

Design of Face Recognition Course Checking System

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Abstract: This paper proposes a deep learning based facial recognition course checking system to address the issues of low attendance efficiency and easy proxy signing in traditional universities. Extracting 128 dimensional facial feature vectors through the MobileFaceNet lightweight model, combined with the Siamese network's dual tower structure similarity measurement mechanism, implementing identity recognition with a Euclidean distance threshold of 0.5, and introducing liveness detection to prevent image spoofing. The experiment was based on the CASIA and MS1M-V2 datasets, and the results showed that the recognition accuracy of MobileFaceNet alone reached 98.6%. After 100 iterations of integrating Siamese network, the accuracy improved to 100%. The model file was only 65KB, which meets the real-time update and lightweight requirements of embedded devices. This system can achieve non-contact and efficient attendance, support cross campus management and academic analysis related to attendance data. In the future, we plan to optimize model compression technology and integrate multimodal biometric features to expand to scenarios such as enterprise attendance and security access control.

Keywords: Facial Recognition; Course Checking System; MobileFaceNet; Siamese Network.

1. Introduction

The research inspiration for this topic is based on the current learning situation of college students.

1.1. Research Background

Firstly, the college has installed high-definition cameras to enhance security, which can make full use of them and achieve optimal utilization of resources; Secondly, college students who have been studying for three years have become less disciplined and gradually lazy. Conducting course inspections can effectively supervise and urge their learning; Once again, the college or teachers need to check the attendance of students. When there are too many students, calling them names one by one not only wastes the energy and time of teachers and classmates, but also largely leads to the phenomenon of signing in on behalf of others, which can easily disrupt the normal order of the classroom. To address these drawbacks, we plan to use facial recognition to design a fully automated course checking system. As an emerging attendance method, the application of multi face recognition intelligent attendance system in university management has significant necessity and advantages [1,2]. In recent years, with the rapid development of Internet software and hardware technology, artificial intelligence technology has been greatly improved, and it also affects other industries, imperceptibly changing life. Deep learning technology is also growing explosively, and the implementation of related applications has brought significant economic value, such as biometric fusion technology in the construction of smart classrooms in universities, as seen in [3,4]. Because the information contained in the face is very rich, it is the most important feature in personal identification, unique and cannot be replicated, making it an important way of individual recognition. The facial recognition technology based on deep learning has made significant progress in hardware computing power and algorithms.

1.2. Technological Significance

Facial recognition has been applied in multiple fields,

bringing revolutionary convenience to people's lives. Facial recognition is imperceptible to humans, and users do not need to actively participate to complete it. It also does not have any impact on the human body and requires small hardware size. Prior to this, multi face recognition, as an important component branch in the field of facial recognition, has shown extensive application potential in areas such as public safety, identity verification, and intelligent monitoring, such as real-time monitoring systems in public safety, as seen in [5,6]. Multi face recognition technology can simultaneously process multiple facial information, significantly improving the efficiency of attendance. In a crowded and time constrained university environment, traditional attendance methods often require individual identity verification, which is time-consuming and inefficient. And multi face recognition technology can complete a large number of student check-in tasks in a short period of time, effectively saving time and improving the efficiency of the entire attendance process [7].

1.3. Educational Informatization Value

In the field of education, the facial recognition course inspection system is not only an attendance tool, but also a key step in promoting the process of educational informatization. By integrating facial recognition technology into teaching management, precise analysis of students' learning behavior can be achieved. For example, attendance data recorded by the system can be connected to a learning management system, which teachers can use to analyze the correlation between students' attendance patterns and academic performance, thereby providing data support for personalized teaching. For students who are frequently absent, teachers can intervene in a timely manner, understand their learning difficulties or life problems, implement targeted counseling, and promote educational care. In addition, the system helps to build an intelligent classroom environment.

Facial recognition technology can be connected to intelligent teaching devices. When students enter the classroom, the system automatically recognizes their identity and adjusts seating arrangements, loads personal learning materials onto terminal devices, and even pre-set preferred

learning environments based on historical data (such as lighting, temperature, etc.) to create personalized learning spaces centered around students. At the same time, in large universities, this system can effectively manage the attendance of elective courses across campuses, break down management barriers between campuses, promote the balanced utilization and sharing of educational resources, and improve the overall teaching management efficiency of universities.

2. Method

2.1. Facial Recognition Workflow

At present, the implementation of facial recognition technology generally involves the following steps: first, collect and record a local facial database, which should contain multiple facial data; second, obtain preliminary facial feature data for recognition, compare the collected facial feature data with the data in the database, and obtain the recognition result. Simply put, it means using a camera to capture portrait images, distinguishing facial features in the image according to established rules, and locating key points. If a face can be detected, facial feature data is extracted according to regulations and integrated for analysis. Essentially, the extracted facial feature data is compared with the feature data in the database. If the similarity of the data is not less than a reasonable value set in advance, it indicates successful recognition and determines that the facial feature identity is consistent. To prevent image deception, liveness detection algorithms are used to determine whether the face in front of the recognition camera is a real existence rather than an image. Existing liveness detection algorithms are based on the principle that the face is moving rather than stationary, and verify that the face is a real living being for detection and recognition rather than for image recognition through a series of individual or combined actions such as shaking head left and right, nodding up and down, blinking and opening mouth, etc. [8,9]. The live detection technology based on 3D structured light can enhance anti deception, as shown in [10,11].

2.2. Technological Evolution and Model Comparison

Facial recognition technology was first proposed in the 1950s and 1960s, and since then, research and development have been continuously updated and advanced. Previously, research mainly focused on the relative positional geometric relationships of key facial feature points, such as kernel methods, active shape models, "feature faces" and Fisher's algorithm, boosting algorithm, genetic algorithm, etc. However, traditional facial recognition technology is not ideal for certain complex scenarios, with a high error rate. Factors such as changes in lighting, facial expressions caused by individual emotions, and partial occlusion have a significant impact on it. With the support of modern technology, deep learning based facial recognition technology has solved many problems in previous technologies and has shown good performance in terms of facial recognition accuracy[12].

There are many commonly used technologies or models in the field of facial recognition, including methods based on geometric features, template matching, PCA, LBP, CNN, Siamese networks, triplet loss functions, MobileFaceNet, and FaceNet. However, through analysis and search, the combination of MobileFaceNet and Siamese can improve the

accuracy of facial recognition [12].

2.3. MobileFaceNet Model Architecture

MobileFaceNet is an efficient facial recognition model designed specifically for mobile and embedded devices, with a focus on lightweight structure and high computational performance. It uses deeply separable convolution instead of traditional convolution to significantly reduce the amount of parameters and computation. The size of the model is only about 4MB, and the number of multiplication and addition operations is only 2.17B. It can run in real time on mobile devices to meet the needs of real-time face recognition, such as the application of lightweight design in edge computing scenarios such as smartphone unlocking, mobile payment, etc. See [3,13]. The network structure of MobileFaceNet consists of convolutional layers, deep convolutional layers, bottleneck layers, etc. The input is a $112 \times 112 \times 3$ image, which undergoes a series of convolution and pooling operations to finally output a 128 dimensional feature vector for face recognition. The loss function used is the ArcFace loss function, which enhances discriminative ability and improves accuracy by adding angular margins between the feature vector and classification weights. MobileFaceNet achieves an accuracy of 99.55% on the LFW dataset and on the MegaFace dataset TAR@FAR1e-6 The accuracy reaches 92.59%, which is comparable to large CNN models [12]. Its advantages lie in high efficiency, high precision, and good compatibility. It can be used as a standalone facial recognition model or combined with other facial detection algorithms (such as MTCNN) to form a complete facial recognition system [12].

2.4. Siamese Network Mechanism

The Siamese model is a special neural network architecture primarily used to compare the similarity or difference between two inputs. Its structure consists of two or more identical and weighted sub networks that map input data to a feature space, and then determine the similarity of input data through distance metrics such as Euclidean distance and cosine similarity. During training, Siamese models often combine contrastive loss functions or triplet loss functions to learn effective feature representations, making similar inputs closer in the feature space and dissimilar inputs farther away [12]. Its core advantage is sharing weights, reducing the number of parameters, and improving generalization ability; Focusing on similarity measurement, suitable for tasks such as facial recognition, signature verification, image matching, etc. that require comparison of inputs.

In the field of facial recognition, Siamese models can be used for facial verification and recognition tasks. Input two facial images into the model, and the network learns their similarity to achieve identity authentication and recognition. Its unique dual tower network structure and similarity measurement mechanism make it perform well in handling one to many comparison tasks [12]. However, Siamese models only output similarity scores and require two sub network structures to be strictly identical to ensure that the input image can be mapped to the same feature space. Compared to MobileFaceNet outputting category labels, Siamese models focus more on comparing the similarity between inputs, and both have their own strengths in the field of facial recognition.

3. Test

3.1. Model Structure and Parameter Challenges

Facial recognition aims to use image path reading to complete facial recognition operations. The MobileFaceNet model is used to predict facial features in order to obtain comparative similarity between features and feature values in

the facial database, and finally obtain the highest similarity result with a threshold value greater than 0.6, thus achieving high accuracy. The MobileFaceNet model involves a large number of parameters to meet the requirements that can be adjusted on personal computers or servers. Due to the influence of algorithms, some devices are unable to meet the requirements of online training for the entire network [12]. The structure of the MobileFaceNet model is shown in Table 1.

Table 1. Table of MobileFaceNet Model Structure and Parameters

Input	7×7×512	56×56×64	14×14×128	112×112×3	7×7×128	7×7×512	28×28×64	56×56×64	14×14×128	7×7×128
Operator	Linear GDConv 7×7	Bottleneck	Bottleneck	Conv 3×3	Bottleneck	Linear Conv 1×1	Bottleneck	Depthwise Conv 3×3	Bottleneck	Conv 1×1
t	--	2	4	--	2	--	4	--	2	--
c	512	64	128	64	128	128	128	64	128	512
N	1	5	1	1	2	1	1	1	6	1
s	1	2	2	2	1	1	2	1	1	1

Due to the limitations of embedded terminal algorithms, it is difficult to add new detected facial feature values and original functional libraries, so MobileFaceNet model training cannot proceed smoothly. At the same time, the above operations require a large amount of work and high professional spirit, which is difficult to apply to practical scenarios [12].

3.2. Siamese Network Integration Solution

However, the Siamese model based on the combination of MobileFaceNet model and online learning can solve the above problems. It supports porting trained models to embedded devices on PC/servers to achieve initial function extraction operations, obtain new function vectors, and update the function vector dataset in real-time. The real-time update function configured by Siamese models can effectively improve the effectiveness of facial recognition. The Siamese model is a neural network used to evaluate input feature vectors. The input meets the sharing requirements. The new input space is determined by the shared model, and the similarity of input values is evaluated by the loss function. Since the parameters set for each network are the same, only one model needs to be trained during the training operation, which can effectively reduce the number of training samples. Input the extracted facial feature vectors and other information into the Siamese model to obtain the corresponding 64 dimensional feature vectors, and then solve for the Euclidean distance [14]. When the Euclidean minimum distance is less than the set threshold, it indicates that the facial image to be recognized is in the database. When the minimum Euclidean distance is greater than the set threshold, it means that the person signing during this period is a stranger. If the system needs to add strangers, the MobileFaceNet model is used to extract relevant feature values and create a dataset, and the Siamese model network is trained. This time, Siamese models can be used for facial recognition and model training on embedded devices [12]. Here, this is a relatively complete facial recognition system.

3.3. Dataset Collection and Preprocessing

The CASIA dataset contains 2500 Asian facial images of 500 people. 100 facial images of people were extracted from the images and the dataset was preprocessed. The facial

detection algorithm of MTCNN is used for facial detection, and the facial size is modified to 112x112. The MobileFaceNet model has been pre trained on the MS1M-V2 facial dataset and used to extract facial features.

3.4. Model Training and Accuracy Metrics

After continuous debugging, set the Euclidean distance threshold to 0.5, which means that when the distance between facial feature vectors is less than 0.5, it will be judged as the same person, otherwise it will be judged as another person. When only running MobileFaceNet, the recognition accuracy is 98.6%. To validate the new method, the MobileFaceNet model was used to extract facial features to construct the training set for the Siamese model, which was trained using the TensorFlow neural network framework to evaluate the effectiveness of the online update mechanism, as shown in [15]. In contrast, the recognition results using the MobileFaceNet+Siamese new model are better than those using only the MobileFaceNet model, that is, without adjusting the MobileFaceNet model, retraining only the Siamese model can improve the accuracy of face recognition [12].

3.5. Offline Testing and Update Mechanism

The next step is the offline testing of the facial recognition system, which collected facial photos of 15 people. Among them, 10 are known, while the other 5 are unknown, that is, strangers. The facial features of these 10 people were extracted using the MobileFaceNet model, and the Siamese model was trained using the Numpy library in the STM32MP157 processor. The training lasted for about 10 minutes and underwent 100 iterations. The size of the well-trained model file is only 65kb [12]. After training, non-contact signature or login can be implemented on the flags in the system [12]. When meeting strangers, the boarding system can add new friends online (saving the corresponding function vectors to the function library). When the number of strangers is small, the accuracy of not updating the existing Siamese model is also high. However, as the number of strangers increases, the accuracy gradually decreases. On the contrary, every time a new person is added, the parameters of the Siamese model are fine tuned. The more fine-tuning time, the stronger the function extraction ability, and the higher the

accuracy of the entire system after updating the model. From the training results, it can be seen that online update methods can greatly improve accuracy. After 100 iterations, the accuracy has reached 100% and training can be stopped [12]. In summary, non-contact sign in systems based on artificial intelligence can be detected with the help of infrared sensors. By opening the camera to capture the face and accurately extracting facial features that can be detected using MobileFaceNet, the Siamese model can obtain the corresponding feature vectors and fully recognize the face based on Euclidean distance [12].

The system has good stability and accuracy. This system is used in collective symbols, only requiring the collection of a few images, and has a recognition accuracy rate of over 99% through preprocessing and algorithm optimization, which is beneficial for solving the slow traditional problems of speed and low data utilization.

4. Prospect

In practical applications, the non-contact check-in system proposed in this study has shown great potential for application.

4.1. Application Scenarios

Except for university scenarios, this system can be widely applied in enterprise attendance, conference attendance, security access control, and other scenarios after simple adaptation [1]. In enterprise attendance, multi face recognition function can quickly complete daily attendance of employees, effectively avoiding cheating behavior in traditional attendance methods and improving management efficiency; In the scenario of conference check-in, the system can complete identity recognition and check-in records at the moment of participant entry, reducing conference preparation time and making the conference process smoother and more efficient; In the field of security access control, compared with traditional access control systems, facial recognition access control not only improves the speed of passage, but also enhances security, prevents security risks such as tailgating, and reduces the production and management costs of physical cards.

4.2. Future Research Directions

Future work will focus on further optimizing system performance and expanding functionality. On the one hand, we will continue to explore model compression and optimization techniques to reduce the system's dependence on hardware resources while ensuring recognition accuracy, achieve wider device compatibility, including efficient operation on low-power, low-cost embedded devices, and promote the popularization and application of facial recognition technology in resource constrained environments. On the other hand, we will conduct in-depth research on how to combine other biometric recognition technologies (such as fingerprint recognition, iris recognition, etc.) to construct a robust multimodal biometric recognition system for fingerprint face fusion recognition, as shown in [4,10]. Multimodal biometric recognition can significantly improve the robustness and accuracy of recognition systems by integrating multiple biometric information. Especially in

complex environments or facing special groups, it can effectively compensate for the shortcomings of single biometric recognition, provide more reliable and accurate solutions for identity authentication, further expand the application fields and scenarios of facial recognition technology, and bring more convenience and security guarantees to people's lives and work.

References

- [1] Lu, L. X., Qiang, Z. C., Yu, M., & Ren, Q. Y. (2023). Design of contactless check-in system based on embedded artificial intelligence. *Laboratory Research and Exploration*, 42(03), 130–134, 170.
- [2] Liu, H. H., & Yin, S. Q. (2024). Multi face recognition intelligent attendance system for universities based on SeeTaface. *Information Technology and Informatization*, (07), 199–202.
- [3] Wang, Z. H., & Li, J. G. (2024). Optimization of lightweight face recognition model based on edge computing. *Computer Engineering and Applications*, 60(12), 189–195.
- [4] Chen, Y. J., & Zhang, W. (2023). Design of Multi modal Biometric Recognition System for Smart Classroom in Universities. *Modern Educational Technology*, 33(08), 112–118.
- [5] Liu, H. R., & Zhou, M. (2024). Research on Public Safety Monitoring System Based on Multi Face Recognition. *Security Technology*, (05), 45–49.
- [6] Zhang, J. J., & Yang, L. (2023). Application of Real time Multi face Recognition in Intelligent Monitoring. *Information Technology*, 47(06), 102–106.
- [7] Yuan, K. (2024). Design of contactless check-in system based on artificial intelligence. *Electronic Products World*, 31(06), 73–76.
- [8] Luan, X., & Li, X. S. (2021). Facial liveness detection algorithm based on multi feature fusion. *Computer Science*, 48(S2), 409–415.
- [9] Yang, R. J., & Zheng, G. L. (2022). Face liveness detection based on InceptionV3 and feature fusion. *Computer Applications*, 42(07), 2037–2042.
- [10] Zhao, K., & Wu, M. (2024). 3D structured light and multi feature fusion based liveness detection algorithm. *Electronic Technology Applications*, 50(04), 132–136.
- [11] Sun, X. Y., & Huang, J. P. (2023). Research on Face liveness Detection Based on Dynamic Texture Analysis. *Computer Application Research*, 40(11), 3478–3482.
- [12] Xue, J. P. (2024). Research and Application of Deep Learning based Facial Recognition Algorithm. (Unpublished doctoral dissertation). Beijing University of Posts and Telecommunications, Beijing.
- [13] Zhou, B., & Xu, L. (2024). Model Compression Technology of MobileFaceNet in Embedded Devices. *Microcomputer and Applications*, 43(03), 38–62.
- [14] Zhang, H., Sun, W. Y., & Song, G. P. (2024). Teaching roll call software based on facial recognition. *Journal of Jilin Radio and Television University*, (01), 19–21.
- [15] Li, M. M., & Chen, H. B. (2023). Update mechanism of facial recognition model based on online learning. *Data Collection and Processing*, 38(05), 923–930.