Malaria Cell Detection Using Evolutionary Convolutional Deep Networks

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***Abstract*—With the rapid development of deep learning and computer-vision, accurate identification of medical imaging has become one of the most important factors in medical diagnosis and decision-making. To this end, for detecting the malaria parasite, we propose a data-driven approach named Evolutionary Convolutional Deep Network (ECDN), which can automatically generate deep neural networks, and optimized its network structure during the evolution process. Extensive experiments based on the large-scale thin-blood smear images data validate the effectiveness of ECDN for detecting malaria. To be specific, compared with the traditional artificial convolution network, the experimental results show that the model robustness of ECDN is better and the accuracy is 99%, which provides an important basis for this research.**

Keywords-Evolutionary Algorithm; Deep Learning; Malaria; Neural Network

I. INTRODUCTION

Malaria is a life-threatening disease caused by Plasmodium parasites that infect the red blood cells (RBCs)[1]. Computer-aided diagnostic (CADx) tools using machine learning (ML) algorithms applied to microscopic blood smear images have the potential to reduce clinical burden by assisting with triage and disease interpretation[2]. To overcome challenges of devising hand-engineered features that capture variations in the underlying data, Deep Learning (DL)[3], also known as deep hierarchical learning, is used with significant success. Liang[4] proposed a 16-layer CNN toward classifying the uninfected and parasitized cells. As the number of layers in the network deepens, the expressiveness and abstraction capabilities of the network become stronger, and the more parameters that can be adjusted. At present, most of the network architectures we use are manually set, and designing these architectures requires sufficient experience as a guide. This is a time-consuming and error-prone process, such as gradient explosion, over-fitting and so on. This raises a natural question: how to get the optimal network architecture and hyperparameters automatically? To this end, we have adopted the Evolutionary Convolutional Deep Networks, an algorithm that automatically calculates an effective neural architecture through evolutionary methods, and can be connected to any deep neural network platform such as Keras.

Neural architecture search (NAS)[5] is a process of automatic architecture engineering, which is the development trend of machine learning automation. NAS can be considered a sub-area of AutoML[6] and similar to hyperparameter optimization and meta-learning in some place. In this, paper, we have implemented a Neuro-Evolution[7] deep network, which can be widely used in image classification problems, automatically generate some deep neural networks according to different image classification data, and optimize the network structure in the process of evolution. The architecture search process is combined with evolutionary algorithms to achieve the effect of expanding the search space[8] and improving search efficiency. Finally, export an optimal network structure that can detect Plasmodium cells. The network structure can approximate the performance of an artificially designed network, even more than an artificially designed network. Meanwhile, we take into account the consumption of computing resources.

II. DATA DESCRIPTION

The malaria datasets we used the official released by NIH[9]. A total of 27,558 images of the dataset, which includes infected and uninfected images. Building an effective neural network model requires careful consideration of the network architecture and input data format.

The operation we processing these images are as follows.

- Sample purification: When drawing a random image of the data set, we found that some of the images in the training sample were incorrectly marked. So we will remove this part of the data to eliminate its impact.
- Image Rescaling: This operation re-adjusts the values of each dimension of the data (these dimensions may be independent of each other) such that the final data vector falls within the interval [0,1] or [−1,1].
- PCA Whitening: Many deep learning algorithms rely on whitening to get good features. In reconstruction-based models, it is often preferred to choose the appropriate epsilon to achieve whitening to achieve low-pass filtering. We visualize the data before and after whitening. If the epsilon value is too low, the whitened data will appear very noisy. The size of the epsilon value we finally chose $1e^{-0.6}$.

- Data Enhancement[10]: In order to increase the diversity of data, we present the spatial diversity of the image by means of rotation, mirroring, and cropping. The model trained based on this will also have better robustness.

In the malaria cell image, we see that the contrast between the data points of the valid image and the background color of the image is small. In other words, the noise has a greater impact on the results, so we use the histogram equalization method[11] to increase the global contrast of the image. In this paper, we use YUV-Space[12] for brightness equalization. It maps the original map to the new map according to a certain transformation formula. Among them, the cumulative distribution function of the histogram as a transformation formula is as follows.

$$S(k) = T(r_k) = \sum_{j=0}^{k} P_r(r_j) \tag{1}$$

$$P_r(r_k) = \frac{n_k}{N} \tag{2}$$

Where $P_r(r_j)$ is actually a histogram of an image with a pixel value of r_j, normalized to [0,1]. The histogram equalization calculation formula is as follows:

$$H(v) = round\left(\frac{S(v) - S_{min}}{(M \times N) - S_{min}} \times (L-1)\right) \tag{3}$$

Where S_{min} is the minimum value of the cumulative distribution function, M and N represent the number of length and width pixels of the image, L is the number of gray levels, and *v* is the pixel value in the original image.

III. Evolutionary Convolutional Deep Network

A. Evolutionary Algorithms

Evolutionary algorithm (EA)[13] is an algorithm used to solve the optimization problem, which is inspired by the idea of "survival of the fittest" in biology. Using evolutionary algorithms, we first should set the initial size of the population, then define our fitness function to assess how much each chromosome can solve the problem, and then iterate multiple times until a predetermined condition is met. Table I shows the evolutionary algorithm used in this paper.

TABLE I. Evolutionary Algorithm

Evolutionary Algorithm
input: max_generation: maximum number of EA generations population_size: population_size begin: generation ← 0. initial chromosomes. evaluate the initial population. while generation≤ max_ generation do select parents. create offsprings using the mutation operation. select the excellent chromosome with the highest fitness. evaluate generation. generation ← (generation + 1). return the best chromosome.

B. Initial Chromosome

The algorithm first initializes the first-generation population through user-defined parameters and then completes the creation of chromosomes, which represents the solution of the first-generation optimization problem. By assessing each chromosome, you can see how close it is to the ideal solution. The chromosomes that created the first-generation population are shown in Table II, and the chromosomes encoding the network structure are shown in Table III.

TABLE II. Create an Initial Population of Chromosomes

Create An Initial Population of Chromosomes
input: population_size: population_size begin: for i in population_size: Generate chromosome Add chromosome to initial population

TABLE III. Create Network Structure Encode Chromosomes

Create Network Structure Encode Chromosomes

input:
layer_list: network layer list
layer_list_len: maximum number of network layer list
add_pooling_layer_chioce: whether to add max pooling layer
begin:
initial an empty chromosome.
for i in layer_list_len -1:
if i == 0:
create the input cnn layer
append new_layer to chromosome
else:
if layer_type == 'cnn':
CreateLayer()
if new_layer is fully_connected_layer:
CreateLayer()
append new_layer to chromosome
Randomly create fully_connected_layer and append to chromosome.
return chromosome
 	
Function CreateLayer(layer_type)
if layer_type ← 'cnn':
Randomly create convolution
if add_pooling_layer_chioce:
Randomly create max_pooling layer
else:
Randomly create fully connected
Randomly create dropout layer

C. Parent Selection

In each generation of evolutionary algorithms, we must ensure that parents are selected before mutation to use genetic operators and mutation mechanisms to derive offspring. The three common methods of parent selection are roulette selection methods, rankings and game selection. In this paper, we use the roulette selection method to select the parent. A detailed mutation process is introduced in Table IV.

D. Fitness Function

The selection of the fitness function directly affects the convergence speed of the genetic algorithm. Besides, the genetic algorithm is based on the fitness function to find the optimal

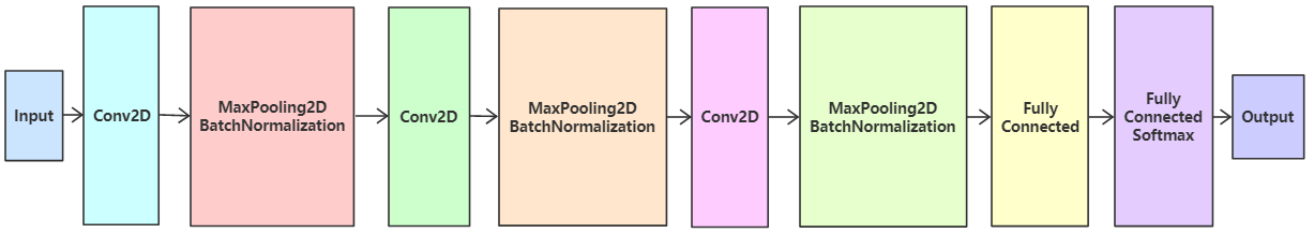

Fig. 1. The model created by ECDN.

the solution, so the genetic algorithm cannot find the optimal solution if the fitness function is not well selected.

The complexity of the fitness function is the main component of the complexity of the genetic algorithm, so the design of the fitness function should be as simple as possible. Only in this way can we minimalize the time complexity of the calculation. The fitness function used in this paper is as follow.

$$fitness(i)=accuracy(i)+punish\_factor(i) \tag{4}$$

$$punish\_factor(i)=\frac{1}{layer\_num+unit\_num} \tag{5}$$

Where accuracy represents the accuracy of the network *i*, layer_num is the number of the layer, unit_num is the number of units in the fully connected layer.

TABLE IV. MUTATION OPERATION

Create An Initial Population of Chromosomes
input: threshold: threshold of mutation operation max_num: maximum number of layer layer_num: number of current layer list layer_type: randomly create layer type begin: layer = CreateLayer(layer_type) if threshold < layer_num < max_num: Add, Replace or Delete layer If layer_num <= threshold: Add or Replace layer If layer_num == max_num: Replace or Delete layer

IV. EXPERIMENTS

A. Experimental Setup

The hyperparameters setting is listed below.

- Physical calculation environment: 1080ti graphics card.
- Number of filters in 2D convolution: [10,100]
- Filter size for 2D convolution: [1,6]
- Kernel size for 2D max pooling: [1,6]
- Number of units in fully connected layers: [10,100]
- Dropout rate: (0,1]
- The selection for activation function of 2D convolution layer: [linear, leaky relu, prelu, relu]
- The selection for activation function of fully connected layer: [linear, sigmoid, softmax, relu]
- The selection for activation function of last fully connected layer: [softmax]

For each individual in the population, the number of iterations trained is no more than 13 times, effectively reduces the time spent by the algorithm on network training to improve the efficiency of the algorithm.

B. Experimental Results

In this paper, the self-organizing network structure obtained by EA is shown in Fig. 1. Through a lot of iteration and training, we finally get a model with a 6-layer network structure. In this experiment, we use CNN as the baseline, and its network structure has 7 layers. Compared with the traditional CNN model, our model has better accuracy and robustness. Given that this is an image classification problem, which focuses on the model's accuracy. Finally, our ECDN model has an accuracy rate of 99.69%, which has achieved our desired effect.

C. Model Evaluation

Model performance evaluation is an essential element. For the comprehensive verification of ECDN, we use four indicators to evaluate metrics including *accuracy*, *precision*, *F1 Score* and *recall*. We use the NIH officially published malaria dataset to conduct experiments that are expected to accurately identify malaria cells. In this paper, the precision of the ECDN model has reached 99.85%. The results are shown in Table V.

TABLE V. MODEL PERFORMANCE INDEX COMPARSION

Model	**Precision**	**Accuracy**	**F1 Score**	**Recall**
CNN	0.92	0.92	0.94	0.96
ECDN	0.99	0.99	0.99	1.00

D. Confusion matrix

To more comprehensively evaluate the network model, we introduce the Confusion matrix, which used to evaluate the model's performance. They are the most important indicators for evaluating the performance of a classification model.

According to the confusion matrix, the experiment has achieved the expected result for malaria detection. In 5531 positive samples, only 17 samples classified to parasitized class by mistake, while in 5493 negative samples, all samples are correctly classified. Fig. 2 shows the roc curve of the ECDN model.

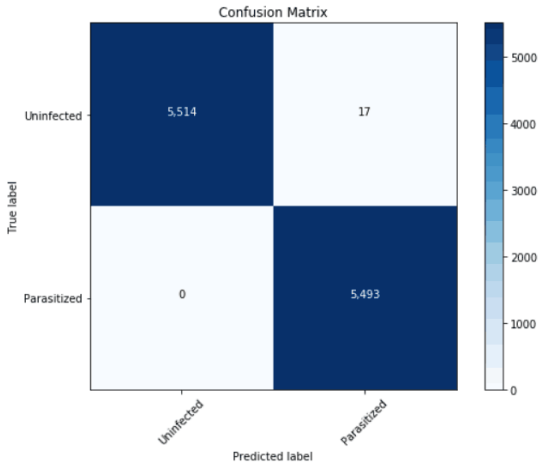

Fig. 2. Confusion matrix.

V. CONCLUSION

In this paper, we propose a novel model based on an evolutionary algorithm, which can solve the problem that the design of network architecture and parameters in deep learning needs to manually interfere. A unique perspective of ECDN is that it can integrate different neural networks to automatically select the composition of the optimal network structure and corresponding parameters. Extensive experiments prove that the network model we trained is more accurate and stable than the traditional artificial tissue network.

In the future, we will consider adding crossover operation for our research, to explore the preferable network architecture, making the network more intelligent and more efficient.

ACKNOWLEDGMENT

This research was partially supported by grants from the Ministry of Education and the "Shenzhen University-Sangfor Cloud Computing Innovation Teaching Laboratory" (Grant No. 201801277010).

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