

Abstract

First part of this research, we studied the methods and technologies of facial recognition using artificial intelligence. To build our face recognition system, we were first perform face detection in an image using deep learning, train a face recognition model on the systems, and then finally recognize faces in both images and video streams with OpenCV.

Second part of this research, people began to wear masks to prevent the spread of Covid-19, which is widespread all over the world. Face recognition algorithms tend to be relatively inadequate for people wearing masks because masks cover most of a person's face. We developed Resnet50 based deep learning model for masked face recognition with a competitive result of 86% accuracy. The human eye and forehead parts, which are not covered by a mask, are used for recognition. Dataset is prepared by cutting the eye and forehead parts of human faces from an open dataset Casia-Webface.

We prepared the dataset with 274557 images for 10558 people and the dataset is open on the internet.

Download database link:
https://drive.google.com/file/d/1eCb2t3R7-y53wXDgG7oFCZX-_tZUVa-s/view?usp=sharing

Introduction

Prior to the advent of in deep learning methods, researchers developed facial recognition algorithms using traditional image processing techniques (Gabor [1], Eigenface [2]). These methods have many disadvantages, such as being very sensitive to light and not invariant in position. Researchers have developed facial recognition methods using traditional image processing methods to achieve the best accuracy based on the Labeled Faces in the Wild - LFW [3] database at 95% [4].

DeepFace [6] was the first method to show high results on facial recognition using in deep learning (DeepFace on the LFW database -97.53%). DeepFace is a nine-tiered model that studied four million data. DeepFace was followed by DeepID2 [7], FaceNet [8], Baidu [9], VGGFace [10], SphereFace [11], Arcface [12], and Cosface. All of these show more than 99% accuracy on the LFW database.

However, of these methods, facial recognition had the highest accuracy when the mouth was closed, with a VGGFace of 68.17% on the RMFRD database. The reason these models perform poorly on face recognition in masked individuals is that all models have trained faceless masks. This is because some of the facial features used in facial recognition, such as the mouth and nose, are masked, which reduces the accuracy of facial recognition.

Therefore, researchers are developing and testing facial recognition algorithms that do not use masked areas, and methods that artificially restore those areas. We did not use masked parts, but experimented with identifying the person only on the eyes and forehead.

Methods and Materials

We chose Casia Webface as our model training database, and it is a 4.94 GB database with 494,414 images of 10,575 different people without masks. From this database, it is necessary to detect the parts of the eyes and forehead that are not covered by the mask. To do this, we first detected the human face from each image. In doing so, we used the MTCNN model, which is commonly used to find faces. During the processing of the data using the MTCNN model, the database was cleaned by filtering each image and deleting the image if no face was found. Because the pictures of the faces found were of different sizes, they were all resized to 120x120x3. After this processing, the eyes and forehead were isolated by image aspect ratio (120x55x3).

Also we developed a facial recognition system in C# programming language using by OpenCV and trained Mongolian people's 1000 facial data.

Results

We developed a facial recognition system with 80% probability in C # programming language using by OpenCV and created a database of Mongolian people's facial training data.

This face recognition system was implemented in several stages.

1. Research part: (To study a facial recognition algorithms, methods)
2. Create a database: (To include images of Mongolian people in the MSSQL server -Figure 1)
3. Create a training database: (To develop a software to train raw images in the database, create a database with trained images)
4. Face Recognition from Recording: (To develop a software that recognizes faces from Web camera video recordings and displays additional information -Figure 3)
5. Face recognition from pictures: (To develop a software that recognizes the face of a person depicted in a given image and displays additional information)



Figure 1. Images of Mongolian people



Figure 3. A face recognition from Web camera



Figure 2. Trained images in database



Figure 4. A face recognition from image

Discussion

We conducted two trainings. The first training was taken using Haar-eye to filter 336,452 images of 10,575 different people before filtering. Adam was selected as the optimizer, and Figure 1 and Figure 2 show the training parameters after training 100 iterations using a TESLA-V100 graphics calculator with a batch size of 1024 and learning rate 0.0001. The training lasted approximately 19 hours and was 73.61% accurate. The second training was conducted using 274557 images of 10558 different people filtered using Haar-eye. The amount of experimental data and the settings for the training were the same as in the previous training, and the following figures show the training parameters after 100 iterations. The second training lasted approximately 16 hours and was identified with 86.07% accuracy.

To build our face recognition system, we were first perform face detection, extract face from each face using deep learning, train a face recognition model on the systems, and finally recognize faces with OpenCV.

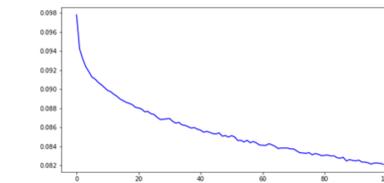


Figure 1. The error function -vertical axis, iteration -horizontal axis.

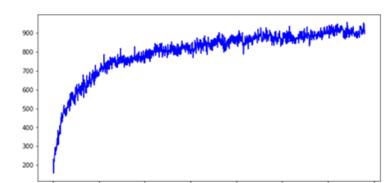


Figure 2. Number of people correctly recognized from 1300 people -vertical axis, the gradient step -horizontal axis.

Conclusions

- We conducted research and experiments using the OpenCV lib, which is a commonly used facial recognition method, and we developed a face recognition system and DB of Mongolian people's 1000 facial training data.
- Our developed face recognition system shows that it is possible to recognize the faces of one or more people at the same time from photos and videos.
- In this study, we developed a model of in-depth training to identify a masked person.
- The purity of the data in the database and the accuracy of the model are highly correlated.
- The CasiaWebface database also has a lot of pictures of the same person at different ages. As person get older, the area around their eyes changes. However, the model learns to reduce the distance between the embedding vectors resulting from these images. This is another factor that can negatively affect the accuracy of eye and forehead recognition.
- There were also many low-resolution images that were indistinguishable to the naked eye, and these images also had a decreased impact on the accuracy of the model.
- Our model recognizes pairs that are difficult to distinguish between two images of the same person..

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References

1. C. Liu and H. Wechsler. Gabor feature based classification using the enhanced fisher linear discriminant model for face recognition. Image processing, IEEE Transactions on, 11(4):467-476, 2002.
2. M. Turk and A. Pentland. Eigenfaces for recognition. Journal of cognitive neuroscience, 3(1):71-86, 1991.
3. G. B. Huang, M. Ramesh and T. Berg. Labeled faces in the wild: A database for studying face recognition in unconstrained environments. Technical report, Technical Report 07-49, University of Massachusetts, Amherst, 2007.
4. D. Chen, X. Cao and F. Wen "Blessing of dimensionality: High-dimensional feature and its efficient compression for face verification," in Proceedings of the IEEE conference on computer vision and pattern recognition, 2013, pp. 3025-3032.
5. A. Krizhevsky, I. Sutskever, and G. E. Hinton, "Imagenet classification with deep convolutional neural networks," in Advances in neural information processing systems, 2012, pp. 1097-1105.
6. Y. Taigman, M. Yang and M. Ranzato "Deepface: Closing the gap to human-level performance in face verification," in Proceedings of the IEEE conference on computer vision and pattern recognition, 2014, pp. 1701-1708.
7. Y. Sun, Y. Chen and X. Wang "Deep learning face representation by joint identification/verification," in Advances in neural information processing systems, 2014, pp. 1988-1996.
8. F. Schroff, D. Kalenichenko, and J. Philbin, "Facenet: A unified embedding for face recognition and clustering," in Proceedings of the IEEE conference on computer vision and pattern recognition, 2015, pp. 815-823.
9. J. Liu, Y. Deng and T. Bai, Z. Wei "Targeting ultimate accuracy: Face recognition via deep embedding," arXiv preprint arXiv:1506.07310, 2015.
10. O. M. Parkhi, A. Vedaldi, A. Zisserman et al., "Deep face recognition," in BMVC, vol. 1, no. 3, 2015, p. 6.
11. W. Liu, Y. Wen, and Z. Yu "Sphereface: Deep hypersphere embedding for face recognition," in Proceedings of the IEEE conference on computer vision and pattern recognition, 2017, pp. 212-220.
12. J. Deng, J. Guo and N. Xue "Arcface: Additive angular margin loss for deep face recognition," in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2019, pp. 4690-4699.