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Face Recognition for Person Identification Based on Deep Learning Techniques

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Abstract:

Face recognition is a technology that enables the identification and verification of persons. Smart cards, security information, access to restricted places, law enforcement by various agencies, and surveillance technology have all utilized this technology. The traditional face recognition methods usually consist of capturing data, pre-processing the database, extracting features, matching features, and finally getting recognition results. The existing face recognition techniques have performed each step separately, and these techniques have not worked on large databases very well. Deep learning has recently gained popularity due to its exceptional performance in the facial recognition field over previous approaches. In this work, we used the modified CNN with VGG16, VGG19, and ResNet50 transfer learning models for recognizing faces. First, we collect the face KVKR database in the multimodal biometric lab of the department of CS & IT in Aurangabad. The face data collected ten positions of the face such as the frontal face, left 90 and 60 degrees, right 90 and 60 degrees, chin up chin down, small smile, big, small, and closed eyes, etc. Then, we use data augmentation techniques to artificially increase the database size and improve the performance of our system. Finally, we apply VGG16, VGG19, and ResNet 50 with a modified CNN model using transfer learning for face recognition. This work compares Pre-train models VGG16, VGG19 and ResNet50 with CNN. We have got in VGG16 with CNN model in KVKR face database good performances 99.28% recognition accuracy and EER is 0.72%.

Keywords: Face Recognition, VGG16, ResNet50, VGG19, Deep Learning

I INTRODUCTION

The biometric identification system is a type of authentication that makes advantage of a person's physical attributes or behavioral features to verify their identity. This system is categorized into two types: physical-based identification, such as fingerprint, face, iris, etc., and behavioral-based identification, such as signature, keystroke, gai, etc [1]. In this study, the authors proposed an identification system of persons on their face modality. The biometric system has some techniques that may be used to recognize faces, such as recognizing patterns, computer vision, image processing, deep learning, and graphics. Pattern recognition can be used to solve different types of pattern recognition problems [42], and image processing techniques can be used to recontact images, remove noise, etc. [43,44]. This computer program uses video or digital images from a video source to automatically identify and authenticate a person [2]. With the growth in security needs, technology's law enforcement and business, there is a lot of opportunity in recent years. This technology can be emphasized as an active research topic [3, 45, 4].

The face recognition system may work in two ways. First, one-to-one matching is the term used in biometrics to describe the verification mode [5, 6]. The verification operating mode is used to choose a face from a vast database of faces in order to determine whether the details on the face correspond to a certain person and second, one-to-many matching is the identification mode of Identification entails taking a person's biometrics and comparing them to a database of possible IDs. These steps are used for face recognition, such as face detection, alignment, facial feature extraction and feature categorization [7]. The main issue in the face recognition system is determining the optimum feature representation technique to extract features and applying the best approach representation for a certain biometric modality. In the biometric system, the classification of images is one of the most significant methods of feature extraction, extract the useful information of images and extracted information classify using appropriate classification techniques is called as classification. In these systems many feature extraction techniques have been developed [8, 9, 10, 11]. Convolution neural networks based on deep learning have recently acquired prominence as a feature extraction strategy for face recognition [12]. There are various ways for recognizing things that can be employed with deep learning being the most popular. Deep learning is just a network in which each layer of neurons linked to each the output neuron in the following layer. Deep learning CNN model is a specifically used classification and recognition of images in various applications [13, 14].

II. LITERATURE SURVEY

Table 1. Related Existing Work.

References/Year	Database	Algorithm/Method	Recognition Result
[16] (2016)	FG-NET and MORPH	CNN and VGG16	92.20%
[17] (2006)	ORL, UMIST and Yale	IPCA and ICA	98.24%
[18] (2007)	AT&T, ORL	PCA, ONPP and KPCA	93.50
[19] (2008)	CMU PIE. FERET and FRU	ISSN	99.79%
[20] (2009)	FERET, ORL, UMIST and AT & T	KPCA	92.82%
[21] (2011)	Yale and ORL	WLD and NN	99.25%
[22] (2013)	Asian face	ICA and PCA	97.00%
[23] (2014)	ORL and Yale	LBP and Improve LBP	99.78%
[24] (2015)	Yale and LFW	HE, GF, ICA	95.67%
[25] (2017)	FG-NET	CNN	EER 0.28%

[26] (2016)	RGB-D and Super Faces datasets	CNN and SVM	98.60%
[27] (2017)	LFW dataset	Inception-v3, CNN	99.50%
[28] (2017)	ORL	PCA, LBPH, KNN and CNN	98.30%
[29] (2019)	Self-Created	CNN and Alex Net	98.50%
[30] (2019)	PUCV-TTF	CNN	98.87%
[31] (2019)	YTF, IJB-A and LFW	CNN	98.80%
[32] (2020)	ROSE-Youtu	VGG16 and CNN	94.40%
[33] (2020)	Freely available	PCA, 2DPCA	98.75%
[34] (2020)	AT&T and real-time inputs respectively	CNN	98.00
[35] (2021)	ORL	CNN	99.50%
[37] (2022)	IMDB WIKI	Google Net-M	98.00

III. PROPOSED METHODOLOGY

In this study, we have first applied the KVKR face database data augmentation pre-processing technique for artificially expanding database size, then proposed work we have used pre-train transfer learning VGG16, VGG19, ResNet50 models with additional design CNN model for face features extraction and classifying these extracted features using SoftMax classifier for person identification.

The experiment work, we divided the database into different sizes for training models and used the first time 2700 images, and 80:10:10% split was made for train, test and validation, second time 3600 images and 60:20:20% train, test and validation split were made. Then calculate recognition accuracy these above three models. The performance analysis of the face recognition system calculates the classification matrix, model training and validation accuracy, modal training loss, model layer-wise features map, and result and discussion. In Table 2. shows different hyper parameters of the face recognition models.

Table 2. Hyper parameters of modes

Parameter	Value
Optimizer	RMSprop(1r=le-4)
Activation Function	SoftMax
Epoch	25/30
Batch Size	32
Loss Function	Categorical Cross Entropy
Train, test and validation split	

The proposed system shown in Figure 1 divides the face recognition system into two phases. The first is the training phase, which converts label data into 224 by 224 pixels and uses the proposed system to train a face model. We have trained three models one by one. first VGG16 with CNN, Second VGG19 with CNN and Lastly ResNet50 with CNN. In the second testing phase, After utilizing the previously trained model to perform the face recognition operation, The face labels with confidence ratings below the threshold are discarded, while the face labels with confidence scores above the threshold are accepted. By using this strategy, the model's inaccurate classifications will decline. The face label shows on the screen as a result of the facial recognition technology [13].

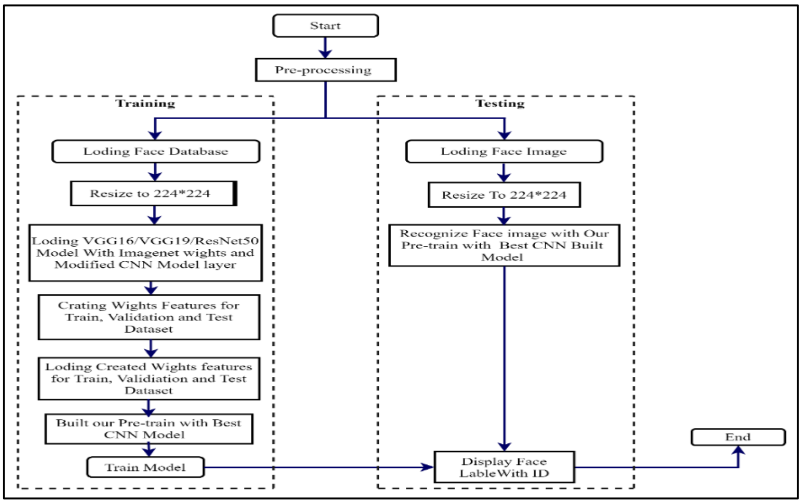


Figure 1. Proposed Methodology.

3.1 Image Acquisition

This study, we have used our own collected KVKR face database for face recognition. This dataset was collected in "Multimodal Biometrics Research Lab. at the Department of Computer Science and Information Technology, Dr. BAM University, Aurangabad. Under the observation of Prof. Dr. K. V. Kale, Programme Coordinator of UGC SAP (II) DRS Phase-I". For the face database, we have collected ten various positions images, such as the frontal face, left 90 and 45 degrees, 90 and 45 right degree, small smile, big smile, class eys, etc. The data set was collected using an Intex 5 Mp camera, collecting a total of 45 subject images. The images capture operation distance one meters, the captures images resolution is set 640*480 dimension, collecting color images, set as a natural and smiling facial expression.

3.2 Pre-processing

The KVKR face database has applied data augmentation pre-processing techniques for artificially increase the size of the KVKR face database.

3.2.1. Data Augmentation

In this proposed system we have without collecting additional data, use Data Augmentation to enlarge the data size. These techniques have many methods for artificially expanding data size, but in this study, we have used rotation, zoom, and horizontal flip because the large data size trained a model to perform well in deep learning [38, 39].

3.3 Features Extraction and Classification Techniques

We have used pre-train transfer learning VGG16, VGG19 and ResNet50 model with CNN model for the features extraction.

3.3.1. CNN Model

A convolutional neural network is a deep learning technique that can be used as image input. CNN are one of the most common types of neural networks used to recognize and classify Images. These models are employed in a variety of applications and domains, but they're particularly commonly used in image and video processing. CNN gets a 3-dimensional image as input (width, height and depth), with the width and height being the image dimensions. The depth refers to the number of input channels, which are red, green and blue color channels (RGB). The CNN modes pass input images pass through a series of layers, such as convolution layers. These layers extract meaningful features of input images, the Relu layer is used to convert negative value into zero, pooling layers are used to reduce the extracted features map size, lastly, FC (fully connected layers) is used to flatten out the matrix into vector and use SoftMax classifier function to probabilistic values prediction of the face.

This transfer learning, which we have used in Figure 4, shows the best CNN layers model summary. This model has used the last few layers of modification of pre-train modes [40]. The last such layers of VGG16, VGG19, ResNet50 models are modified and replaced with a new classifier layer using CNN models. The following Fig 3.16 (a) shows our best CNN model summary for unimodal recognition of the face, fingerprint, Iris, and signature for the training model, and Fig 3.16 (b) shows the modified CNN model summary for multimodal biometric recognition for the training model.

Model: Built CNN Model For Compling and Traning

Layer (type)	Output Shape	Param #
flatten_1 (Flatten)	(None, 25088)	0
dense_1 (Dense)	(None, 100)	2508900
dropout_1 (Dropout)	(None, 100)	0
dense_2 (Dense)	(None, 50)	5050
dropout_2 (Dropout)	(None, 50)	0
dense_3 (Dense)	(None, 45)	2295

Total params: 2,516,245
Trainable params: 2,516,245
Non-trainable params: 0

Figure 2. CNN Models Summary.

3.3.2. VGG16 and VGG19 Models

The VGG models were designed by the Visual Geometry Group at Oxford University. This model 16 and 19 has indicated the layers of models. The VGG16 and VGG19 models have trained with ImageNet database and this dataset has over 14 million photos separated into 20000 categories. There are five convolution blocks in the VGG16 model. There are two convolutional (size: 3X3) and one max-pooling in each convolution block (size: 2×2). The fully connected (FC) layers are in charge of both prediction and classification [40].

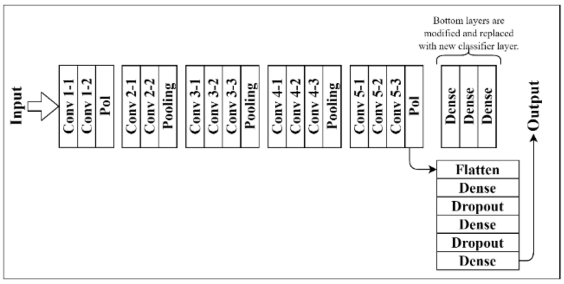


Figure 3. Summary of VGG19 Model.

3.3.4. Features Classification

SoftMax: Classification of objects is a very important task normally. Different literature uses SVM based classifier, which works on the classification score based on a hyperplane that separates the data into two categories. But, SoftMax classifier predicts the class label on the basis of calculated probabilities we used the fully connected layer for the final calculation of score, as we calculating probabilities in previous layer and got the value for calculating label. The SoftMax function is the activation function most often utilized at the output layer for multi-class classification. When using real values, the SoftMax function calculates the probability distribution and returns a value in the range of 0 to 1, with the total of the probabilities equating 1. The output layer in multiclass issues would have 'n' neurons, where n is the number of classes. Each neuron would provide a probability value for each class, with the predicted class being the neuron with the greatest value.

IV. EXPERIMENTAL SETUP

In the experimental setup, we have used open-source tools, Python 3.6 programming language with deep learning libraries such as karas, TensorFlow, etc and image processing libraries such as OpenCV, sklearn etc. The proposed system is run on a laptop with a Core-i5 Intel processor, graphs 2GB and Ram is 8 GB with windows 10 platform. For training, all models used Jupyter Notebook IDE and pre-processing have performed in Spyder IDE. We first applied data augmentation techniques, divided the KVKR database into different percentages for train, test and validation, and trained the models using pre-train transfer learning VGG16, VGG19 and Resnet50 with CNN model. The images size is set 224 by 224, using categorical cross-entropy loss function, RMSpro optimizer and performance measurement analysis using classification and confusion matrix, models training accuracy and loss, features map and comparative analysis of these three models recognition results.

- *Model Training Accuracy and Loss*

A successful prediction result in deep learning depends on a model with appropriate hyper parameters. We have cross-validation because it helps us decide "how the decision should be made" when we have to choose between two models. Any dataset should have an appropriate split of the available data. The entire dataset may be divided into train, valid and test groups.

The collection of data used for real training is known as the train data, is called as by fine-tuning after each epoch of the model, validation split helps in enhancing the model's performance, and after the training phase is through, the test set provides information about the model's ultimate accuracy. Each model the training and testing data split should be done because it is useful for improving the performance. The distinction between validation data and testing data is that the model views the former for validation after each epoch, while the latter is not observed by the model until the training is complete.

We have calculated the modal training accuracy and modal training loss. The following figures shows, that the first-time train KVKR face data 1 in to VGG16 with CNN got 84.44 accuracy. In VGG19 with CNN 84.44 accuracy and ResNet50 with CNN 77.78 accuracy, second-time KVKR face data 2 VGG16 with CNN got 99.28% accuracy, and VGG19 with CNN 99.25% accuracy and ResNet50 with CNN 87.00 accuracy. These models train a model set epochs 30 and batch size is 32 using RMSprop optimizer. The model accuracy and loss from the model are observed. Figure 17 shows KVKR face data 1 and 2 using VGG16 with CNN models modal training and validation accuracy and loss.

- *Visualizing Intermediate Layer Activations*

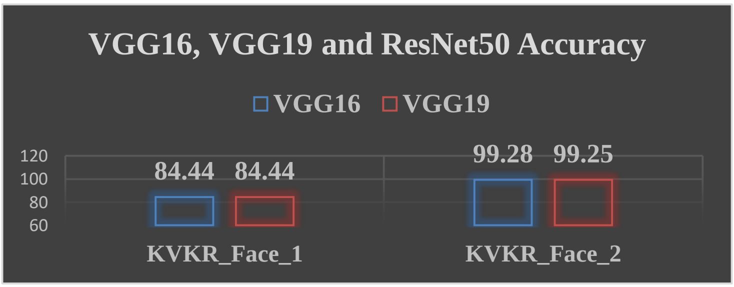
By examining the output of my model's intermediate layers, we can learn how it interprets the input image, in order to understand how the deep CNN model can categories the input image. We can learn more about the workings of these levels by doing so. In the next section, I'll take a picture of a face and try to see the outputs of some of the intermediate convolutions of the trained VGG-16 and VGG19 models. It's easy to observe how Convolution layers' filters work by looking at the varied images they produce. Various filters in various layers emphasize or activate different areas of the image (see in Figure 13 and 14. The first layer is made up of a variety of edge and shape detection; the activations have retained the majority of the information from the initial image. The activations grow progressively abstract and less visually interpretable as we progress up in the hierarchy. They begin to encode higher-level notions like "person nose" and "person eye." Higher-level presentations provide the model more information about the image's class while giving less information about the image's visual components. The input image activates all of the filters in the first layer, but as the layer depth rises, more and more filters go blank, indicating that the pattern the filter represents was not picked up in the input image. This phenomenon is known as the sparsity of activations. The most crucial observation to make when viewing the output of different convolution layers in this way is that the deeper layers in the network tend to highlight more specific features of the train data, whereas the superficial layers frequently highlight more general patterns like edges, texture, background, and so forth. When employing Transfer Learning, which entails training a piece of a previously learned network on a fresh dataset, this knowledge is essential. The key idea is to freeze the weights of earlier layers because they will naturally acquire their general traits. This is to just train the deeper layers' weights, which are the ones that recognize our faces.

V. RESULTS AND DISCUSSION

In the Table 2 show that the face recognition accuracy resalt analysis. This table first column show database, second train test and validation data split percentages, third show that the applied models with transfer learning, fourth used number of subjects for training models, fifth show that the calculate model training loss, six show that training time of model and lastly recognition result. In the table show that the more loss data at a time of modal training there will be decrease accuracy and minimum loss of data at a training time of model there will be good recognition accuracy. In this work we have got in combination of VGG16 with CNN model transfer learning good recognition accuracy. The relative detailed of VGG16 model, VGG19 model and ResNet50 model with CNN recognition accuracy is shown in Table 3. In the Graph 1. Shows comparative analysis of face data 1 and 2 using above three models with transfer learning using CNN. The face data 1 split was 40:10:10% good recognition accuracy in VGG16 and VGG19 with CNN both models have got 84.44% accuracy. In the face data 2 split was 40:20:20% good recognition accuracy in VGG16 with CNN have got 99.28% accuracy and VGG19 with CNN have got 99.25% accuracy. In this work data splitting was done 40:20:40 percentages have got a good recognition accuracy.

Table 3. Recognition Result of Face Recognition.

Data	TR:TE:VA	Model	No of Subject	Loss	Time	Accuracy
$KVKR_{\_Face\_1}$	40:06:06	VGG16 & CNN	45	2.769499086301981	0:00:49.537235	84.44%
$KVKR_{\_Face\_1}$	40:06:06	VGG19 & CNN	45	2.541089620469138	0:01:34.109306	84.44%
$KVKR_{\_Face\_2}$	40:16:16	VGG16 & CNN	45	0.0011942909508555507	0:00:51.220372	**99.28%**
$KVKR_{\_Face\_2}$	40:16:16	VGG19 & CNN	45	0.0018791694479942736	0:00:50.996817	**99.25%**



Graph 1. VGG16, VGG19 and ResNet50 with CNN Comparative Analysis.

VI. CONCLUSION

The face recognition system we have face so many challenges like this pose variation, noise in sense data, age factors etc. In this research we have covered the pose variation and noise in sense data problem. In this article, we have used deep learning-based Pre-trained VGG16, VGG19 and ResNet50 transfer learning to additionally modify our best CNN models for person identification using face biometric traits. In the pre-processing steps, we have used the data augmentation technique for artificially increasing the size of the database and extracting and classification features; we have used pre-train VGG16, VGG19, and ResNet50 with our best CNN model. First, we have divided the KVKR face database into different percentages and trained the above models one by one. We have got in first time VGG16 84.44% accuracy, VGG19 84.44% accuracy and ResNet50 77.78% accuracy, second time we have got in VGG16 98.28 accuracy, VGG19 98.25% accuracy and ResNet50 87.00% accuracy. The comparative analysis of VGG16 with Best CNN, VGG19 with best CNN, and ResNet50 with best CNN models we got in VGG16 with best CNN model with good recognition accuracy. In the future, we have to collect other biometric traits databases such as (fingerprints and iris) and perform a multimodal biometric fusion system for person identification using a deep learning approach.

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