pictures automatically. The image characteristics that are extracted could be a vector of integers that the model uses to describe a specific feature in the image [22].

Despite the fact that there are other high-performing image recognition models, we will use one of the best categorization models:

- **VGG16:** A deep convolutional neural network, which is commonly employed in the field of photo identification, scored 92.7 percent top-5 test accuracy in the ImageNet dataset, which has 14 million pictures belonging to 1000 classes. The network includes 41 layers in total, 16 of which have learnable weights: 13 convolutional layers and 3 fully connected layers, and it accepts images with dimensions of (224, 224, 3)(224, 224, 3). Figure 3 [23] shows the VGG-16 design, which has 138,357,544 parameters.

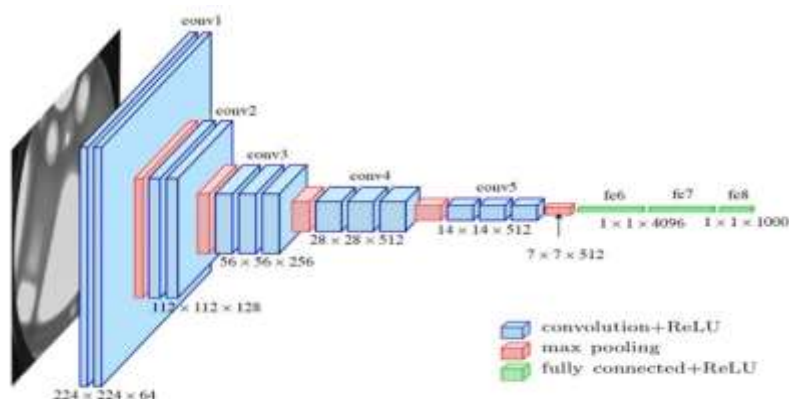


Figure 3: Represents the VGG16 architecture

- **Face Recognition using Transfer Learning with VGG16:** When a machine learning model has already been trained to handle a different but related problem, transfer learning is applied. We strive to apply what we've learned in one activity to improve generalisation in another through transfer learning. A network's learned weights are transferred from task A to a new level, but similar, task B. Transfer learning is extensively utilised in sentiment analysis and other computer vision and natural language processing applications. since it requires a lot of CPU computing power [5].

3.5. PROPOSED SYSTEM METHODOLOGY

The image classification framework's performance is determined by the picture feature combinations and the classifier model utilised. There are two distinct designs for the classifier models have been suggested in this paper for Yale dataset where in 1st configuration only newly added layers have been trained using YALE dataset and remaining layers were frozen while training and in 2nd configuration last 3 convolution layers have been unfreezed and trained them along with the newly added layer on Yale dataset. On top of the std. VGG-16 model, new layers have been added for fine tuning so that it may be used for intended task of face recognition. With the help of customized VGG-16 architecture, higher accuracy has been achieved on YALE Face Dataset using Transfer learning along with Hyper-parameter tuning. Figure 5 illustrates the customized architecture.

The suggested system design is depicted in Figures 4 and 5. The study in this paper compares the standard VGG16 architecture to the modified VGG16 design. The following steps were taken to construct a face recognition system utilising VGG-16 and transfer learning:

- Keras apps with Tensorflow as the backend are used to load the VGG-16 model and its weights. Because include top is False, the output layer isn't included. After that, the layers are frozen.
- New layers has been append on the top of VGG-16 model for fine tuning so that it can used for intended task which is face recognition. It can be seen in Figure 5.

3.6. SOFTMAX LAYER

The Softmax layer provides output by using the Softmax algorithm to activate the net input from the previous layer. The Softmax function, like a sigmoid function, squashes each unit's outputs to a range of 0 to 1. However, it divides each outcome so that the total number of outputs equals one. The Softmax function gives a categorical probability distribution, indicating the probability that any of the classes is correct. As a result, Softmax is employed as an activation function in Deep Neural Networks at the output node.

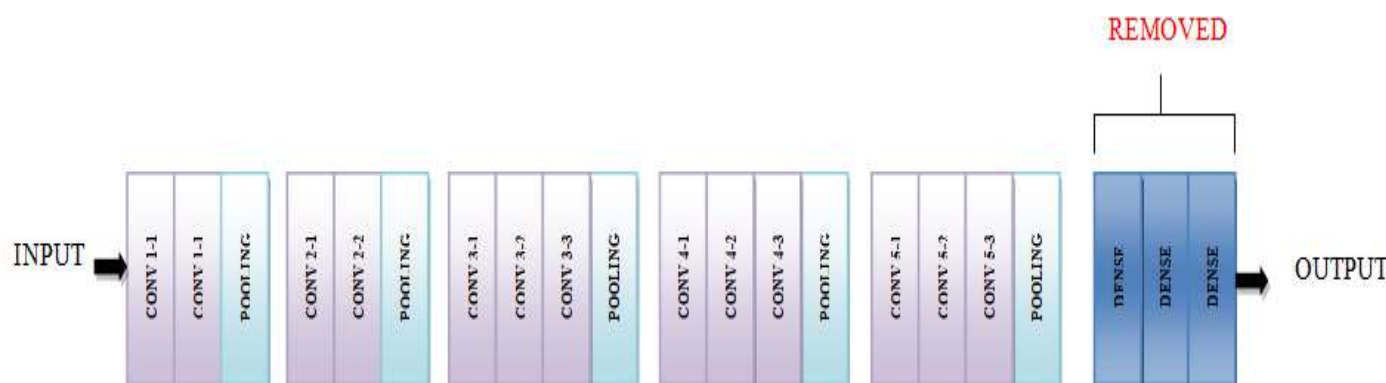


Figure 4: Leave out the “top portion” of the model (the Fully-Connected layer).

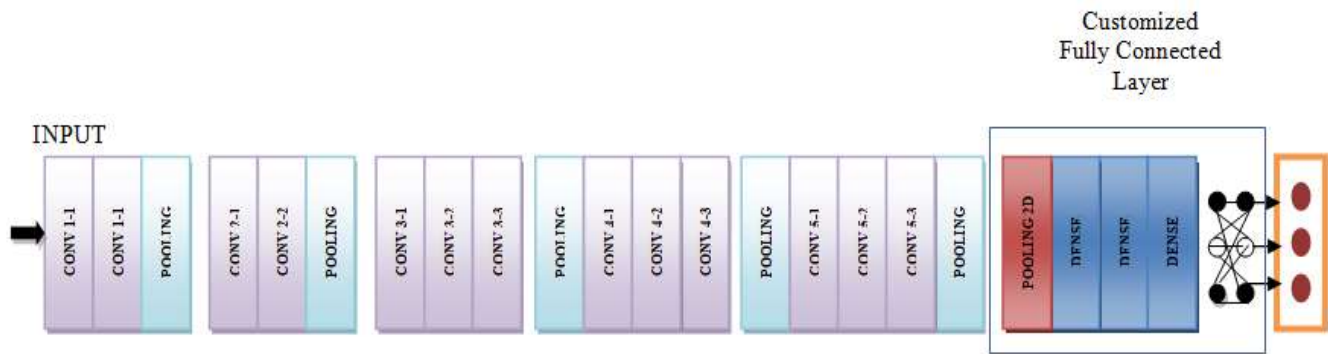


Figure 5: Adding New layers on the top of std. VGG-16 model

4. RESULT ANALYSIS

The performance measures specified for the evaluation of the classifier model will be discussed in this section of the article. The quality metric utilized to do facial recognition is accuracy. Two variants of customized VGG-16 have been applied on Yale Face Dataset. 83.11% accuracy has been achieved on Yale dataset using 1st configuration where only customized fully connected layers have been trained and 92.80% accuracy has been achieved using 2nd configuration of customized VGG-16 model in which last 3 convolutional layers have been unfreeze and trained them along with the newly added fully connected layers.

Table 1 Test score

Training Models		
	Customized VGG-16 (1 st Configuration)	Customized VGG-16 (2 nd Configuration)
Test Accuracy	83.11%	92.80%

4.1. 10 FOLD CROSS VALIDATION ANALYSIS

We utilised the 10-fold cross validation approach to see how well our models performed on new data that had not been used during the training period. On average cross validation score of the implemented methods is shown in the Table 1.

Table 2 Validation Score

Training Models		
	Customized VGG-16 (1 st Configuration)	Customized VGG-16 (2 nd Configuration)
10 Fold Cross Validation Accuracy(avg.)	81.73%	91.13%

4.2. COMPARISON WITH RELATED WORK

On the Yale dataset, the proposed framework is compared to all existing face recognition algorithms that use machine learning, deep learning, or hybrid tactics. Table 1 displays a comparison of facial recognition frameworks. Our framework beats state-of-the-art frameworks, according to the findings. Because accuracy is a common measurement utilized in all relevant works, Table 1 simply designates it as a performance metric.

Table 3 Comparison between predefine and proposed method

S. No	Author	Method	Accuracy
1	Sirovich et al [25].	PCA	64-96%
2	Kim et al[26]	kPCA	83.3%
3	Xu et al [27].	Coupled Auto-Encoder	86.5%
4	Yang et al [28].	2d-PCA	84%
5	Saad Shakeel et al.[6]	AlexNet	94%
6	K. Alhanaee et.al.[30]	GoogleNet	93.33%
7	Proposed model	Customized VGG-16	92.80%

5. CONCLUSIONS AND FUTURE SCOPE

In the last 20 years, Face recognition technology has progressed significantly.. For secure transactions, surveillance, security, and building access control, identifying information can now be reviewed automatically. These systems are widely used in controlled conditions, and recognition algorithms may benefit from environmental constraints. The next generation of face-recognition technology will be widely employed in smart surroundings, where computers and robotics will function as supporting assistants. Face recognition systems are also being used as a result of the COVID-19 epidemic. According to observation, we may develop a model that outperforms a custom-written CNN using various Transfer Learning methods, such as Fine-Tuning. When you don't have a lot of data, transfer learning is a good place to start when building a model. Pre-training a model on a trustworthy task that can be easily adjusted to tackle a similar target problem is required for transfer learning. It's straightforward to use because to the Keras API. By fine-tuning a portion of the pre-trained layers, model performance can be considerably enhanced.

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