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The application and challenges of different face recognition technologies in the three major fields of security, social media, and medical care

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Abstract. Face recognition technology is a very important part of modern technology, which can not only be used to ensure security, but also can be used in the field of information organization and content division. However, with the popularization and application of face recognition technology, many problems that need to be solved urgently have emerged: excessive computing resources are consumed in order to pursue high-precision recognition, which brings computing pressure; The basis for improving recall is the need for a lot of power and memory; If security is not guaranteed, it can cause problems such as data breaches. The demand for face recognition technology is different in different use fields, so the purpose of this study is to combine the scene requirements and technical advantages more reasonably. The research results are as follows: the high accuracy and recall rate of 3D convolutional neural networks (3DCNNs) ensure that it can be used safely in high-precision and high-security scenarios. Lightweight Convolutional Neural Network (MobileNetV2) is suitable for resource-constrained environments due to its low memory consumption and low communication cost. Edge computing real-time face recognition (EC-RFERNet) is the most suitable for large-scale popularization and application among the three because of its lowest power consumption and latency. This study deeply explores the advantages and disadvantages of different facial recognition technologies and finds solutions to their shortcomings. According to their unique advantages combined with the requirements of commonly used scenarios, it provides a scientific basis for the deployment of face recognition technology in different fields. However, due to limited information, this paper cannot cover all application scenarios and the latest technologies, so it is hoped that in the future, we can combine the advantages of different technologies to develop more comprehensive face recognition technology and make more reasonable technical planning.

Keywords: Face Recognition, 3D facial recognition, Lightweight convolutional neural network, Edge computing, Deep Learning.

1. Introduction

As an important branch of computer vision, face recognition technology has made significant progress in many fields. After combining face recognition technology with deep learning, the accuracy and robustness of other technologies have been significantly improved. Among the three common areas of face recognition technology, face recognition technology reflects the following functions: in the security

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system, it can be used to monitor and identify target people in real time, which can improve social security and stability [1]. On social media platforms, it can be used to beautify photos, sort albums, as well as authenticate accounts, greatly improving the security of accounts [2]. In the medical field, facial recognition technology can be used to improve medical efficiency by authenticating patients and analyzing facial structures for disease [3].

Although facial recognition technology has gradually matured, there are still some unavoidable shortcomings. For example, the latest facial recognition technologies, 3D Convolutional Neural Networks (3DCNNs), Lightweight Convolutional Neural Networks (MobileNetV2) and Edge Computing Real-Time Face Recognition (EC-RFERNet), have the following advantages and disadvantages:

3D face recognition is extremely accurate, so it can be used most in scenarios that require high accuracy and robustness. In addition, 3D technology is better able to handle changes in light and facial posture, so it can enable facial recognition to function properly at unfixed angles [4][5]. As a result, this identification technology can play a vital role in security systems in places such as police stations and airports. It can also play a key role in systems that diagnose diseases based on facial structure [6].

Lightweight convolutional neural networks can run efficiently on resource-constrained devices due to their relatively average parameters and low-cost but efficient operation [1]. The technology is suitable for smart home systems and social platforms [7].

As a computing method with the lowest memory cost and the fastest communication speed, real-time face recognition in edge computing can significantly reduce latency while maintaining security [2]. The technology is suitable for environments that can only provide low power consumption and low latency, such as large-scale urban surveillance and border patrol systems.

The purpose of this article is to evaluate the specific applications of these three technologies in the fields of security, social media, and medical by comparing and analyzing their performance in six aspects. The evaluation process is carried out according to the following steps: First, the accuracy rate, recall rate, computing cost, communication cost, memory cost and security of the three identification technologies are calculated and displayed in the form of a table. Then, according to the literature and practical application, the defects of the technology are found, and the optimization method is proposed. Finally, the three most common areas of security system, social media and medical care are analyzed to summarize which technology should be matched under different requirements in different scenarios.

2. Related work

2.1. 3D Face Recognition

Yin et al. proposed a deep learning-based 3D facial reconstruction method to achieve high-fidelity facial reconstruction and recognition by using 3D Convolutional Neural Networks (3DCNNs) and Generative Adversarial Networks (GANs) [4]. Mian et al. also introduced an efficient 2D-3D hybrid method for automated facial recognition, emphasizing that the comprehensive use of facial texture and geometric information can improve the accuracy of recognition [8]. In addition, Bessaoudi et al. proposed an enhanced Fisher discriminant analysis method to improve the robustness of 3D facial verification [9].

2.2. Lightweight Convolutional Neural Networks for Face Recognition

Hassanpour and Kowsari proposed an improved MobileFaceNet model, called MMobileFaceNet, which significantly reduces the computational cost of the model while improving the recognition performance [1]. In addition, Li et al. introduced a spatial attention mechanism to further optimize the performance of lightweight CNNs, so that they can still operate efficiently in resource-constrained environments [6].

2.3. Edge Computing for Real-Time Face Recognition

Xie et al. proposed an optimized facial recognition algorithm designed for edge computing that significantly reduces resource consumption by replacing the traditional VGG16 model with a compact

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MobileNet [2]. At the same time, Moussaoui et al. evaluated the performance of different edge devices to ensure that the system can be used effectively in a variety of real-world application scenarios [3].

Most of the current research focuses on the performance improvement of specific technologies, and there is a lack of systematic comparison of the comprehensive performance of different technologies, let alone a detailed study of how to comprehensively utilize these technologies in practical applications. Future work can focus on how to combine the advantages of different technologies in practical applications and apply them to suitable scenarios in different categories to improve the overall performance of facial recognition systems.

3. Methodology

3.1. Comparison Standards and Methods

We selected three facial recognition technologies: 3D facial recognition, lightweight convolutional neural networks (CNNs), and real-time facial recognition in edge computing, and compared them in the following aspects:

Accuracy: the recognition accuracy of the algorithm on a standard dataset.

Recall: The recall rate of the algorithm under different test conditions.

Computational Cost: the computational complexity and resource consumption of the algorithm.

Communication Cost: the cost of the algorithm during data transmission.

Memory Cost: The memory resources required by the algorithm when it is running.

Security: The robustness of the algorithm in the face of different attack methods.

3.2. Algorithm Descriptions

The core equations for 3D facial recognition (3DCNNs) are:

$$f = g(X)\,,$$

$$X = \{(x_i, y_i, z_i) \mid i = 1,2,\cdots,N\}\,,$$

$$g(X) = CNN3D\left(\sum_{i=1}^{N} w_i \cdot (x_i, y_i, z_i)\right),$$

X represents the input 3D face data, g is a 3D convolutional neural network (3DCNN). (x_i, y_i, z_i)represents the 3D coordinates of the i-th point, $w_i$represents the weights and $CNN3D$is a 3D convolutional neural network [4] [5].

The core equations for lightweight convolutional neural networks (MobileNetV2) are:

$$f = h(I)\,,$$

$$I = \{I_{ij} \mid i = 1,2,\cdots,H; j = 1,2,\cdots,W\}\,,$$

$$h(I) = CNN_{lightweight}\left(\sum_{i=1}^{H} \sum_{j=i}^{W} w_{ij} \cdot I_{ij}\right),$$

I represents the input two-dimensional face image, h is a lightweight convolutional neural network. I_{ij} represents the pixel value of the input image, w_{ij} represents the weight, $CNN_{lightweight}$ is a lightweight convolutional neural network [1] [6].

The core equations for real-time facial recognition in edge computing (EC-RFERNet) are:

$$f = h(I) + \in,$$

$$I = \{I_{ij} \mid i = 1,2,\cdots,H; j = 1,2,\cdots,W\}\,,$$

$$h(I) = Edge - CNN\left(\sum_{i=1}^{H} \sum j = 1^{W} w_{ij} \cdot I_{ij}\right) + \epsilon,$$

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ϵ represents the real-time processing error correction brought about by edge computing. I_{ij} represents the pixel value of the input image, w_{ij} represents the weight and $Edge - CNN$ is a convolutional neural network used for edge computing [2] [3].

3.3. Data Analysis Methods

1. Performance evaluation: Each algorithm is evaluated using experimental results such as accuracy, recall, compute cost, communication cost, memory cost, and security.

2. Comparison of results: The experimental results are compared, the advantages and disadvantages of each algorithm are identified, and the most suitable facial recognition technology for this scenario is summarized according to the needs of specific application scenarios.

4. Result

Table 1. Comparison of three Face Recognition Models: Performance, Computational Cost, and Security Metrics

Model	Accuracy (%)	Recall (%)	Computational Cost	Communication Cost	Memory Cost	Security (%)
3D Face Recognition (3DCNNs)	98.5	97.2	0.5 - 1(s/frame)	Hundreds of MB to several GB	Hundreds of MB to several GB	95
Lightweight CNN (MobileNetV2)	95.3	94.1	30(ms/frame)	Few MB to tens of MB	Tens of MB	85
Edge Computing for Real-Time Face Recognition (EC-RFERNet)	97.8	96.4	0.39(ms/frame)	Few MB	Few MB	88

3D Convolutional Neural Networks (3DCNNs) have the highest accuracy and security of the three, making them suitable for highly accurate work environments.

Lightweight convolutional neural networks (MobileNetV2) have the most balanced metrics, so they are suitable for fast operation on resource-constrained devices.

Edge Computing Real-Time Face Recognition (EC-RFERNet) is optimized for edge computing with low power consumption and low latency, making it ideal for use in edge devices with low power consumption and latency.

5. Limitations and Improvement Suggestions

3D Facial Recognition (3DCNNs):

Because the processing time of each frame is 0.5-1 second, it is not difficult to see from the graph that the computational cost is much higher than that of the other two recognition methods [10]. And because of the improvement of computing accuracy, it is inevitable that the memory cost will also increase. In order to process and store three-dimensional feature maps and intermediate calculation results, the memory cost of 3DCNNs is tens or even hundreds of times that of the other two recognition technologies [11]. Li et al. proposed that the inputs and weights in the convolutional and fully connected layers can be converted into binary values to significantly accelerate the network and reduce memory and computational costs [12].

Lightweight Convolutional Neural Network (MobileNetV2):

In order to be able to meet the needs of mobile and embedded devices, the identification method is designed to be as lightweight as possible to reduce computing and communication costs. But inevitably, only 95.3% accuracy would force it to not be used in high-precision scenarios [10]. And can not accept and handle tasks of large dimensions that are too complex. The Depthwise Separable Convolutions proposed by Sandler et al. can split the standard convolution operation into two simpler operations, thereby significantly reducing the amount of computation and parameters. This can effectively help MobileNetV2 handle larger task scenarios [13].

Edge Computing for Real-Time Face Recognition (EC-RFERNet):

It is not difficult to see that the EC-RFERNet recognition technology is the one with the lowest cost of computational communication memory among the three models. However, due to the deliberate pursuit of low energy consumption, it cannot fully exert its accuracy in the environment of limited edge device performance and broadband. In order to improve the operational efficiency and real-time performance on edge devices, Yu et al. proposed that model compression techniques and hardware acceleration techniques can be used. Model compression techniques can reduce the number of model parameters by removing unimportant weights, while hardware acceleration techniques can utilize specialized accelerators to improve operational efficiency [7].

6. Discussion

We bring the three facial recognition technologies to the three most commonly used scenarios and analyze how the three models can be used most efficiently and accurately in each scenario.

Security Systems:

In the field of security systems, the key modules of facial recognition technology need to include accuracy, security, and communication costs. High accuracy can reduce the error rate, while misidentification can lead to serious security issues. Security can meet the need for efficient operations while protecting data privacy. The reduction of communication costs can reduce the overall overhead of the system and adapt to large-scale deployments.

Based on our comparisons, combined with the needs of the security system sector, we can find:

3D Convolutional Neural Networks (3DCNNs) have a recognition accuracy of up to 98.5% and a security accuracy of up to 95%, which is a prominent advantage among the three, so it is suitable for security systems that require high precision and high recognition effect [5]. However, because it requires a large amount of memory to store and process data, it is not suitable for use in situations where computing resources are limited [10]. From this, we can find that 3DCNNs recognition technology is suitable for police stations that require high-precision recognition technology to ensure identity accuracy and can be used for 3D reconstruction and analysis of crime scenes. Airports that require high-precision identification technology to prevent illegal entry and terrorist activities.

Although the accuracy and security of the lightweight convolutional neural network (MobileNetV2) are the most inferior of the three, it is suitable for security systems with high real-time requirements because its computational cost is only 30ms and the memory cost is moderate [14]. For example, smart home security systems that are suitable for running on resource-constrained devices and can reason quickly. and commercial site monitoring suitable for large number of deployments in the environment.

Edge computing real-time facial recognition (EC-RFERNet) has the fastest communication cost of several megabytes and the lowest computing cost of 0.39ms among the three [15]. And it's specifically optimized for edge computing, making it suitable for edge security devices. For example, large-scale urban surveillance systems that need to operate in low-power and low-latency environments, as well as border area patrol systems that can operate efficiently in remote areas and unstable network environments.

Social media:

In the field of social media, recall and safety are the two most important indicators, which play a decisive role in the user's experience and the safety of the platform. Facial recognition technology with a high recall rate can accurately capture all faces in user-uploaded images and videos, which can help with the organization function. And because social media contains a lot of user information, high recall recognition technology can identify all faces in massive amounts of data. As a medium for disseminating information, the security of data and private information can only be ensured under the premise of ensuring a high level of security. In addition, the high-security identification method can ensure the security of the platform and gain user trust at the same time, so as to increase user stickiness.

Based on the above analysis, we can further analyze the three recognition technologies:

3D Convolutional Neural Networks (3DCNNs) have a recall rate of 97.2% and a safety rate of 95%, which is the highest among the three [5]. As a result, it is ideal for handling scenarios that require high-precision facial recognition to prevent spoofing and professional content creation. For example, on Instagram, creators can use 3DCNNs to beautify images, which can improve the quality of their works and ensure authenticity [7].

Although the recall and security rates of Lightweight Convolutional Neural Network (MobileNetV2) are the lowest among the three, they are suitable for real-time interactive applications of everyday users because of the most balanced indicators. For example, on the Facebook platform, this technology can be used to automatically tag photos based on the results of facial recognition, which can help users easily manage photos [7].

Although the edge computing real-time face recognition (EC-RFERNet) has only a moderate recall and security rate, it is suitable for use in low-power and low-latency environments because of its extremely low computing cost and communication cost. For example, in video chat software, this recognition technology can be used for facial recognition and security verification in real-time chats, which can ensure the security of communication [16].

Medical resources:

In the field of medical resources, accuracy and security are the two most important indicators, which play a decisive role in the user's experience and the security of the platform. Highly accurate facial recognition technology can detect diseases through facial features, or assess patients' emotions through changes in facial expressions to assist in the early detection of diseases [6]. And high security can protect patients' medical data and even prevent hacker attacks. Ensuring the security of data and privacy is key to maintaining patient trust and compliance with laws and regulations.

Based on the above analysis, we can further analyze these three recognition technologies:

3D Convolutional Neural Network (3DCNN) has the highest accuracy and safety rate among the three, and is well suited for detecting and diagnosing complex genetic diseases with different facial features. For example, analyzing a patient's facial structure and comparing it to that of a person with Down syndrome can identify whether a patient has disease features [6]. This is important for the accurate and efficient identification of genetic diseases with specific facial structures.

Although the accuracy and security of the lightweight convolutional neural network (MobileNetV2) are mediocre, it is well suited for routine medical testing because the performance is balanced in all aspects. For example, real-time and remote monitoring of the user's health status can be achieved by using it in smartphones and wearable smart medical devices [12]. This can help users take control of their physical condition in an effective and cost-effective manner.

Because edge computing real-time face recognition (EC-RFERNet) has the lowest computing and memory costs among the three, it can achieve good results in low-power and low-latency environments. For example, it can use facial recognition technology to control access personnel in hospitals, ensuring that only authorized personnel can operate [7].

7. Conclusion

In this paper, we study the applications of three facial recognition technologies, 3D convolutional neural networks (3DCNNs), lightweight convolutional neural networks (MobileNetV2), and edge computing real-time face recognition (EC-RFERNet), in three fields: security systems, social media, and medical resources. By comparing the different performances of these technologies in six aspects: accuracy, recall rate, computing cost, communication cost, memory cost, and security, the focus and application direction of these technologies in three different application scenarios are analyzed.

It is found that 3DCNN performs best in high-precision recognition, and is suitable for scenarios that require high accuracy and security, such as police stations and airports. MobileNetV2 is ideal for applications that require real-time responses, such as smart home and business monitoring, due to its low compute cost and memory usage. EC-RFERNet optimizes communication and computational costs for low-power and low-latency environments such as large-scale urban surveillance and border patrols.

This paper systematically compares the advantages and disadvantages of different face recognition technologies, supplements and enriches the existing research, provides a scientific basis for the practical deployment of face recognition technologies in different fields, and points out the best application methods of each technology in specific scenarios.

Although this paper provides a detailed analysis of the three facial recognition technologies, there are still some limitations to the research. For example, it is not possible to cover all possible application scenarios and more recent technological advances. Future research can further explore how to combine the advantages of different technologies to create a unique new facial recognition technology to cover a wide range of needs, so as to further improve the overall performance and development prospects of facial recognition technology.

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