Research on classification of spiral galaxies and stars based on convolutional neural network

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Abstract. In astronomy, the shape of galaxies can often reflect the course of its evolution, and can further reveal the development law of the universe. With the progress and development of observation technology, image data has grown explosively, and the efficiency of traditional manual astronomical image classification is far from enough. Image classification based on machine learning effectively solves the problem of low efficiency of artificial classification, but in the face of massive data sets, the classification effect of traditional machine learning is often not as good as deep learning. In this paper, relevant concepts based on neural network image classification algorithm are introduced. Then, according to the characteristics of the mainstream CNN (convolutional neural network) model, the design and optimization of the custom RS CNN model are completed. Finally, the custom RS CNN is used to conduct classification experiments on spiral galaxies and stars.

1. Introduction

In astronomy, galaxy morphology is a very important part. Classification of galaxies according to their morphology can help humans understand the evolution of galaxies and the distinction between galaxies. In 1926, Hubble divided galaxies into three categories\cite{1}: elliptical galaxies, spiral galaxies, and irregular galaxies, which have been continuously improved and expanded\cite{2}. Facing such massive data in the current era, the efficiency of manual visual classification is no longer able to meet the requirements of processing large-scale data sets, and the research and development of computer automated classification has become an inevitable trend.

The accuracy of traditional machine learning classification is not very ideal. It usually takes a lot of energy to design the process of feature extraction, but the accuracy of classification is not significantly improved. In recent years, with the extensive application of deep learning in image processing, galaxy image classification based on deep learning algorithm has become one of the key research directions. Deep learning has obvious advantages over traditional machine learning. On the one hand, deep learning algorithm can extract deep-seated features of objects through learning a large number of data, which has strong generalization ability; on the other hand, researchers can take different logical strategies, technical fusion and parameter adjustment to create deep learning algorithm that meet their own needs. Therefore, it has practical significance and feasibility to apply the deep learning algorithm to galaxy image classification.
2. Image classification algorithm based on neural network

2.1. Traditional neural network

Inspired by the working mechanism of neurons in human brain, traditional neural networks build a network model similar to human brain computing. The basic unit of neural network is artificial neuron. Each neuron will sum all the inputs according to the corresponding weight, which will affect the process of data transmission and promote the operation of the model, and then output to the next layer through the activation function.

Figure 1 shows the structure of neural network. Neural network has hierarchical structure[3], including output layer, hidden layer and output layer. Each layer of the neural network is composed of a number of artificial neurons, and the neurons between adjacent layers are connected to each other, so each neuron is the medium of information transmission of the neural network.

![Figure 1. Schematic diagram of neural network](image)

2.2. Convolutional neural network

The neurons of the traditional neural network are usually connected with all neurons in the network of the previous layer, so the scale of weight parameters in the training process is quite large. The CNN solves the above problems well[4]. Figure 2 shows the basic structure of CNN, which transforms neurons from two-dimensional space to three-dimensional space. Neurons are arranged according to width, height and depth. Its main structure includes input layer, convolution layer, pooling layer, full connection layer, Softmax layer and output layer.

CNN has natural advantages in image processing, mainly because it has the following three important features: The first feature is local connection, which greatly reduces model parameters and floating point computation; the second feature is parameter sharing, which further reduces the redundant data of the model; the third feature is the overlapping of sliding windows, which can extract the features of the image more effectively.

![Figure 2. Schematic diagram of CNN structure](image)
This paper mainly studies and analyzes four mainstream neural network models, namely VGG[5], GoogLeNet[6] (Google Inception Net), ResNet[7], SENet[8] (Squeeze-and-Excitation Networks).

It is concluded from VGG that the repeated stacking of small-size convolution kernels can obtain the same receptive field as the large-size convolution kernels, and it is easier to extract image features. It is concluded from GoogLeNet that the widened sparse structure can effectively improve the classification performance of the model. It is concluded from ResNet that the residual module can effectively solve the problems of gradient transfer and network degradation, so that the depth of the model can be expanded. It is concluded from SENet that adding channels to learning can extract valid features and suppress invalid features. The ideas in the above model bring a lot of inspiration to the following custom RS CNN model. The names of RS CNN are derived from the Residual module and SE module adopted in the Block structure.

3. Image preprocessing

When the size of the data set is very small, the model easily learns the outlier characteristics of the sample, which leads to overfitting. Appropriate preprocessing of sample images before model training can prevent overfitting, so that the classification effect is significantly improved.

3.1. Affine transformation

Affine transformation refers to tilting the image at any Angle, that is, scaling the image in two random directions, which can be realized by combining translation, scaling, flipping, rotation and shearing, as shown in equation 1.

\[
\begin{bmatrix}
    x' \\
    y' \\
    1
\end{bmatrix} =
\begin{bmatrix}
    a_1 & a_2 & t_x \\
    a_3 & a_4 & t_y \\
    0 & 0 & 1
\end{bmatrix}
\begin{bmatrix}
    x \\
    y \\
    1
\end{bmatrix}
\]

(1)

In the above equation, \( t \) represents the offset in the specified direction, \( a \) represents the change of scaling, rotation and other operations.

3.2. Normalization and standardization

The function of normalization is to limit all eigenvalues to 0 ~ 1. After normalizing the data, although the distribution of different data will be changed, the accuracy of the solution will be improved and the convergence speed will be accelerated. Equation 2 shows the maximum and minimum normalization formula, which is the most commonly used normalization method.

\[
y_i = \frac{x_i - \min_{i \in[j,n]}(x_j)}{\max_{i \in[j,n]}(x_j) - \min_{i \in[j,n]}(x_j)}
\]

(2)

The role of standardization is to change the dimensions of different features in proportion, and limit them to 0 ~ 1. In this way, the features of different dimensions can be compared, which increases the generalization ability of the model. Equation 3 shows z-score standardization.

\[
y_i = \frac{x_i - \bar{x}}{s}, \bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i, s = \frac{1}{n-1}\sum_{i=1}^{n} (x_i - \bar{x})^2
\]

(3)

The effect of normalization and standardization is shown in Figure 3.
3.3. Image preprocessing flow

Figure 4 shows the preprocessing flow of training set image in this paper. The first step is to dither the original image to make the brightness, contrast and saturation of the image change in different degrees. The second step is to standardize the image. In the third step, the normalized image is randomly flipped horizontally with a probability of 50%. In the fourth step, the image is affine transformed. In the fifth step, the image is randomly flipped at 45 degrees with 50% probability. In the sixth step, the image size is adjusted to $224 \times 224$ by using the center clipping algorithm. In the seventh step, the image is grayed randomly with a probability of 10%. At this point, the preprocessing of astronomical image is basically completed, and the enhanced data set is input into the model for training. The preprocessing of test set is relatively simple, and it can be cut randomly after standardization.

![Image preprocessing process of training set](image)

Figure 4. Image preprocessing process of training set

4. Classification of spiral galaxies and stars based on custom RS CNN model

4.1. Hardware and software environment of classification experiment

In order to ensure the objectivity of the results, the subsequent classification experiment in this chapter will be carried out in the same soft and hard environment. The software part will be implemented using PyTorch.

The hardware environment of classification experiment: Windows 10, 64 bit, Intel (R) core (TM) i9-9900k, 3.60ghz/16 core, NVIDIA GeForce RTX 2080ti, 32.0GB memory.

The software environment of classification experiment: python-3.7.4, pycharm-professional-2019.2.5, Anaconda 3-2019.10, cuda-10.1, cudnn-10.1, pytorch-1.3.1.

4.2. Main steps of classification experiment

The experimental flow of the algorithm is basically the same under different convolution methods, shortcut structure, convolution kernel size and super parameters. The sample set is downloaded from the "Galaxy Zoo" project. The training set samples consisted of 13,305 spiral star images and 14832 star images, and the validation set samples consisted of 3000 spiral star images and 4000 star images. The number of iterations in the measurement process is 10000, and the epoch and iterate parameters will be adjusted according to the number of iterations. The main steps of classified measurement are as follows:

1. First, set the Batch Size parameter, and select pictures from the samples batch by batch according to the size of Batch Size for preprocessing.

2. Secondly, the set of samples and labels is obtained by trianData() method, and the gradient is set to 0.

3. Thirdly, the network is transformed into a training mode. After the output of training results, the loss value is calculated by cross entropy function.

4. Then, the gradient is calculated according to the optimization algorithm, and all the weight parameters are updated.

5. Then, when the iteration is over 200 times, the average loss value is calculated, and the accuracy of the model in the training set and the test set is obtained at the same time.
Finally, repeat the above steps until the iteration is complete.

4.3. Classification of spiral galaxies and stars based on custom RS CNN model

According to the classification results of the custom RS CNN in different convolution modes, Shortcut structures, convolution kernel sizes and super parameters, the most suitable scheme for the classification of spiral galaxies and stars is obtained. Finally, the structure of the custom RS CNN is optimized by using the hole convolution based on the depth separable, the shortcut structure based on the BN layer and the convolution check based on the size of $3 \times 3$, and set the optimizer as Adam, the weight initialization as Kaiming method, the learning rate as 0.001, the batch size as 128.

In this paper, the classification test results of the custom RS CNN model are compared with the SENet model which has better classification effect in the mainstream neural network model, as shown in table 1. The results show that the classification accuracy and AUC value of the model are 99.5% and 0.996 respectively. Compared with SENet, the accuracy of classification is improved by about 9.7%, the amount of model parameters is reduced by about 90%, and the amount of floating-point calculation is reduced by about 96.7%. It proves the effectiveness and superiority of the custom RS CNN in the classification of spiral galaxies and stars.

Table 1. Performance comparison between custom RS CNN model and SENet

| Classification algorithm | Acc  | AUC  | Params  | FLOPS   | Operation time (SEC) |
|--------------------------|------|------|---------|---------|----------------------|
| SENet                    | 90.7%| 0.917| 11.27M  | 1.82G   | 3887.796             |
| Custom RS CNN            | 99.5%| 0.996| 1M      | 60M     | 3357.105             |

5. Conclusion

Deep learning algorithms have more advantages than traditional machine learning algorithms in the classification of galaxy images. The purpose of this paper is to find a CNN model suitable for the classification of spiral galaxies and stars. In order to achieve this goal, this paper designs a custom RS convolutional neural network model according to the characteristics of VGG, GoogLeNet, ResNet, SENet and other mainstream networks, and then proves the success of the custom RS CNN algorithm through experiments.

Through the study and exploration of the mainstream neural network model, the preprocessing of galaxy image, and the continuous optimization and improvement of the galaxy morphology classification algorithm based on the custom RS CNN model, thinking ability and software design capabilities have been exercised.

Reference

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