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Photo Recognition of Alzheimer's disease Using Convolutional Neural Network through Artificial Intelligence

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ABSTRACT

As an algorithm with excellent performance, convolutional neural network has been widely used in the field of image processing and achieved good results by relying on its own local receptive fields, weight sharing, pooling, and sparse connections. In order to improve the convergence speed and recognition accu- racy of the convolutional neural network algorithm, this paper proposes a new convolutional neural network algorithm. First, a recurrent neural network is introduced into the convolutional neural network, and the deep features of the image are learned in parallelusingtheconvolutionalneuralnetworkandtherecurrent neural network. Secondly, according to the idea of ResNet'sskip convolution layer, a new residual module ShortCut3-ResNet is constructed. Then, a dual optimization model is established to realize the integrated optimization of the convolution and full connection process. This paper helps a person to recognisethe severity of a person with Alzheimer 's disease by simply viewing the image of the affected area. Alzheimer's disease can be classified as early-onset or late-onset. The signs and symptoms of the early-onset form appear between a person's thirties and mid-sixties, while the late-onset form appears during or after a person'smid-sixties

Index Terms—CNN, ReLU, AD, AI, MCI

I. INTRODUCTION

With the rapid development of the mobile Internet, the widespread use of smart phones and the popularization of social media self-media, a large amount of picture information has accompanied. Nevertheless, as pictures become important carrier of network information, problems also arise. Traditional information materials are recorded by words, and we can retrieve and process the required content by searching keywords. However, when pictures express the information, we cannot retrieve or process the information expressed in the pictures. The picture brings us a convenient way of information recording and sharing, but it is difficult for us to use the information expressed by the image. In this case, how to use a computer to intelligently classify and recognize data of these images is particularly important. In traditional pattern recognition methods, the most important thing is to express this image

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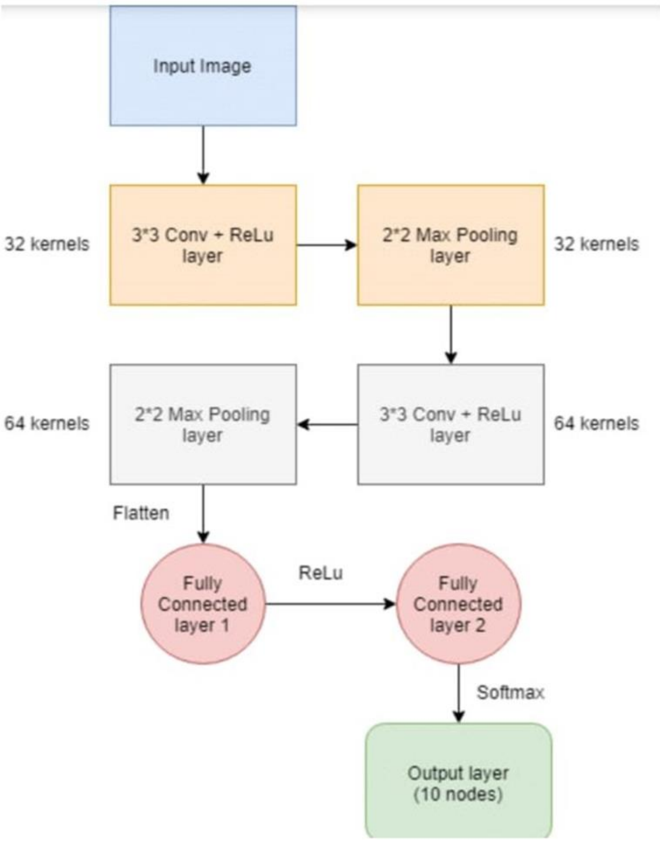
through a mathematical statistical model after extracting a certain amount of artificial feature points. Then identify the image by the method of image matching. The basic principle of this method is that the similar samples are very close in the pattern space and form a “clustering”, and then combined with the classifier for classification and recognition. For example, object recognition uses scale-invariant feature transform (SIFT) features, recognition uses local binary pat- terns (LBP) features, and pedestrian detection uses histogram of oriented gradient (HOG) features, but such shallow machine learning methods have low recognition. With the development of artificial success in the elds of speech recognition, NLP processing, computer vision, video analysis, multimedia, and so on. More and more enterprise companies and researchers use deep learning to discuss and study image classification, which provides a good development for artificial intelligence.

II. ARCHITECTURAL DESIGN



III. RELATEDWORK

Convolutional Neural Networks (CNNs) have been established as a powerful class of models for image classification and related tasks. Kernel Extreme Learning Machines (KELMs), known as an outstanding classifier, cannot only converge extremely fast but also ensure an outstanding generalization performance. In this paper, the author Xiabin Zhu [1] proposed a novel image classification frame- work, in which CNN and KELM are well integrated. In our work, Densely connected network (DenseNet) is employed as the feature extractor, while a radial basis function kernel ELM instead of linear fully connected layer is adopted as a classifier to discriminate categories of extracted features to promote the image classification performance. Experiments conducted on four publicly available datasets demonstrate the promising performance of the proposed framework against the state of-the-art methods.

During the last few years, significant attention has been paid to surface electromyographic (sEMG) signal–based gesture recognition. Nevertheless, sEMG signal is sensitive to vari- ous user-dependent factors, like skin impedance and muscle strength, which causes the existing gesture recognition models not suitable for new users and huge precision dropping. There- fore, we propose a dual layer transfer learning framework, named dualTL, to realize user-independent gesture recognition based on sEMG signal. Dual TL is composed of two layers. The first layer of dual TL leverages the correlations of sEMG signal among different users to label partial gestures with high confidence from new users. As referred by the author, Hanchaoyu [10] according to the consistencies of sEMG signal from the same users, the rest gestures are labelled in the second layer. We compare our method with three universal machine learning methods, seven representative transfer learning methods, and two deep learning–based sEMG gesture recognition methods. Experimental results show that the average recognition accuracy of dualTL is80.17%.

An ontology-driven hierarchical sparse representation is developed in this paper, which aims to support hierarchical learning for large scale image classification. Firstly, a two- layer ontology (semantic ontology and visual ontology) is built to organize large number of image classes hierarchically, where WordNet is used to construct semantic ontology and deep features extracted by Inception V3 are used to construct visual ontology (visual tree). Secondly, a novel algorithm based on Split Bregman Iteration is developed to learn hierar- chical sparse representation, i.e., learning a shared dictionary and a set of class-specified dictionaries depending on the two- layer ontology. For multi-class image classification, the author Yang Zang [2] introduced a tree classifier trained according to the two-layer ontology by using the hierarchical sparse representation.

IV. METHODOLOGY

This paper first introduces a recurrent neural network into the convolutional neural network, and uses the convolutional neural network and the recurrent neural network to learn the deep features of the image in parallel. Secondly, according to ResNet's idea of skipping convolutional layer, a new residual module ShortCut3-ResNet is constructed. Finally, a dual optimization model is established to achieve integrated optimization of the convolution and full connection process.

Recurrent Neural Network

Recursive neural network is similar to the combination of convolution operation and sampling operation. By repeatedly using the same set of weights and selecting the acceptance domain to achieve the purpose of reducing the feature dimension layer by layer. Among them, variable K_1 is the number of feature maps output by the first-level network. The size of the bottommost feature map is 4 *4, which is the unit of the bottom feature map. Let the acceptance be 2* 2 and the learning machines for image classification.

Connection weight is W. Each unit of the second-layer network feature map is connected to the 2 * 2 acceptance of the bottom layer feature map, and finally a 2* 2 size feature map is obtained. In the same way, the second layer of feature maps gets a 1* 1 size feature map after going through a layer of recurrent neural network.

Construct A New Residual Module

Shortcut in ResNet skips the two convolutional layers and connects to the corresponding output layer. According to ResNet's idea of skipping convolutional layers, this paper builds a new residual module that skips three convolutional layers. The resulting ResNet is called ShortCut3-ResNet. The most important part of ResNet is the shortcut. Although its presence makes the network look more complicated, it does not add additional parameters and calculations, but improves the accuracy of recognition.

Double Optimization

The design principle of the convolution optimization model is to realize the weight optimization.

V. CONCLUSION

In order to improve the ability of the convolutional neural network to classify and recognize two-dimensional images and speed up the convergence of the algorithm, this paper pro-poses a new convolutional network algorithm. First, a recur-rent neural network is introduced into the convolutional neural network, and the deep features of the image are learned in parallel using the convolutional neural network and the recurrent neural network. Not only can we use convolutional neural networks to learn high-level features, but also recursive neural networks to learn the combined features of low-level features. Secondly, according to ResNet's idea of skipping convolutional layers, we construct a new residual module ShortCut3-ResNet. Finally, the convolutional layer and the full connection process are optimized. Experiments show that the proposed convolutional neural network algorithm can improve the feature extraction accuracy and image recognition ability of convolutional neural network.

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