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A New Convolutional Neural Network Model Based on P System

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Abstract: The purpose of this paper is to propose a new kind of Convolutional Neural Network Model Based on P System. With the advent of the era of big data, contains more implicit layer depth of the Convolutional neural network (Convolutional neural networks, CNNs) has a more complex network structure, compared with the traditional machine learning method has a more powerful features and learning skills. Convolutional neural network model trained by deep learning algorithm has made remarkable achievements in many large-scale recognition tasks in the field of computer vision since it was proposed. This paper first briefly introduces the basic concepts of convolutional neural network and P system, and summarizes the basic model structure of convolutional neural network, convolution feature extraction and pooling operation, as well as the basic model of P system. In this paper, P system is combined with deep neural network, and the concept of membrane calculation is added on the basis of convolutional neural network to form a new convolutional neural network model. This new convolutional neural network increases the "isolation" of membrane system and various rules of intra-membrane calculation on the basis of the original one, making it more convenient for convolution calculation. This new convolutional neural network based on membrane system will be more accurate in image classification and other problems.
Keywords: Convolutional Neural Network, P System, Computational Completeness.

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1. INTRODUCTION

As a branch of machine learning, deep learning is one of the major breakthroughs and research hotspots in the field of machine learning in recent years. In 2006, geoff Hinton, a professor at the university of Toronto and a leading machine learning figure, and his student Ruslan Salakhutdinov published an article in Science, one of the leading international academic journals, which put forward the idea of deep learning for the first time. [1]

Convolution Neural network (Convolutional Neural Networks, CNN) is a kind of containing convolution or related calculation and the depth of the structure of the Feedforward Neural network (Feedforward Neural Networks), is a deep learning (deep learning) one of the representatives of the algorithm. Since convolutional Neural Networks are capable of

Shift-invariant classification, they are also known as "shift-invariant Artificial Neural Networks (SIANN)" in the literature. In the early 1960s, Hubel and Wiesel et al. proposed the concept of sensory field [2] by studying the visual cortex system of cats, and further discovered the hierarchical processing mechanism of information in visual cortex pathways, thus winning the Nobel Prize in physiology or medicine. By the mid-1980s, the neural cognitive machine proposed by Fukushima et al. based on the concept of sensory field [3] could be regarded as the first implementation of convolutional neural network and the first artificial neural network based on local connectivity and hierarchical structure organization of neuron questions. The neural cognitive machine decomposes a visual pattern into many sub-patterns, and processes these sub-pattern features through the feature plane connected step by step, so that the model has good recognition ability even in the case of slight distortion of the target object. After this, researchers have been trying to use known as a multilayer perceptron [4] artificial neural network (international is only a layer of hidden layer nodes of shallow model) to replace the manual feature extraction, and use simple stochastic gradient bligh drop method to train the model, and further puts forward the back propagation algorithm is used to calculate the error of the gradient, the algorithm is then proved very effective. [41].In 1990, LeCun [5] et al. proposed the convolution neural network model trained by gradient back-propagation algorithm when studying handwritten digital recognition, and showed better performance than other methods at that time on the handwritten digital data set of MNIST [6].The success of gradient back-propagation algorithm and convolutional neural network has brought new hope to the field of machine learning and started a wave of machine learning based on statistical learning model. Meanwhile, artificial neural network has entered a new stage of vigorous development. At present, convolutional neural network has become a research hotspot in the field of speech analysis and image recognition. It is the first truly successful learning algorithm model to train multi-layer neural network, and it has more obvious advantages when the network input is multi-dimensional signal. With the new machine learning upsurge of deep learning, convolutional neural network has been applied to speech recognition, image recognition and natural speech processing and other small-scale large-scale machine learning problems.

Membrane computing is by the European academy of sciences, academician of academy of sciences of the romanian Gheorghe Pă un put forward in 1998, and the results meet the publication in 2002 [7].Membrane computing is a branch of natural computing, which is similar to DNA computing, quantum computing and so on. Membrane computing is a new non-traditional computing model, and its calculation model can be called membrane system or P system. This is a distributed computing model inspired by the structure and function of biological cells. In 2003, the Institute for Scientific Information (ISI) listed membrane computing as a frontier area of rapid development in computer science. Since then, membrane computing has become a new research field. Membrane computing, as a new branch, integrates biological theory and technology and develops rapidly since it was proposed. So far, there are 5

Monographs on membrane computing [8-12].In 2010, professor zhang gexiang summarized the development of membrane computing through a review.

Inspired by the above research, this paper focuses on the combination of membrane computing and convolutional neural network .This article incorporates the membrane structure into the convolutional neural network to create a new convolutional neural network system. Specically, this new convolutional neural network has special structure and operation rules of membrane cells. At the same time, we have written new, more convenient rules for this new CNN system. The computational completeness is proved.

2. CONVOLUTIONAL NEURAL NETWORK

Convolutional neural network is a kind of multi-layer artificial neural network specially designed for processing two-dimensional input data. Each layer of the network is composed of multiple two-dimensional planes, and each plane is composed of multiple independent neurons. The neurons of adjacent two layers are connected to each other, while the neurons in the same layer are not connected. CNNs are subjected to time-delay neural networks at an early stage. Inspired by TDNNs), TDNN reduces the computational complexity in the network training process by sharing weights in the time dimension, which is suitable for processing voice signals and time series signals. CNNs adopts the weight sharing network structure to make it more similar to the biological neural network. At the same time, the capacity of the model can be adjusted by changing the depth and width of the network, and it has a strong assumption on the natural image (statistical stability and local correlation of pixels).Therefore, CNNs can effectively reduce the learning complexity of the network model and have fewer network connection number and weight parameters compared with the full-connected network with a relatively large size in each layer, so that it is easier to train.

2.1 The structure of traditional CNNs

Convolutional neural network is a multi-layer neural network, each layer is composed of multiple two-dimensional planes, and each plane is composed of multiple independent neurons.

The schematic diagram of a simple convolutional neural network model is shown in figure 1. The network model consists of two convolution layers (C1, C2) and two sub-sampling layers (S1, S2) alternately. First, the original image is convolved with 3 trainable filters (or convolution kernel) to generate 3 feature maps in C1 layer, and then the weighted average sum of the local regions of each feature map is carried out. After adding the bias, 3 new feature maps are obtained in S1 layer through a nonlinear activation function. Subsequently, these feature maps are convolved with 3 trainable filters in layer C2, and further output 3 feature maps after layer S2.Finally, three outputs of layer S2 are vectorized respectively, and then input into the traditional neural network for training.

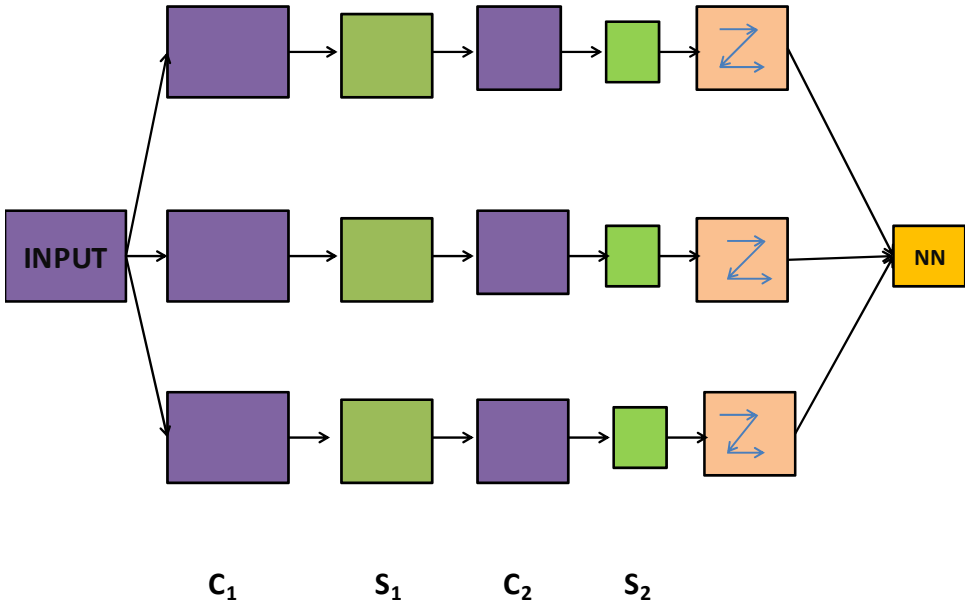

Fig 1. The structure of traditional CNNs

Generally, layer C is the feature extraction layer, and the input of each neuron is connected to the local sensory field of the previous layer, and the local feature is extracted. Once the local feature is extracted, the location relationship between it and other features is determined accordingly. The S-layer is the feature mapping layer, and each computing layer of the network is composed of multiple feature maps, each of which is mapped to a plane with equal weights of all neurons. The sigmoid function with small kernel of influence function is used as the activation function of convolution network in the feature mapping structure, so that the feature mapping has invariant displacement.

In addition, because neurons on a mapping surface share weights, the number of network free parameters is reduced and the complexity of network parameter selection is reduced. Each feature extraction layer (C-layer) in the convolutional neural network is followed by a computing layer (S-layer) for local mean and secondary extraction. This unique two-feature extraction structure enables the network to have a high tolerance for distortion of input samples in identification.

2.2 Sparse connectivity

Convolution network takes advantage of the spatial local characteristics of images by forcing the use of local connection mode between adjacent two layers. The hidden layer element at the m-th layer is only connected with the local area of the input unit at the m-1st layer. These local Areas at the m-1st layer are called the spatial continuous acceptance fields. We can describe this structure as follows:

Let the m-1st layer be the retinal input layer, and the width of the receiving field of the m-th layer be 3, that is, each unit of this layer is connected to and only to the 3 adjacent neurons of

the input layer, and the m-th layer and m± 1 layer have similar linkage rules, as shown in the figure below.

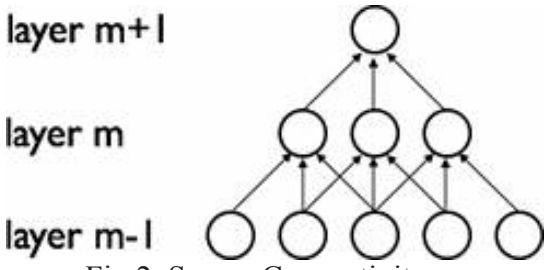

Fig 2. Sparse Connectivity

We can see that the m+1 layer of neurons relative to the layer m accept domain width of 3, but relative to the input layer to accept a domain for 5, this structure will learn to filter (corresponding to the input signal is the largest active unit) limit in local space mode (for each unit of its acceptance of the variation of outside reaction).As you can see from the figure above, stacking multiple such layers will gradually make the filter (no longer linear) global (i.e., covering a larger visual area).For example, neurons in the m+1 layer in the figure above can encode nonlinear characteristics of input with width of 5.

2.3 Shared weights

In the convolution network, each sparse filter hi will cover the entire viewable field by sharing weights, and the units of these Shared weights constitute a feature map, as shown in the figure below

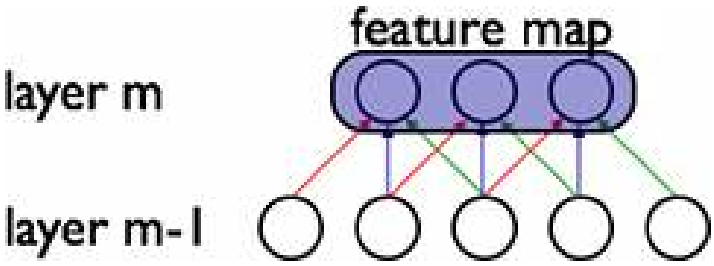

Fig 3. Shared Weights

In the figure, there are three hidden layer elements that belong to the same feature map. The weights of links of the same color are the same, we can still use gradient descent to learn these weights, only need to make some small changes to the original algorithm, where the gradient of the Shared weight is the sum of the gradients of all the Shared parameters. We can't help but ask

Why weight sharing? On the one hand, a repeating unit can recognize a feature regardless of its position in the viewable field. On the other hand, weight sharing enables us to extract features more effectively, because it greatly reduces the number of free variables to learn. By controlling the scale of the model, the convolution network has a good generalization ability for visual problems.

3. TRADITIONAL P SYSTEM

So far, membrane computing models are mainly divided into three types: cellular computing model, tissue computing model and neural computing model. The cellular model is based on the single-cell structure, the histological model is based on the cell group structure in the tissue, and the neural model is based on the neuron cell. It has been proved that all three models have Turing equivalent computing power. In this paper, we mainly use the cellular membrane system.

A membrane is a structure used to protect a reactor. We will use a separate space to identify the membrane m. When we say the inclusion body of a film, it is always strictly inclusion. Now we list some basic concepts about the basic operation of the membrane:

m, m' are vicinal, if m' ⊂ m and there is no m'' such that m' ⊂ m'' ⊂ m,

Elementary membrane: with no lower vicinal membranes, skin membrane: with no upper vicinal membranes, we assume there is always a unique skin,

Degree: number of membranes,

sibling membranes m, m': if there is an m which is upper vicinal for both m and m'.

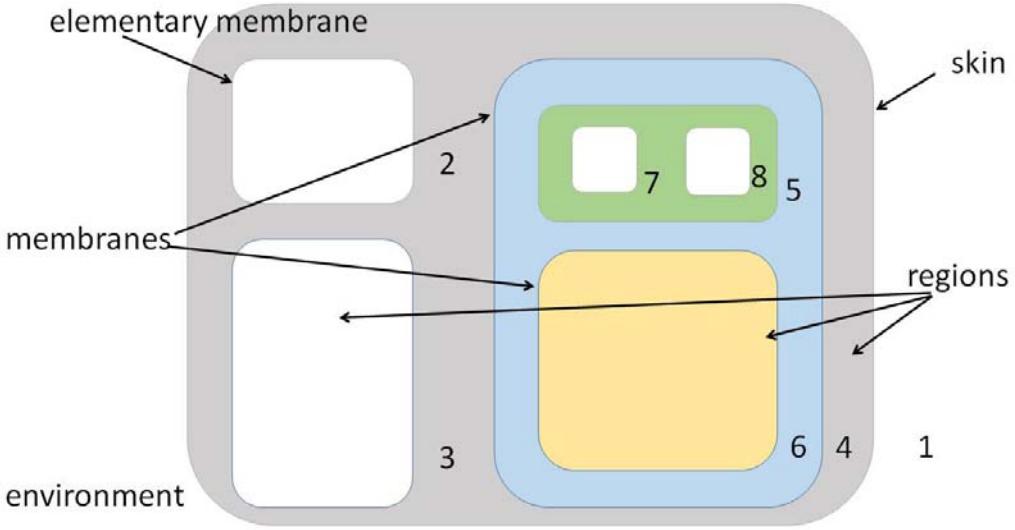

Fig 4. Membrane structure

A parentheses expression

Parenthesis expressions are often used to describe membrane structures. For example, in the membrane structure shown in Fig. 4, the parenthetical expression of the film is as follows:

$$[[]_2[]_3[[[]_7[]_8]_5[]_6]_4]_1$$

For a set U, a multiset over U is a mapping M: U → N, where N is the set of nonnegative integers. For a ∈U, M(a) is the multiplicity of a in M. Suppose the set of objects is O with a subset E such that objects from E are available in the environment in arbitrary multiplicities,

that is, its multiset is M: E → {∞}. A P system with symport/ antiport rules of degree m ≥ 1 is a construct

$$\Pi=(O, T, c, \mu, \omega_1, \ldots, \omega_m, (R_1, \ldots, R_m), i_0)$$

Is the alphabet, the elements of it is called objects;
T ⊂ O is the alphabet of terminal objects;
C ⊂ O - T is the catalyst, the elements of it do not change during evolution and do not produce new characters, but some evolutionary rules must have its participation;
μis a membrane structure that contains a degree of m;
ω1, . . . ,ωm are the multisets of objects contained by the region i of membrane structure μ;
R1, Rm are finite sets of symport and antiport rules, Ri (i = 1, m) is associated with the m membranes of μ;
I0 is the input/output mark of membrance.
Rule: u→ v, u is a string on O, v is over Otar, Otar = OTAR, TAR = {here, out, in}.

4. A NEW CONVOLUTIONAL NEURAL NETWORK MODEL BASED ON P SYSTEM

4.1 P-CNN

In this section, we covered the structure of the membrane for the traditional convolutional neural network, and we named the new convolutional neural network based on the membrane system P-Convolutional Neural Network (P-CNN).We take the convolutional neural network shown in figure 1 as an example to cover the structure of the membrane, P-CNN can be represented by figure 5.

In this P-CNN structure, we covered membranes m1, m2 and m3 respectively on layers C1→S1, C2→S2 and all-connection.

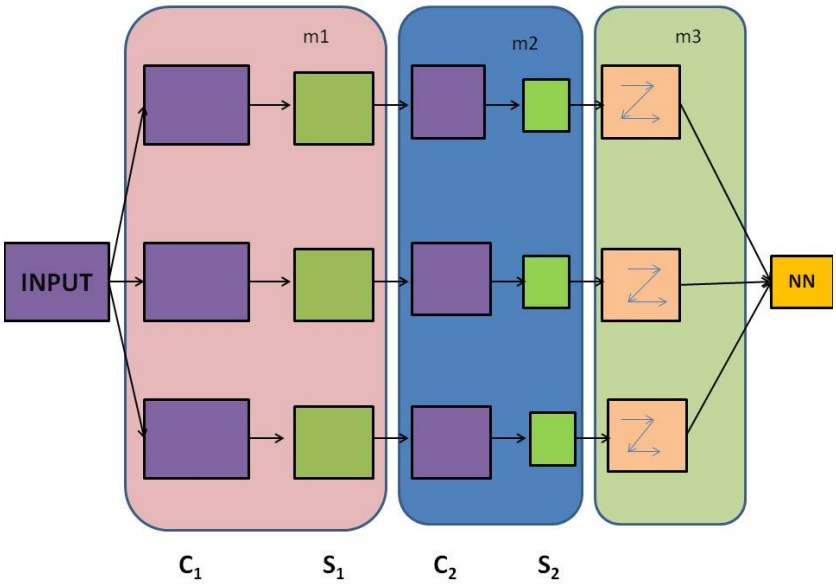

Fig 5. A new convolutional neural network model based on P system

We make the following rules for each membrane:
For m1, m2: The convolution kernel in the membrane is taken as the difference and the difference and the convolution kernel are vectorized to obtain the value, and the weight is allocated according to the ratio of the difference and the maximum convolution kernel.
for m3: After the operation of this rule, two pairs of input in the membrane are made worse, and one of the two inputs with a value of 0 is dissolved.
Before the convolutional neural network performs image classification, we will motivate the operating rules of the membranes m1 and m2. This step analyzes the relationship between the convolution kernels and assigns weights to each convolution kernel according to this relationship. So we used the relationship between the features of the image to better classify the image.
After the end of the operation of the membranes m1 and m2, we perform a weighted convolution and pooling operation on the input image. When the fully connected layer enters the data, we first run the operation inside m3. The residual convolution output is removed by doing the difference, thereby utilizing the relationship between the classes to optimize the image classification result.

4.2 Configuration and computation

In this section, we describe the configuration and computation of P-Convolutional Neural Network. In this paper, we will never change the structure of the membrane.
In this paper, the calculation in membrane follows the principle of maximal parallelism. The principle of maximum parallelism means that rules should be used in parallel with maximum extent. That is, all the rules that can be used must be used. An object can only be used by a rule that selects by priority; any object that can be used by the rule must choose a rule that evolves according to the rule.
This evolution, called computation, is done by applying rules in the membrane. Rules and the links to neural networks have the form of rewrite rules, or other processes, such as passing objects through the membrane. Rules are used in a cell in each time unit. If there is no rules or promoters in a membrane m, then the objects in it will never change. We say that the computation halts if there is no input in each layer.

5. CONCLUSION

This article mainly introduces the traditional convolutional neural network and P system, and combines them to create a new convolutional neural network (p-cnn). This new convolutional neural network combines the structure of a membrane system to make it easier to run and calculate.
We analyzed the advantages and feasibility of P-CNN in the application of image classification. This kind of system can help us better analyze the relationship between features and classes, so it is more accurate to use this convolutional neural network structure for image classification.

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