Pisco Med Publishing

Original Research Article

Face Recognition Algorithms Based on Deep Learning

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Abstract: In recent years,technologies related to face recognition have achieved rapid development.The application of face recognition can be easily seen in daily life,especially used in technology companies.Based on deep learning(DL),this paper shows 4 characteristic open-source algorithms,which has better performance in LFW datasets.This paper also summarizes the future challenges and the next step of face recognition.Finally,with the progress of technology,data security brought by face recognition is also a point we need to consider.
Keywords: Face Recognition; Deep Learning

1. Introduction

Face recognition is an important means of identifying personal information due to its advantages such as concealment and uniqueness.In recent years,face recognition technology has been widely seen in daily life,e.g.,payment by Face ID,face comparison,face verification,and beautification of portrait.Face recognition is a kind of biometric recognition technology.In a narrow sense,face recognition is the use of biological information for identity verification technology.Broadly speaking,face recognition is a technology for identifying and verifying faces in images or videos.

DL is a new research direction in the field of machine learning(ML).It is introduced into machine learning to make it closer to the original goal artificial intelligence(AI).Deep learning refers to a collection of algorithms that use various machine learning algorithms to solve various problems such as images and texts on a multi-layer neural network.Deep learning can be classified into neural networks from a broad category,but there are many changes in specific implementation.The core of deep learning is feature learning,which aims to obtain hierarchical feature information through a hierarchical network,so as to solve the important problem of manually designing features in the past.Deep learning is a framework that includes multiple important algorithms,such as:Convolutional Neural Networks(CNN),Recurrent neural Network(RNN)etc.

The algorithms summarized in this paper are validated on the LFW dataset.LFW datasets released by the Computer Vision Laboratory of the University of Massachusetts Armstrong contains 13,233 face pictures of 5,749 people which from Yahoo and belong to an unconstrained scene.

This paper exemplifies 4 algorithms with outstanding performance and summarizes the future research directions and challenges proposed by the author.I hope to provide some help to researchers who study face recognition.

2. Face recognition algorithm based on deep learning

2.1 Face++(0.9950)

The author establishes a Megvii Face Recognition System,which gets 99.50%accuracy on the LFW benchmark[1].The performance of this system is better than humans.It’s disappointing there still exists a clear gap between machine recognition and human performance when test in a real-world security certification scenario.They summed up three challenges in the field of face recognition:data bias,very low false positive criteria,and cross factors.Their research focuses on data:how to collect data and how to use data.Based on this,they proposed two future research directions.

Research more efficient and smarter methods to mine domain-specific data:

Use data synthesis techniques to generate more data:

The author collects Internet data to build an MFC dataset,which contains 20,000 people and 5 million instances.The model contains 10 convolutional layers and a softmax layer.Randomly select 4000 to 16000 people from the MFC dataset,and each sub-dataset maintains the distribution of the original dataset,and the performance increases linearly with the accumulation of data.Arrange the number of pictures of each person in the database in descending order.Individuals with more pictures are ranked in front,and those with fewer pictures are ranked behind.When using individual training with more pictures,the accuracy of the system will be significantly improved.In the second half of the experiment,there are more and more Individuals with a small amount of pictures,which will have a negative impact on the learning of the network.In this case,despite the increasing training data,the accuracy of the network will decrease.

The author also tried a series of complex algorithms on MFC,such as joint Bayesian algorithm and clustering algorithm.Compared

doi: 10.18282/l-e.v10i4.2560

with the simple CNN network,there is no obvious advantage

2.2 VGGNet(0.9913)

VGGNet is a series of deep convolutional neural networks proposed by Oxford University professors in 2014.There are a total of five structures with very large parameters which more than 130 million.Its success proves that increasing the number of network layers can improve the performance of the network to a certain extent,but correspondingly brings difficulties in model training.

VGGNet can be seen as AlexNet with a deeper network layer.It has 5 layers of convolutional layers,three Fully-Connected(FC) layers,and soft-max layers.Max-pooling is used between layers,and all the activation functions are equipped with ReLU[2].

Features of the VGGNet network include:

VGGNet uses a convolutional layer composed of multiple small convolution kernels instead of a larger convolutional layer. They use filters with a very small receptive field:3×3.using two 3×3 convolution kernels are relative to the field of view of a 5x5 convolution kernel,and a stack of three 3×3 convolution kernels is equivalent to 7×7 The field of view of the convolution kernel.On the one hand,this design reduces the amount of parameters.On the other hand,this is equivalent to more nonlinear mapping,which can increase the fitting ability.

Max-pooling is performed over a 2×2 pixel window,with stride 2.Compared with AlexNet's 3x3 pooling core,VGGNet all uses 2×2 pooling cores.There are more convolution kernels which make more channels of the feature map,so that the feature extraction is more comprehensive.The number of channels in the first layer is 64,and each subsequent layer is doubled,and even the largest layer can have 512 channels

The fully connected layer is not used in the test.Instead,it is replaced with three convolutional layers,so that it is no longer limited to a fixed size input,and can accept any width or height.

2.3 FaceNet(0.9963)

The author proposes a new face recognition system:FaceNet,which solves recognition(who is this),verification(is this the same person),and clustering(finding the same person in a bunch of faces).The innovation of this system is to map the face image to the Euclidean space,and the distance in the space represents the similarity of the face.Learning the mapping of the face image to the 128-dimensional Euclidean space through the convolutional neural network is associated with the definition of the correlation coefficient in the two-dimensional space.It uses the reciprocal of the distance between feature vectors to characterize the correlation coefficient between face images.For different pictures of the same individual,the distance between the feature vectors is small. Finally,the recognition,verification and clustering of face images are solved based on the similarity between feature vectors.

Author's follow-up work:

Analyze the wrong samples to further improve the model accuracy,especially in the real scene.

Will use the model in real application development.

Reduce the model size and reduce the consumption of CPU calculation,so as to reduce the training time

2.4 Targeting Ultimate Accuracy:Face Recognition via Deep Embedding(0.9977)

The research proposes a model that is a two-stage method:a multi-patch deep CNN and metric learning for reducing dimensionality. It is used to extract low-dimensional features useful for recognition for face verification and recognition.

Deep CNNs on Multi-patch:

Different areas of the face are extracted separately through deep convolutional neural networks.

They use a network structure with 9 convolution layers and a softmax layer at the end for supervised multiclass learning.The input of the network is a 2D aligned RGB face image.Pooling and Normalization layers are between some convolution layers.

metric learning for reducing dimensionality:

The features extracted by the deep convolutional neural network are then reduced to 128 dimensions through metric learning

They use a metric learning method supervised by a triplet loss to reduce the feature to low dimension such as 128/256 float and meanwhile make it more discriminative in verification and retrieval problems.

The author also mentioned that the training data has a great influence on the performance of face recognition.If you can collect a lot of data in real situations,you can get better results.

3. Conclusion and prospect

This paper briefly introduces four algorithms which work well in face recognition.It can be seen that the accuracy of machines has far exceeded that of humans in some datasets.Unfortunately,in real life,there is obvious difference between machines and humans. Face recognition confront many challenges with applications in real life.

The collection of face data is affected by ambient light,face collection equipment,and collection distance.

Human beings have a certain growth stage,and cross-age recognition is a major difficulty.

With the popularity of face recognition,this technology may be used by criminals,causing security risks.

Due to the global epidemic,it is more difficult to recognize faces when people wear masks.

Based on this,we hope to find more unique facial features to improve the accuracy of face recognition in real life.At the same time,improving privacy protection-related laws is equally important.While developing technology,we should try our best to prevent personal biological privacy from leaking.

References:

[1] Zhou E,Cao Z,Yin Q(2015).Naive-Deep Face Recognition:Touching the Limit of LFW Benchmark or Not?[J].Computer Science.

[2] Simonyan,K.and Zisserman,A.(2015).Very Deep Convolutional Networks for Large-Scale Image Recognition.International Conference on Learning Representations,San Diego,7-9 May ,1-14.