Radio Galaxy Classification Based on U-Shaped Attentional Feature Fusion Network

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Abstract. With the tremendous advances made by large modern astronomical detectors and telescopes, the depth and range of observations of the sky by these devices is expanding, allowing for an enormous amount of imaging data to be collected. These data contain many radio galaxies, but due to their huge size, manual search for classification is not feasible. We thus study an automatic classifier for radio galaxies based on deep learning and adopt a new classification scheme for radio galaxy classification. Considering that radio galaxy classification is based on morphological features and needs to focus on feature scale information, we design a U-shaped multi-scale feature fusion network to achieve the fusion of deep and shallow feature information; and add an attention mechanism to allow the model to focus on information-rich features. We also use Fine-tune strategy of migration learning in the training process to speed up the convergence of the network model. The experimental results show that our model can achieve higher accuracy classification performance in the case of six types of classification of radio galaxies.

Keywords: Astronomy · Radio galaxy · Deep learning · Attentional mechanisms

1 Introduction

Astronomy is one of the oldest observation-based natural sciences and provides the basis for further studies of space by taking a census of objects in the sky to create a catalog. The purpose of astronomical target detection, also known as "source finding" [1], is to identify individual objects in astronomical images and then retrieve information about these objects to form a catalog. Currently, new radio observatories are generating large amounts of imaging data, and it is impossible to identify such a large number of galaxies by visual inspection, so automatic radio galaxy finding and classification methods need to be developed.

In recent years AI technology has been widely used in various fields such as geological monitoring, robotics, self-driving car systems, face recognition technology, and medical image analysis [2]. When AI technology is applied to the field of astronomy, it

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also has a positive effect on the study of galaxy classification. For example, in 2019 Ma Z et al. [3] designed a convolutional neural network-based MCRGNet autoencoder to achieve six types of radio galaxies classification. Wu C et al. [4] proposed a Faster-Rcnn [5] radio galaxy source finder CLARAN based on VGGNet [6], using the VGGNet backbone network to achieve radio localization and identification of stars. In 2021 Bowles M et al. [7] propose a radio galaxy classification model based on an attention mechanism [8], which enables good classification performance even for small models with a small number of parameters. BL et al. [1] proposed the HeTu source finder using a residual network (ResNet) [9] and a feature pyramid network (FPN) [10] as the network for feature extraction to achieve radio galaxy classification. In 2022 Slijepcevic I V et al. [11] Using semi-supervised learning to leverage large unlabelled data-sets for radio galaxy classification under data-set shift.

In this paper, we propose a radio galaxy classification network based on a U-shaped attentional feature fusion module, which uses a U-shaped [12] feature fusion network for the fusion of deep and shallow features for the multiscale feature maps generated by the feature extraction network, while adding an attentional mechanism to focus the model on the most informative feature maps and using a finetune strategy for migration learning to accelerate the network model training [13]. Ultimately, our proposed model has higher accuracy classification performance on six types of radio galaxies classification compared to other models.

2 Description of the Model Structure

The proposed U-shaped attentional feature fusion classification network for radio galaxy is shown in Fig. 1. The overall network is mainly divided into feature extraction phase, U-shaped attentional feature fusion phase, target region generation phase, target region unification pooling phase, classification and border regression phase.

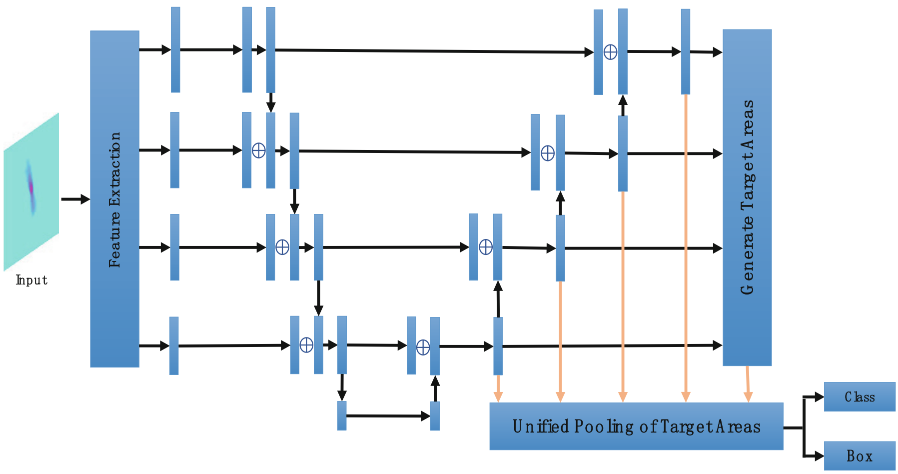

Fig. 1. Overall structure of U-shaped attentional feature fusion classification network

For the target detection and classification task, the multi-scale feature maps containing rich feature information are first obtained by feature extraction of the input images, and then these multi-scale feature maps are used to obtain the target region feature maps in the target region generation phase and the target region unification pooling phase, and finally the target region feature maps are used in the classification and border regression phases. However, these feature maps have the relative problem that the low-level feature maps, which have high resolution but only low semantic information, and the high-level feature maps, which have low resolution but high semantic information features, are not conducive to the detection and classification of radio galaxies with multiscale morphology. For this reason, we design a U-shaped attentional feature fusion network to build a feature pyramid with strong semantic information at all scales, so that the features at all scales are rich in semantic information.

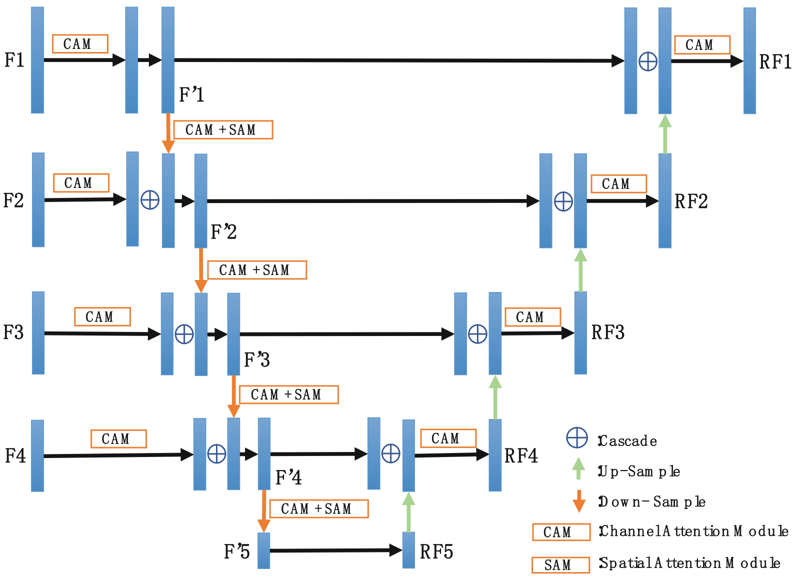

Fig. 2. Details of U-shaped attentional feature fusion network

The specific details of our U-shaped attentional feature fusion network are shown in Fig. 2. First, according to the top-down structure, the channel attentional feature enhancement is performed on the F1 feature map at the first layer to obtain the feature map F'1, and then the feature enhancement of the channel and spatial attention modules is performed before downsampling, and finally it is used for the next layer of feature map stitching to obtain F'2. And so on for attentional feature enhancement, downsampling, feature map stitching operation to obtain F'3, F'4, and finally attentional feature enhancement and downsampling for F'4 to obtain F'5.

$$F'1 = Conv(CAM(F1)) \tag{1}$$

$$\mathrm{F'i} = Conv\left(Concat\left(CAM\,(\mathrm{Fi}), Down\left(SAM\left(CAM\left(\mathrm{F'(i - 1)}\right)\right)\right)\right)\right) \tag{2}$$

$$F'5 = Down(SAM(CAM(F'4))) \tag{3}$$

where i is taken as an integer from 2 to 4, *Conv* is the convolution operation, *Concat* is the cascade operation, *Down* is the downsampling operation, *CAM* and *SAM* are the channel attention and spatial attention mechanisms, respectively.

Then, according to the bottom-up structure, RF5 is first upsampled, then stitched with F'4, and finally the enhanced feature map RF4 is obtained by the channel attention module. And so on for upsampling, feature map stitching, and channel attention enhancement to obtain the enhanced feature maps RF1, RF2, RF3, and RF4 containing rich scale features.

$$RFi = CAM(Concat(F'i, Up(RF(i+1)))) \tag{4}$$

where i is taken as an integer from 1 to 4 and *Up* is the upsampling operation.

Since the number of channels in the feature maps at different scales is different before inputting into the U-shaped feature fusion network, the number of channels needs to be unified, and top-down feature fusion makes the feature maps increasingly low resolution, these processes may lose important feature information.So using we designed the channel attention module (CAM) and spatial attention module (SAM) [14] to allow the U-shaped feature fusion model to focus on the information-rich features.

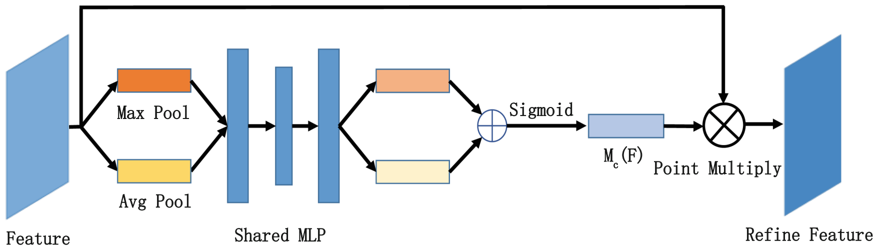

Fig. 3. Channel attention module

The channel attention structure (CAM) is shown in Fig. 3, and the role is to focus on that channel with information-rich parts. First, the input feature map F is pooled with the maximum value and the mean value to obtain the feature maps of F^c_{max} and F^c_{avg}, , then they are fed into the Multi-layer perception machine(MLP), and the features output from the MLP are summed at the pixel level and then activated by sigmoid to obtain the final channel attention feature Mc(F). Finally, the input feature map F is point multiplied with the channel attention feature Mc(F) to obtain the channel attention enhanced feature map.

$$M_c(F) = sigmoid\left(MLP(F^c_{max}) + MLP\left(F^c_{avg}\right)\right) \tag{5}$$

The spatial attention structure (SAM) is shown in Fig. 4, and the role is to focus on that location which is the information-rich part. First, the feature map F is max-pooled and average-pooled along the channel dimension to obtain F^s_{max}, F^s_{avg} feature maps,

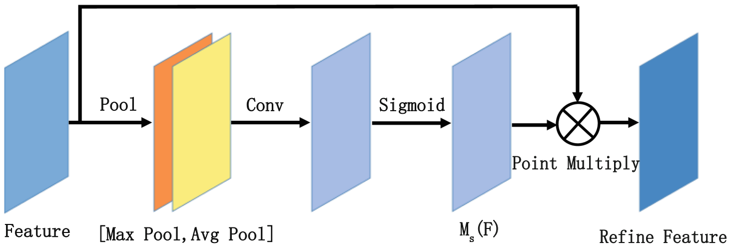

Fig. 4. Spatial attention module

then the feature map channels are cascaded, followed by a 7 × 7 convolutional layer to downscale to a single channel, and finally activated by sigmoid to obtain the final spatial attention feature $M_S(F)$. Finally, the input feature map F is point multiplied with the spatial attention feature M_S (F) to obtain the spatial attention enhanced feature map.

$$M_s(F) = sigmoid\left(f^{7\times7}\left(F^s_{\max} \oplus F^s_{avg}\right)\right) \tag{6}$$

where $f^{7\times7}$ represents a convolution operation with the filter size of 7 × 7, ⊕ denotes cascade.

3 Experiment

3.1 Data Set

The data set used for radio galaxy classification in this paper is the galaxy catalog of CLARAM and MCRGNet, and then we download the galaxy data from The VLA FIRST Survey website (http://sundog.stsci.edu/index.html) and use the PIL library of python to generate the 'cool' type images, and finally six types of classification according to the idea of morphological classification [15] and the classification strategy of CLARAM and HeTu. As shown in Fig. 5, we define the six types of radio galaxies as CS-1, CS-2, CS-3, FRl, CJ, FRIl. Set 2148 images for training the model and 1432 images for validating the model.

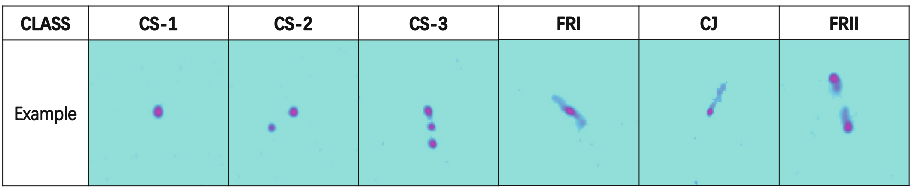

Fig. 5. Example of radio galaxy classification

3.2 Experimental Process

Before inputting into the network, we performed data augmentation with random horizontal flipping and vertical flipping of the training images to improve the robustness of the network model. Due to the small number of training datasets, the fine-tune strategy of migration learning was considered to train the model, so the pre-trained model of the 50-layer residual feature extraction network was used, which can accelerate the model convergence, and the network freeze stepwise training strategy was also used to make the performance of the classification regression network gradually improve.

3.3 Comparison of Classification Accuracy of Models

We use the mean average precision (mAP) metric, a measure of detection accuracy in target detection, to evaluate the classification performance of our U-shaped attentional feature fusion network. Where mAP@0.70 indicates that the Intersection over Union (IOU) value of the real edges of the target and the predicted edges of the network should be greater than the 0.70 threshold, and mAP@0.50 ~ 0.95 indicates that the results are averaged for each threshold. We compare the classification performance with the underlying network RFFNet (ResNet + FPN + Faster-Rcnn) of HeTu [1], and all experiments are performed on the same device and in the same dataset.

From the experimental comparison results in Table 1, our network has a 6.3% advantage over RFFNet-50 classification network in mAP@0.70 detection accuracy and 7.3% advantage in mAP@0.50 ~ 0.95 detection accuracy on the 50-layer residual network. For the deeper 101-layer residual network of RFFNet-101, our network has a 1.1% advantage in mAP@0.70 detection accuracy and a 1.4% advantage in mAP@0.50 ~ 0.95 detection accuracy.

Table 1. Model classification accuracy comparison

Model	RFFNet-50	RFFNet-101	Our Model
mAP@0.70	88.5%	93.7%	94.8%
mAP@0.50 ~ 0.95	65.9%	71.8%	73.2%

In order to visualize the advantages of our model, we have selected some examples of radio galaxies that show detection errors in the RFFNet-50 network and can be correctly detected and classified by our network model, as shown in Fig. 6. It can be seen that our model can correctly detect and classify some multi-scale and noise-influenced radio galaxies. From the experimental comparison results, our proposed U-shaped attentional feature fusion classification network effectively promotes the fusion of deep and shallow features of the feature map, so that the network can better learn the information of radio galaxy scale contours and make the network have better classification accuracy, which can further promote the study of automated classification of radio galaxies.

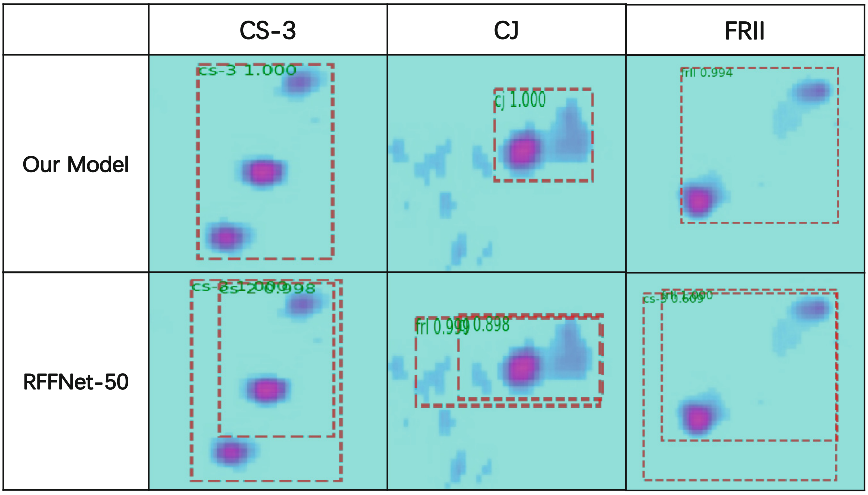

Fig. 6. Comparison of model classification example results

4 Conclusion

In this paper, we propose a radio galaxy classification method based on a U-shaped attentional feature fusion network, which has good performance in classifying radio galaxies. The U-shaped feature fusion network in this paper enables the fusion of deep and shallow features from feature maps of different scales, while the attention mechanism is set to make the model more focused on information-rich features. In addition, we adopt a new six-category classification scheme for radio galaxies; and choose the fine-tune pre-training strategy of migration learning to accelerate the model convergence; meanwhile, we use the network freeze step-by-step training strategy to make the performance of the classification regression network improve gradually. The experimental results show that our U-shaped attentional feature fusion network has higher classification accuracy and better performance for radio galaxies, which has a positive effect on the reliability and accuracy of the automated classification of radio galaxies for astrophysics research.

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