FACIAL RECOGNITION USING CONVOLUTION NEURAL NETWORK

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Abstract—**The importance of continuous security development of technology due to the ongoing security challenges of computer technology. The expansion of human dependence on network technology. User authentication is required to prevent attacks and vulnerabilities. Facial recognition, voice recognition, one-time SMS password, and fingerprint scanning are a few types of authentication. Face recognition is one of the most important aspects of image processing in both still and moving images. Creating a technology that can distinguish faces and people is difficult. Analyzing the usefulness of CNNs, explaining the various data used by face recognition, and analyzing different CNN models are the main objectives of this study. Deep learning of facial recognition technology CNN can make the recognition process more accurate. The model achieved a learning accuracy of 93.72%.**

Keywords - Deep Learning, Face Recognition, Deep Learning Networks, CNN

INTRODUCTION

Due to the requirement of computer technology, daily work is done electronically instead of an individual's pen and paper. With the development of computer technology, there is an increasing need for fast and accurate user identification and authentication. Understanding customer authentication is important as it is an essential part of the process of preventing access to sensitive information. Various biometric authentication technologies are available, such as voice, typing, face recognition, fingerprint recognition and typing. Skin deformation reduces fingerprint recognition accuracy. It is difficult to take advantage of voice authentication with a system that can fully recognize every change, due to background noise and the fact that if the user is cold it will not be recognized as a match data is noisy and has effects such as smears or background.

Today, facial recognition is frequently used to identify people. The features of the human face vary from person to person. All you need for facial recognition is a camera. Therefore, it provides a low-cost, reliable identity that can be used for many different purposes. User identification and verification is possible thanks to fast, accurate and efficient face recognition. It plays an important role in many applications, including government, business, security gates, time and attendance tracking, smart cards, access control and biometrics.

Face recognition is a method of using facial recognition to identify people. In the past, different algorithms such as eigen face-based method and face identifier-based method have been used for face recognition. Because of the high frequency and excellent recognition of CNNs, their images have been used for face recognition.

This article discusses various CNN models and important CNNs used in face recognition. This will enable researchers to use best practices for further development in the field. The ability to recognize faces from photos or videos is the idea behind face recognition technology.

I. RELATED WORK

This section discusses researchers' various studies in the field of face recognition and summarizes their contributions.

Yaniv Taigman et al. [1] published Deep Face: Closing the Gap to Human-Level Performance in Face Verification. Using the deep CNN architecture, the Deep Face system, which first appeared in this important study, can identify the face with the accuracy of the LFW data of the face.To learn how to distinguish between agents, the model uses a nine-layer deep CNN and outperforms previous methods in terms of accuracy. The uses the multi-featured CNN architecture.
Performance measurement: True, positive value and negative value.
Pros: Requires more training material; It is sensitive to changes in position and lighting.

Florian Schroff et al. [2] FaceNet: Unified Embeds for Face Recognition and Clustering. FaceNet introduced a CNN-based face recognition system that learns a map to a small Euclidean space where distance is directly related to a similar face. Triple regression is used to train the model and

shows the performance of various metrics, including resulting face embeds, LFW, and YouTube Faces. Uses feature, Triple loss, CNN architecture, Accuracy, Precision, Return, ROC curves.
Disadvantage: Training triad must be chosen carefully and is computationally costly to train.

Yi Sun et al. [3] published DeepID3: Face Recognition Using Deep Neural Networks.The Deep ID model family explores the application of deep CNNs for facial recognition. To capture global and local facial features simultaneously, Dostrid3 has built a 25-layer depth in store in 25-in-1 multitasking and learning multitasking. In the LFW and Mega Face datasets, the model results in a match.
Features: Examination of multiple metrics and functions, Magnetic CNN Architecture.
True, Positive Value, and Negative Value are performance indicators.
The computational complexity is high and insufficient information leads to the risk of overfitting

Kai et al. [4] published Deep Residual Learning for Image Recognition. ResNet now includes networks to make training deep CNNs easier. While ResNet isn't an expert in facial recognition, it has had a huge impact in the field. Thanks to its ability to train deep neural networks, researchers can improve the accuracy of facial recognition using CNN deep models.
Features: Permanent Connections and Complex CNN Architecture
Accuracy, Precision, Recall and F1 Score are performance indicators.Benchmarking needs to be done well and in-depth training can be difficult

Omkar M. Parkhi et al. [5], VGG Faces: A Multidisciplinary Approach to Face Recognition. Based on the VGGNet standard for facial recognition, VGGFace offers a CNN architecture. Small filters are used on the standard 16-layer mesh to better capture facial expressions. In addition to providing pre-trained models for facial recognition, VGGFace performs competitively on LFW and IJB-A datasets. VGGNet architecture and compact filter size are among the features used. Performance Metrics: Precision, True Positive Rate, and False Positive Rate.Inference time is longer than other models and larger samples.

II. DATA DESCRIPTION

The dataset has two folders, the posttest image folder and the final training image folder. The final training image folder contains 244 images and the final test image folder contains 64 images. The size of the dataset is 308 images (244 for training and 64 for testing).


Fig.1a


Fig.1b

The Figure 1a and Figure 1b are examples of test and training data for face recognition.

III. METHODOLOGY

Here, two classes are divided into training and testing. This section discusses ways to design various classifier architectures.

Convolutional Neural Network (CNN) based face recognition is a recommended method. The first step of this method involves applying various transformations to the data using ImageDataGenerator to expand the dataset and improve model performance. The CNN is then trained using the training data, the binary cross-entropy loss function, and the Adam optimizer. 10 training sessions are used to train the model. Convolutional layers, maximum pooling layers, and dense layers are some of the layers that make up the CNN architecture. The output process has the same number of neurons as the number of faces to be recognized, and the input image is scaled to 64x64 pixels. After training, use the model to make predictions using test images.

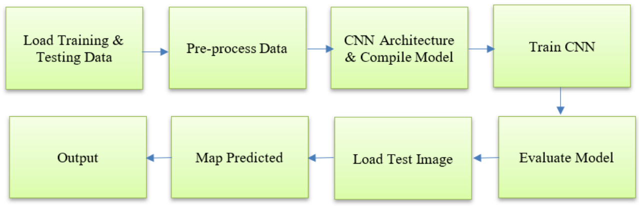

Fig.2. Data flow diagram for conceptual model.

Working of CNN:

Step1: Self-constructed two-dimensional arrays. Before training the image, the data must be processed. The data is processed when each image is converted to a NumPy array. Each line represents an image. It has a special name called NumPy. The model can start training immediately with the dataset.

Step2: The similar layer is the neural network. Nodes in each layer of the neural network calculate values based on features or weights. ReLU is the activation function of the hidden layer while sigmoid or SoftMax is the activation function of the output.

Step3: Identifying features in images is made easier by using a simple algorithm called a convolutional layer. We deliver the core of this layer. For example, an n*n matrix over pixels in an image. Each cell of the kernel has a value. Combined with the original images, it creates features that make it easy to identify similar objects in subsequent images when making predictions.

Step4: Max Pooling

Max Pooling is used to extract the most features from the image during the pooling stage, which is a bidirectional filter on each channel of the feature map. The dimensionality of feature maps is reduced by using layers. Both the number of calculations to be made and the number of parameters to be studied are reduced. The layers of the custom map of the convolution process show the features found in a particular region.

Step5: Flattening

When we want to transform a large output into a long linear vector, we flatten the data.

The fully connected layer takes the flattened matrix as input

Step6: Fully Connection Layer

Full Process is one of the fully feed forward neural networks. It consists of several layers. Images are curled, combined and flattened to create vectors. This vector is then used as the input layer of the ANN that detects the normal image. Each synaptic link is assigned a weight and the input method is weighted and added to the activation function. Every neuron in the lower layer is connected to every neuron in the upper layer. The output is then compared to the actual value, the resulting error is propagated back (i.e. the weight is rescaled) and the whole process is reversed. Do this until the error is minimized or the desired results are achieved.

IV. IMPLEMENTATION

Data Preprocessing Techniques:

Use image generator file in Kera library to render. It uses data augmentation techniques in training images. Cut Spacing, Zoom Spacing, Horizontal Rotation, and other transformation presets are provided by the ImageDataGenerator class and can be applied to the raw image of the training data to create a new image with transformations that help improve the overall structure. The proposed model uses the following pre processing dataset:

Sheer Range: Shear Range is a variable that moves the pixels of the image.

The crop range in the code is set to 0.1 which ensures that the image is only randomly cropped by 10% of the majority.

Zoom Range: This variable changes the zoom level of the image. Since the zoom range is set to 0.1 in the code, the image will be scaled randomly or reduced by 10%.

Flip Horizontal: A change called Flip Horizontal rotates the image horizontally. The Flip Horizontal parameter in the code is set to true which causes the video to randomly rotate horizontally.

Architecture Diagram:

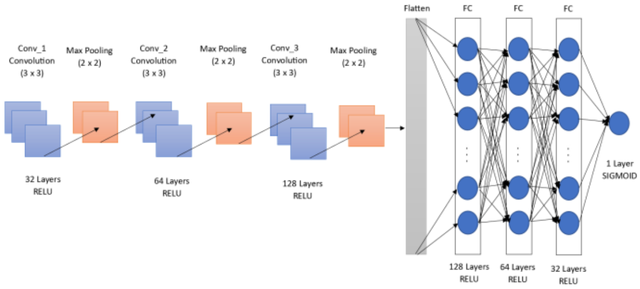

Figure 3. Architecture Diagram (CNN Classification)

V. RESULTS

This article presents an effective face recognition method based on Convolutional Neural Network (CNN) architecture. The model was trained using data containing facial images taken from different angles in different lighting conditions. Evaluation of our model shows that it performs well, achieving over 93% accuracy in testing. This approach shows that the model can accurately identify the face in the image even in the face of facial difficulties such as corners and good lighting.

Model name	CNN	Alex Net	VGG16	VGG19	Mobile Net
Accuracy	93.7%	57%	71%	56%	84%

VI. CONCLUSION

This article presents an effective face recognition method using CNN architecture. Better results are achieved by using advanced techniques such as face detection, clustering, and data augmentation to increase the quality and diversity of training data to complete the build. Overall, the proposed model is promising in facial recognition applications in many areas such as security and surveillance, social media and e-commerce.

VII. FUTURE SCOPE

Facial recognition technology has experienced growth and popularity in recent years, which has led to future needs and developments. Future work may focus on improving the performance of the model by exploring different network structures, dysfunctions and incorporating other features such as faces and emotions. Integration with new technologies such as augmented and virtual reality opens up new possibilities for facial recognition. Facial recognition has the potential to change the way we interact with the world. There are many opportunities for research and development in the future, and it is important to ensure that technology is developed and used in an ethical and responsible manner.

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