Xception-AS: A Postprint of an Automatic Classification Algorithm for Astronomical Objects Based on Xception Architecture

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Abstract

This paper proposes an automatic classification algorithm for astronomical objects based on the Xception architecture, which can be effectively applied to the automatic classification of galaxies, stars, and quasars. The algorithm utilizes the Xception framework as its base and incorporates improvements through selection of optimal activation functions and addition of attention mechanisms, among other approaches. We randomly selected 34,000 observed sources from the SDSS-DR16 photometric image data, comprising 11,543 galaxies, 10,490 quasars, and 11,967 stars, and employed their images in the three bands (g, r, and i) as experimental data. Multiple sets of experiments were designed for algorithm validation and testing. A comprehensive analysis of all experimental results demonstrates that the proposed algorithm achieves 90.26%, 90.01%, 89.86%, and 89.85% on key metrics including accuracy, precision, recall, and F1 score, respectively. Comparative experimental results on the same dataset against 13 other classical and popular Convolutional Neural Network (CNN) algorithms indicate that the proposed Xception-AS algorithm exhibits superior classification performance, thereby proving the superiority of our algorithm in addressing automatic classification problems for astronomical objects.

Full Text

Preamble

Xception-AS: An Automatic Object Classification Algorithm Based on the Xception Model Structure

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Abstract: This paper proposes an automatic classification algorithm for celestial objects based on the Xception architecture, which can be effectively applied to the automatic classification of galaxies, stars, and quasars. The algorithm builds upon the Xception framework and incorporates improvements such as optimal activation function selection and the addition of an attention mechanism. We randomly selected 11,543 galaxies, 10,490 quasars, and 11,967 stars from the SDSS-DR16 photometric image data, totaling 34,000 observation sources across three bands (g, r, and i) as experimental data, and designed multiple experiments for algorithm verification and testing. A comprehensive analysis of all experimental results demonstrates that the proposed algorithm achieves 90.26%, 90.01%, 89.86%, and 89.85% on key metrics including accuracy, precision, recall, and F1-score, respectively. Comparative experimental results with 13 other classical and popular Convolutional Neural Network (CNN) algorithms on the same dataset show that the Xception-AS algorithm proposed in this paper exhibits superior classification performance, proving its advantages in solving automatic celestial object classification problems.

Keywords: Astronomical image classification; Machine learning; Xception; Convolutional neural network

With the advancement of astronomical observation instruments, numerous sky survey projects have been deployed, leading to exponential growth in astronomical data volumes measured in terabytes and petabytes. The massive observational targets captured by telescopes contain various types of celestial objects, and accurate classification of these objects is one of the important issues in astronomical research, particularly the classification of the main celestial types—galaxies, stars, and quasars. Obviously, given the tens of millions or even tens of billions of astronomical observations, manual or human-computer interactive classification is impractical. Therefore, using computers to achieve automatic classification of celestial targets is a more effective approach, where machine learning algorithms demonstrate significant advantages.

For big data processing, machine learning algorithms can automatically learn data features from the data itself to accomplish classification or parameter measurement tasks. This study employs a branch of machine learning—deep learning —which can perform feature learning directly from data through deep neural networks. Currently, various traditional machine learning algorithms and advanced deep learning algorithms have been applied to numerous aspects of astronomy. In the field of spectral analysis, reference [1] proposed a galaxy spectral analysis method based on double-layer clustering under machine learning-based automatic spectral analysis and applied it to classification research on massive astronomical data. In the photometric domain, reference [2] proposed a special machine learning method—Boosted Decision Trees—for separating galaxies in photometric images; reference [3] proposed a new method for galaxy morphology classification—GMC—and applied it to galaxy morphology classification. The aforementioned work provides valuable references and offers new insights for solving astronomical source classification problems with deep learning algorithms.

1.1 Data Selection

The Sloan Digital Sky Survey (SDSS) is one of the largest sky survey projects ever undertaken, covering 14,555 square degrees of sky—more than one-third of the entire celestial sphere. The data used in this paper comes from the 16th Data Release of the Sloan Digital Sky Survey (SDSS-DR16). Following the tradition of SDSS data releases, SDSS-DR16 represents an accumulation of previously released data. SDSS-DR16 contains a total of 930 million photometric images, corresponding to 1.2 billion observation sources and tens of millions of spectra. SDSS photometric data parameters include magnitude, color, profile, and size, while spectral data parameters include redshift, signal-to-noise ratios in each band, and various scientific parameters of celestial targets.

The data for this study was obtained by downloading from the official SDSS website, specifically using SQL (Structured Query Language) queries through the SkyServer API structure in the subsite CasJobs. Since the current SDSS photometric catalog PhotoObj can only classify all observed sources as point sources or extended sources, while spectroscopy can better classify target sources into galaxies, stars, and quasars, we cross-matched the SpecPhoto and PhotoObj catalogs in CasJobs to obtain calibrated sources and acquired target position information (right ascension and declination). Calibrated sources can be accurately and quickly distinguished, with each calibrated source marked with a "Class" parameter as "galaxy," "star," or "quasar."

This paper selected observation sky regions 3462, 3478, 3530, and four other regions from SDSS-DR16 as experimental data because these regions contain large numbers of sources, providing rich sample data for experiments. For example, region 3462 contains 9,891 sources, including 2,790 galaxies, 2,378 stars, and 4,723 quasars; region 3478 contains 3,862 sources, including 1,759 galaxies, 577 stars, and 1,526 quasars. FITS format files are commonly used in the astronomical community. By cross-matching the catalogs of these sky regions with FITS files, we obtained images in five bands (u, g, r, i, and z) for 12,499 galaxy sources, 16,914 quasar sources, and 16,908 star sources as training and testing data.

1.2 Image Synthesis

Since SDSS photometric data includes photometric images in five bands (u, g, r, i, and z), these photometric image data are encapsulated separately in FITS format files for each band. Different band images contain different information. As the g, r, and i bands contain more feature information and less noise, researchers typically synthesize photometric images using the g, r, and i bands corresponding to the R, G, and B channels of the image. Different bands generally cannot be directly synthesized, as direct synthesis of three bands may result in misalignment between images from different bands. Therefore, this paper adopts the RGB multi-band image synthesis software written by He Zhendong et al. [4] to synthesize the g, r, and i band images. This method effectively avoids the misalignment problem between different band images. In this paper, each photometric image has a pixel dimension of 2048$×$1489.

1.3 Data Cropping

This paper first crops the target images. Image cropping can be accomplished using image segmentation tools; this process was implemented using Python in our work. Cropping not only reduces dimensionality but also eliminates noise. During the cropping process, we converted the right ascension and declination of sources from the catalog into pixel coordinates of the photometric images using coordinate conversion formulas. The pixel coordinates determine the specific location of the source, which is treated as the center point for rectangular cropping.

[Figure 1: see original paper] (a) Galaxy images cropped at different sizes; (b) Images of galaxies, stars, and quasars

We found that the size of the input images affects the experimental results. Therefore, based on the target size of the sources, we selected different cropping sizes of 40$×40, 60×60, *and*80×80.*SpecificexperimentalresultsareshowninTable*2*ofSection*3.4.1.*Figure*1(*a*)*s*
sourcegalaxies, *point* − *sourcequasars*, *andstarstoauniformsizeof*40×$40. Images of galaxies, stars, and quasars are shown in Figure 1(b).

1.4 Training and Test Data Division

To enable the algorithm to achieve more accurate recognition performance, we require a sufficient number of image samples. The selection of training, validation, and test sets is an important factor affecting the final recognition accuracy. This paper sets the training, validation, and test sets at a ratio of 8:1:1, where the validation set is used to refine the algorithm and the test set is used to evaluate the final generalization ability of the algorithm. Specific data division information is shown in Table 1 . The total sample consists of 34,000 source images, including 11,543 galaxy sources, 11,967 star sources, and 10,490 quasar sources.

Table 1 Statistics of galaxy, star, and quasar image sample data

Training set	Verification set	Test set	Total data
Galaxy			Total data

1.5 Data Preprocessing

[Figure 2: see original paper] The process of data preprocessing

In this experiment, the training and test sets undergo data preprocessing before serving as algorithm inputs. The quantity and quality of data largely determine the recognition performance of the algorithm. The preprocessing processes for the training and test sets differ. For the training set, we first perform vertical flipping, horizontal flipping, and scaling on the cropped images to enrich the data samples and enhance the algorithm' s generalization ability. Since features in celestial target sources have flip invariance, the labels of galaxies, stars, and quasars remain unchanged after rotation. The preprocessing process for the test set is relatively simple compared to the training set; we perform simple scaling on the input images and use the resulting images for test input. The data preprocessing process is shown in Figure 2.

2.1 Convolutional Neural Networks

Convolutional neural networks are neural networks specifically designed for processing data with grid-like structures (such as image data). Their main structure includes input layers, convolutional layers, pooling layers, and output layers. When selecting the initial deep CNN algorithm, this paper compared 13 different algorithm structures, including AlexNet [3], GoogLeNet-V1 [5], VGG [4], MobileNet [3], ConvNet [3], ShuffleNet [6], DenseNet [7], GoogLeNet-V2 [5], GoogLeNet-V3 [5], GoogLeNet-V4 [8], Inception-ResNet-V1 [8], Inception-ResNet-V2 [8], and Xception [9]. The latter six algorithms are all new algorithms improved based on the GoogLeNet-V1 algorithm structure. The results showed that the Xception algorithm achieved the optimal performance among these 13 algorithms. Therefore, this paper adopts the Xception algorithm as our initial framework for solving celestial classification problems.

2.2 Xception-AS Algorithm

This paper improves upon the Xception algorithm, hence we name it the Xception-AS algorithm (A: astronomy, S: source).

This paper first analyzed the impact of different activation functions on experimental results and found that in each convolutional layer, the Elu activation function can achieve batch normalization effects due to its negative values, and the Elu activation function itself can effectively solve the gradient vanishing problem. Therefore, we replaced the original Relu activation function with the Elu function. Simultaneously, to further improve and enhance algorithm performance, we attempted to add the SE [10] attention mechanism after the depthwise separable modules in the Xception algorithm. The algorithm structure of the SE attention mechanism is shown in Figure 3 [Figure 3: see original paper]. The key to introducing the SE module into the Xception algorithm lies in the fact that the SE attention mechanism is a channel attention mechanism. Since the differences between celestial source targets are extremely subtle, the introduction of the SE attention mechanism can address the loss problem caused by the varying importance of different channels in the feature maps during the convolution and pooling processes. Adding the SE module to the Xception algorithm structure enhances useful features, suppresses useless features, makes the algorithm more stable, improves classification performance, and enhances the algorithm' s generalization ability and prediction accuracy. The improved algorithm structure is shown in Figure 4 [Figure 4: see original paper].

[Figure 3: see original paper] SE attention mechanism module

[Figure 4: see original paper] Structure diagram of the improved Xception algorithm

3.2 Parameter Settings

To achieve optimal training results, we adjusted parameters such as learning rate and batch size for each epoch during the experimental process to ensure better algorithm performance. Through multiple comparisons, the algorithm achieved the best performance when running with 60 epochs, batch size set to 128, and learning rate set to 0.0001.

3.3 Experimental Evaluation Metrics Introduction

Performance measurement is the evaluation standard for measuring algorithm generalization ability and reflects task requirements. According to the combination of true categories and predicted categories of samples, they are divided into true positive (TP), false positive (FP), true negative (TN), and false negative (FN). Precision: , Recall: , and F1-score: . In the Receiver Operating Characteristic (ROC) curve, commonly used for model comparison in classification problems, it mainly represents a trade-off between true positive rate (TPR) and false positive rate (FPR). The area under the ROC curve is AUC (Area Under Curve), primarily used to measure the generalization ability of the algorithm—that is, whether the algorithm is good or bad. The confusion matrix is used to compare the gap between classification results and actual predicted values.

FPTPTPaccuracy FPTPTPprecision TNTPTPrecall FNFPTPTPscoref 22_1

3.4.1 Deep Learning Algorithm Comparison Experiments

During the experiments, we used three datasets of different sizes: 40$×40, 60×60, *and*80×$80 cropping sizes. Through comparative training and testing experiments using the AlexNet algorithm, we found that algorithm accuracy improves as dataset size decreases. Specific results are shown in Table 2.

Table 2 Comparison results of different cropping sizes on algorithm performance

<table>
<tr><th>Cutting size</th><th>Verification accuracy</th><th>Test accuracy</th></tr>
<tr><td>40$×40|87.85×60|86.46</td><td>85.$80%</td><td>85.29%</td></tr>
</table>

After selecting the data size, we further compared multiple high-performance deep learning algorithms in the same test environment, including AlexNet, GoogLeNet-V1, VGG, MobileNet, ShuffleNet, and DenseNet. Through a series of training and testing experiments, we obtained the performance metrics of each algorithm as shown in Table 3 . The experiments demonstrated that among the seven classification algorithms, GoogLeNet-V1' s three metrics were superior to the other six algorithms, with GoogLeNet-V1 achieving the highest accuracy, thus indicating that GoogLeNet-V1 is more suitable for solving celestial target image classification problems.

GoogLeNet is a new deep learning structure proposed by Christian Szegedy in 2014. After years of development, a series of improved algorithms have been formed, all of which improve the network structure based on the GoogLeNet-V1 algorithm structure. Therefore, we further conducted experiments on the GoogLeNet series algorithms to select the best classification algorithm. The comparative experimental results between GoogLeNet-V1 and the six GoogLeNet series algorithms are shown in Table 4 .

Table 3 Comparative results between different models

Network	Accuracy	Precision	Recall	F1-score
AlexNet	87.68%	88.56%	87.55%	86.95%
GoogLeNet-V1	88.77%	88.72%	88.60%	88.59%
MobileNet	88.18%	88.11%	88.02%	88.05%
ConvNet	87.30%	87.18%	87.26%	87.15%
ShuffleNet	83.27%	83.10%	83.18%	83.13%
DenseNet	88.65%	88.44%	88.79%	87.52%

Table 4 Comparison results of GoogLeNet series models

Network	Accuracy	Precision	Recall	F1-score
GoogLeNet-V1	88.77%	88.64%	88.60%	88.59%
GoogLeNet-V2	88.36%	88.21%	88.32%	88.22%
GoogLeNet-V3	88.94%	88.90%	88.97%	88.87%
GoogLeNet-V4	89.12%	88.95%	89.00%	88.94%
Inception-ResNet-V1	88.68%	88.58%	88.69%	88.56%
Inception-ResNet-V2	89.52%	89.81%	89.53%	89.48%
Xception	89.59%	89.56%	89.59%	89.57%

Analyzing the experimental results in Table 4, the GoogLeNet series algorithms show similar performance, but the Xception algorithm demonstrates certain advantages over other classification networks, achieving the highest accuracy. Since the differences in corresponding metrics above are not significant, we consider that there is a certain range of perturbation during the training process of different algorithms, which also causes some deviation in the experimental results. Therefore, we conducted additional experiments on the top three best-performing algorithms to increase experimental reliability. Specifically, we added the SE attention mechanism to GoogLeNet-V4, Inception-ResNet-V2, and Xception algorithms. The comparative experimental results after adding the SE attention mechanism are shown in Table 5 .

Table 5 Comparison results after adding SE

Network	Accuracy	Precision	Recall	F1-score
GoogLeNet-V4	89.12%	88.95%	89.00%	88.94%
GoogLeNet-V4-SE	87.92%	87.88%	87.93%	87.75%
Inception-ResNet-V2	89.52%	89.81%	89.53%	89.48%
Inception-ResNet-V2-SE	88.80%	88.71%	88.77%	88.72%
Xception	89.59%	89.56%	89.59%	89.57%
Xception-SE	90.01%	89.98%	89.86%	89.65%

As shown in Table 5, the GoogLeNet-V4-SE and Inception-ResNet-V2-SE algorithms performed worse than before, while the Xception-SE algorithm improved accuracy by 0.42, precision by 0.42, recall by 0.3, and F1-score by 0.08 compared to the Xception algorithm, indicating that adding the SE attention mechanism to Xception improved its performance.

We then introduced the Elu activation function into the Xception-SE algorithm. The experimental results are shown in Table 6 . The results show that the Xception-AS algorithm improved by 0.7 percentage points in accuracy, 0.5 in precision, 0.48 in recall, and 0.48 in F1-score compared to the original Xception algorithm, indicating that the Xception-AS algorithm achieves the most significant effect. This demonstrates that the Xception-AS algorithm is superior to other deep learning algorithms for classifying astronomical sources such as galaxies, stars, and quasars.

Table 6 Comparison results of the Xception algorithm introducing the ELU activation function

Network	Accuracy	Precision	Recall	F1-score
Xception-SE (ELU)	90.26%	90.01%	89.86%	89.85%
Xception-SE (ReLU)	90.01%	89.98%	89.86%	89.65%

3.4.2 Xception-AS Algorithm Experimental Results

Figure 5(a) [Figure 5: see original paper] shows the Receiver Operating Characteristic (ROC) curve of the Xception-AS algorithm on the test set. Different colored curves represent different categories: the light blue curve represents galaxies, the orange curve represents quasars, the dark blue curve represents stars, and the dark blue dashed line represents the average AUC value. From the ROC curve, we can see that the prediction results for each category are good, with galaxies achieving the best classification performance, followed by stars, and then quasars. The AUC value for galaxies is 0.9850, for quasars is 0.9478, and for stars is 0.9640.

Figure 5(b) [Figure 5: see original paper] shows the confusion matrix of the Xception-AS algorithm on the test set, where columns represent true labels, rows represent predicted labels, and the diagonal represents true positives. Number 0 represents galaxies, 1 represents quasars, and 2 represents stars. From the confusion matrix, we can see that 1,093 galaxy images, 889 quasar images, and 1,042 star images were correctly classified.

[Figure 5: see original paper] (a) ROC curve for 3 categories on Xception-AS algorithm; (b) Confusion matrix for 3 categories on Xception-AS algorithm

4. Conclusion

Using deep learning algorithms to solve the classification problem of galaxies, stars, and quasars in astronomical sources is an effective method in the era of big data astronomy. This paper first selected partial astronomical image data corresponding to the SDSS DR16 photometric catalog, obtained training and test data through reasonable selection, image synthesis, cropping, and data preprocessing. Based on the Xception algorithm, this paper designed an algorithm named Xception-AS by introducing an activation function, adding the SE attention mechanism, and combining the characteristics of galaxies, stars, and quasars. The algorithm achieved 90.26% accuracy, 90.01% precision, 89.86% recall, and 89.85% F1-score on our dataset. Compared with multiple other deep learning algorithms, the Xception-AS algorithm performed optimally, demonstrating its effectiveness in solving galaxy, star, and quasar classification problems. Although this paper has addressed the classification problem of galaxies, stars, and quasars in astronomical target sources to a certain extent and improved classification accuracy within a certain range, there are still some shortcomings. Specifically, due to the overly small differences between sample targets, quasars and stars are difficult to distinguish. Therefore, in future research, we will attempt to use multiple methods to solve this problem and further improve the classification performance of the algorithm.

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Note: Figure translations are in progress. See original paper for figures.

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