Convolutional Neural Networks for Biometrics Applications

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ABSTRACT: A convolutional neural network (CNN) is a feed-forward neural network that can react with other units in a specific range and can handle huge images well as a deep learning algorithm. CNN is a very convenient tool for conveying visual information and can be good for improving recognition accuracy. However, volumetric neural networks also increase the complexity of the networks, making them more challenging to optimize and more prone to overfitting. This paper will focus on the history of CNN development and the current use of the method, and the difficulties encountered. Furthermore, we will analyze its application in bioinformatics by discussing the papers published in the field about CNN. After the CNN was invented by Leon O. Chua and Lee Yang in 1988, researchers transformed a neural network into a CPU with thousands of cores. Improvements to the CNN in recent years have been made in six main parts: convolutional layer, pooling layer, activation function, loss function, regularization, and optimization, which have reduced the redundancy of the CNN and allowed it to process faster and more accurately processing. Nowadays, it is mainly used for image classification, text processing, video processing, etc. Above all, this paper realizes that CNN has excellent advantages in feature extraction and can play a huge role in dealing with eye biometrics, flower recognition, etc.

1. INTRODUCTION

Biometrics is mainly identified by computers analyzing the characteristics of organisms by mathematical and statistical methods. Deep learning has made significant progress in the field of biometrics. In particular, CNN techniques have performed very well; they have powerful feature extraction and information mining capabilities.

Today, many researchers are implementing different solutions based on computer vision. Karan et al. proposed a CNN for periocular verification in the visual spectrum [13], Yong Wu et al. developed an effective floral classification method based on VGG-16, VGG-19, Inception-v3, and ResNet50 models using convolutional neural networks and migration learning [11]. Yuanyuan Liu et al. used convolutional neural networks for plant classification and concluded that CNNs outperformed conventional methods [6].

This paper will analyze previous studies on flower recognition techniques and iris recognition techniques to verify the improvement of CNN techniques in biometrics and briefly introduce the future trends of CNN techniques. This study has helped researchers to better explore the use of CNN in the field of bioinformatics and improve the efficiency of researchers' work.

2. ANALYSIS

2.1. Introduction and Development of Convolutional Neural Networks

2.1.1. Basic Structure of CNN

Neural networks are part of artificial intelligence, and deep convolutional networks are the most popular neural networks that are commonly used to analyze visual images. A convolutional layer, a pooling layer, and a fully connected layer constitute a conventional convolutional neural network. The convolution layer serves to extract the features of an image, the pooling layer is responsible for downscaling to prevent overfitting, and the fully connected layer is responsible for the output result, which is a specific feature space for each image. A typical CNN is a multi-layer structure, not merely a three-layer one as previously stated. Compared to other methods, CNN requires less pre-processing.

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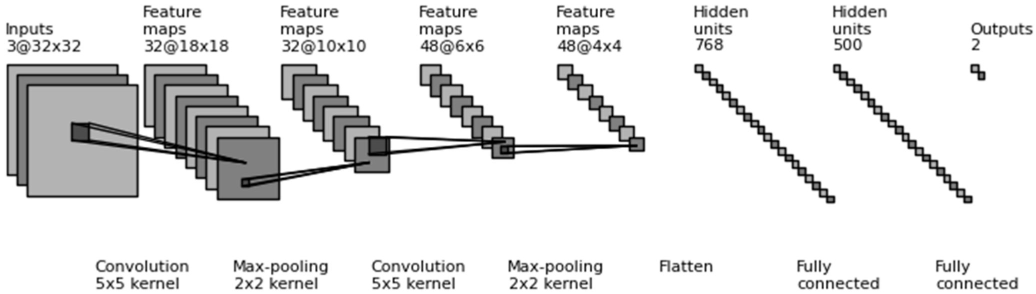

Figure 1 CNN model

The convolution layer is the process of extracting features, which sweeps through the complete image with a convolution kernel. This method is analogous to utilizing the convolution kernel to detect each little section of the picture and extract its feature values. Multiple convolutional kernels are frequently used in applications.

The pooling layer then reduces the dimensionality of the data and avoids overfitting. Pooling layers can be more effective than convolutional layers in reducing the dimensionality of the data and greatly reducing the number of operations.

The fully-connected layer is the finally part of the CNN, where the data handled by the convolutional and pooling layers are fed to the fully-connected layer to obtain the finished result efficiently.

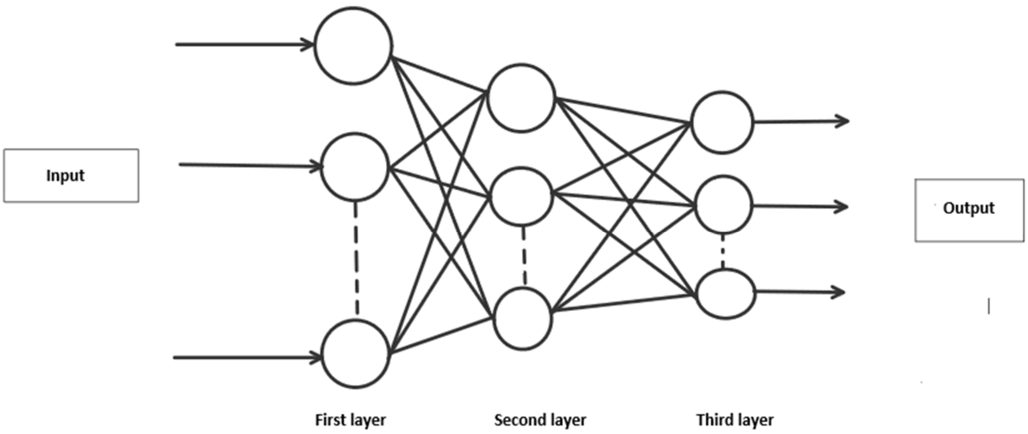

Figure 2 Fully connected Layer

Therefore, CNN is the most productive learning algorithm for understanding visual material. In addition, it demonstrates excellent image classification, recognition, segmentation and retrieval [3].

2.1.2. History of CNN

Leon O. Chua and Lee Yang introduced the Cellular Neural/Nonlinear Network (CNN) in 1988. Tamas Roska's design of the CNN Universal Machine (CNN-UM) was the next essential step in CNN research. From an application standpoint, this was a breakthrough since it demonstrated how to transform a neural network into a multi-thousand core CPU, which was an innovation in the 1990s [3]. And since the success of AlexNet in 2012, various improvements have been made to CNNs. The main improvements to CNNs in recent years have been in six parts: convolutional layer, pooling layer, activation function, loss function, regularization, and optimization [4]. As computer vision and machine learning tasks become more challenging and deep neural network models become more complex, improvements in these sections have reduced the redundancy of CNNs, allowing for faster and more accurate processing.

2.2. Analysis and application of convolutional neural networks

The rapid development of CNNs has led to better solutions for computer vision tasks. In recent years, many advanced works have used CNN techniques, including object recognition, image recognition, image classification, image segmentation This chapter focuses on the recognition and classification of images, object detection, speech recognition, and natural language processing. Among them, the application of CNN in bioinformatics will be explained in detail in the next chapter.

2.2.1. Image Recognition and Classification

Computer vision (CV) is an artificial system that extracts usable information from visual data and recognizes images [3, 12]. CNNs are commonly applied to CV. For a long time, CNNs have been used in picture categorization. Compared to other methods, CNNs can classify images at a finer level. Image recognition and classification are widely utilized in bioinformatics.

Classification and recognition of images can play an important role in education, medicine and other fields. For example, technology is used in teaching to identify realistic objects and in the medical field to identify cancer pictures.

2.2.2. Object Detection

Object detection has been an outstanding problem in computer vision. The design of an artificial system that can sense and extract meaningful information from visual data is referred to as computer vision. Object detection involves recognizing photographs, and its difficulty lies mainly in how to exactly and validly locate objects in images or videos. Although the history of object detection dates back to the 1990s, it was not until these years that significant progress was made in CNN-based object detection. In 2015, Renn proposed R-CNN, a fast method for object detection [4]. Also in 2016, Dai presented the use of fully connected CNNs to detect objects based on their locations [3, 4]. Another object detection approach described by Gidaris et al. is assisted on a multi-region-based deep CNN that assists in learning semantic aware features [2].

Object detection may be used in conjunction with other computer vision techniques such as image segmentation and image recognition to better comprehend and evaluate scenes in movies and photos.

2.2.3. Speech Recognition

The basic structure and functions of CNN show that it is an effective method for processing image tasks. But it also works just as well for speech recognition. Automatic speech recognition (ASR) is a technique for converting human speech into spoken language. Prior to the application of CNN to ASR, the field had long been predominated by Hidden Markov Models and Gaussian Mixture Models (GMM-HMM). In contrast, CNNs are able to capture the ground shift in inverted speech compared to GMM-HMM. To recognize speech emotions, Huang et al. used CNN in combination with LSTM [7]. CNN learned LSTM for recognizing speech features and has been recognized for speech recognition.

Speech recognition can be used in areas such as simultaneous translation and voice input.

2.2.4. Natural Language Processing

Natural language processing's fundamental goal is to translate language into a computer-readable format. Text classification is a key mission in natural language processing (NLP). Natural language sentences have a complex structure, including order and hierarchy, which is crucial for understanding them. And CNN structures handle the problem of text classification very well. Collobert and Weston created a CNN version that can execute a variety of NLP tasks at the same time, including language modeling, chunking, named entity identification, and semantic role modeling [3].

Natural language processing enables computers to speak with humans in their own language by allowing them to read text, hear human voices, and interpret them.

3. APPLICATION OF CONVOLUTIONAL NEURAL NETWORKS IN BIOMETRICS

Biometrics are biometric or physical characteristics that can be used to identify an organism. Examples include facial recognition, iris recognition, and recognition based on plant characteristics.

3.1. Facial Recognition

The human face is one of the most widespread biometric features and is very versatile. So in recent years, face recognition has been receiving a lot of attention from computer vision researchers. Face recognition systems have been widely used in government departments, e-commerce, retail and information security. However, due to different shooting conditions, some facial photos may be very blurred or the accuracy of face recognition may be degraded due to lighting changes.

Face recognition would normally be considered a problem of image classification. And deep learning architectures play an important role in image classification, especially CNNs as feature extractors. Face recognition relies on CNN's capacity to learn local patterns from data. Ramaiah et al. in 2015 used deep convolutional neural networks (CNN) to solve the face recognition problem under non-uniform illumination. The experimental study showed a clear performance improvement (4.96%) of the CNN classifier when the horizontal reflection of the facial data was also regarded during training. [10]. Face recognition technology has failed due to the use of mandatory masks. Masked face recognition has also become a widely discussed topic among researchers. Mundial et al. investigated and trained a CNN-based feature extractor to the support vector machine classifier on a most advanced facial recognition feature vector and obtained 99% accuracy of the suggested method on a classifier based on a masked facial dataset [8].

Face recognition has been widely employed in public security inspections, online fugitive tracking, household registration investigations, document verification, and other areas as a highly essential means of identification. Face recognition may be utilized as an access control system at the same time.

Studies have shown that facial features, an important feature in the field of bioinformatics, are well developed with the support of CNNs. CNNs play an important part in the area of facial recognition.

3.2. Iris Recognition

Biometric systems are constantly developing and are used to effectively identify and verify identities. The complexity of iris features is attributed to the uniqueness and variety of texture details within the iris region, so it has a very high degree of distinctiveness and stochasticity. Therefore, it is widely used in biometric systems. As cameras continue to evolve in the Internet space, iris recognition has become a key area of interest for researchers.

On the MICHE-II dataset, Ahuja et al. suggested a deep learning model based on hybrid convolution, which has an AUROC of 0.986 and a TPR of 99.5 percent at an FPR of 0.001 percent on the VISOB dataset, and may be employed in real applications with low mistakes [1]. Nguyen et al. in 2017 showed that off-the-shelf CNN features can be effectively transferred to the iris recognition problem to efficiently extract discriminative visual features from iris images [9].

Iris recognition can be used in security devices such as access control where there is a need for confidentiality, and police can also determine people's identities by comparing the similarities between iris image features.

Off-the-shelf CNN features, while often used initially in the classification domain, are also excellent at representing iris images. It can efficiently extract distinguishing visual features and achieve effective recognition results.

3.3. Flower Identification

Flowers play a vital part in our lives and have significant scientific and application value. Traditional flower classification methods are mostly focused on form, color, or texture traits, and this method requires individuals to choose the attributes for flower categorization, resulting in low classification accuracy [5].

Liu et al. constructed a large floral image dataset containing 79 categories and used a CNN-based framework to solve the problem, achieving 84.02% classification accuracy, which is better than previously known methods [6]. Wu's research reveals that utilizing a deep convolutional neural network model to extract features is more convenient and practical than manually extracting features, and it enhances flower recognition accuracy significantly [11].

The recognition of objects from images, supported by machine learning techniques, is now very encouraging and CNNs can be used very effectively in the field of biological classification and recognition.

As the most representative classification object among plants, the application for flower recognition can be extended to the medical field, especially for cancer diagnosis and using histological images to identify breast cancer images.

4. CONCLUSION

We give a survey and analysis on the use of CNNs in bioinformatics in this work.

CNNs can be used in bioinformatics fields such as face recognition, iris recognition, and flower classification, etc. CNN can recognize and classify human facial information with extremely high accuracy in the field of face recognition. And in the field of iris recognition, it can also effectively extract iris features. In flower classification, CNN can also perform successful classification of different flowers. The use of CNNs has led to more accurate research in bioinformatics. Researchers have also improved different aspects of CNNs to make them more adaptable to the research subjects.

Although CNN has made great achievements in all fields of bioinformatics, CNNs require large data sets and huge computing power for training. The collection of large-scale datasets is labor-intensive. And CNNs require a lot of experience to tune models and, in turn, rely on the ability of researchers.

The introduction of a large number of unique concepts into CNN designs has transformed research objectives in the computer vision applications. The study of new CNN architectures is a promising field of study that has the potential to become one of the most extensively utilized artificial intelligence approaches. CNN can perform critical information acquisition on images. In the future bioinformatics field, CNNs may be heavily applied to more medical research and have more accurate and fast recognition capabilities. This paper is based on the existing CNN structure, which requires a large volume of data and training to get the desired results through CNN, and the structure of CNN may be improved in the future to greatly reduce the amount of data needed for training.

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