A DM-free scheme for fast radio burst search in multibeam data based on EfficientNet

Yao Chen[1], Rui Luo*[1], Chen Wang*[2], Shiqian Zhao[1], Chengbing Lyu[1] and George Hobbs[3]

[1] Department for Astronomy, School of Physics and Materials Science, Guangzhou University, Guangzhou, 510006, China
[2] CSIRO Data61, 13 Garden Street, Eveleigh, NSW 2015, Australia
[3] CSIRO Space and Astronomy, PO Box 76, Epping, NSW 1710, Australia

Abstract

Here we present a new scheme for searching for fast radio bursts (FRBs) in the multibeam data without dedispersion based on EfficientNet, which is a novel convolutional neural network architecture increasingly applied in deep learning. Using the scaling method, the Efficient-Net model can enhance network performance by simultaneously increasing the width and depth of the network and the resolution of input images. To demonstrate this new scheme for FRB search, we first simulate 1-bit PSRFITS data using the software *simulateSearch* in the observational environment similar to the FAST 19 beams and then train the EfficientNet model with the labeled data of 19 beam observations simultaneously. After that, we will benchmark the performance of this AI-based method by running the pipelines based on commonly used single-pulse search softwares, such as Heimdall, TransientX, and PRESTO. In summary, this new scheme can enhance the efficiency of FRB blind search compared with other traditional algorithms. Additionally, this approach would naturally mitigate the negative impact by radio frequency interference in multibeam data.

Main Idea

Fast Radio Bursts are high-energy astrophysical phenomena of cosmological origin, characterized by transient radio pulses lasting only a few milliseconds[1]. Currently, searching for FRBs signals with traditional methods significantly relies on dedispersion and manual recognition, which are time-consuming. In the recent years, with rapid development of Deep Learning on computer vision, it gradually becomes more and more important to deploy Machine Learning in FRB search[2].

The software *simulateSearch*[3] can be used to mimic the environment of actual data, for example, telescope pointing systems, radio frequency interference (RFI). Traditional FRB candidate searches usually go through the step of removing dispersion. We hope to use machine learning to identify FRB candidates that have not undergone dispersion elimination processing.

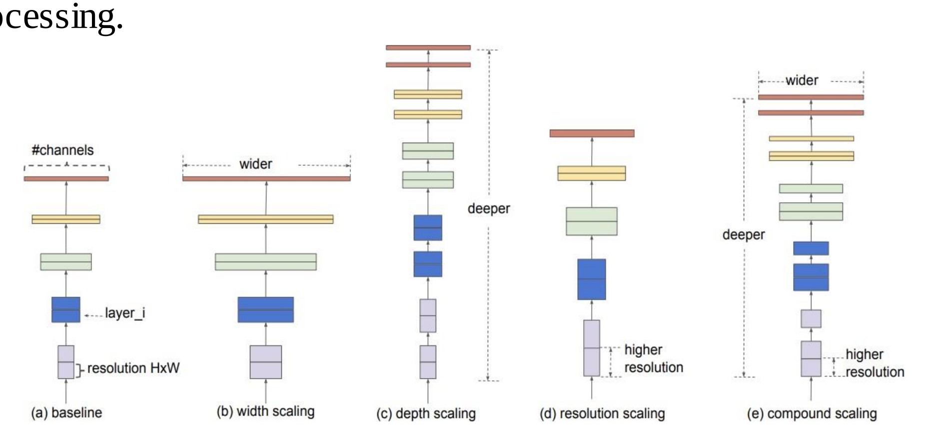

Figure 1: Different design of CNN models with scaling, particularly, EfficientNet proposes a compound scaling method for model expansion. Panel (a) shows a baseline network, while Panels (b), (c), and (d) denote three networks that respectively expand the width, depth, and input resolution of the baseline network. Panel (e) exhibits the main idea of EfficientNet, which includes a compound expansion of width, depth, and resolution for the network. Note that this original image is taken from Tan & Le (2019) .

The extension of Convolthe utional Neural Network (CNN) can generally be achieved by adjusting the input image sizes, network depth, and width (the number of convolutional channels)[4] . As shown in Figure 1, EfficientNet is a result of standardized model expansion. EfficientNet achieves better accuracy compared to other convolutional neural network models while having fewer parameters in Figure 2.

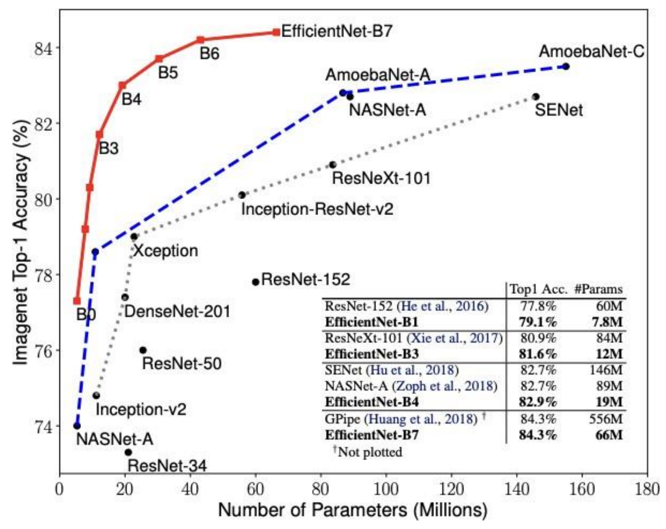

Figure 2: The performance of different CNN models in image recognition. Note that EfficientNet achieves a significant reduction in the number of parameters while significantly increasing accuracy compared to other models. Note that this figure is taken from Tan & Le (2019) .

Preliminary Results

Therefore, we use the *simulateSearch* software to simulate a large number of FRB data images that are close to reality as a sample set for machine learning. The data environment is built according to the FAST 19 beam receiver [5]. RFI is ubiquitous in all the beams, while astronomical sources can only be seen in specific pointing directions (see Figure 3). We use the simulation data as training sample for EfficentNet based on the Pytorch framework, and train the model in our GPU cluster composed of NVIDIA RTX 4090 graphics cards.

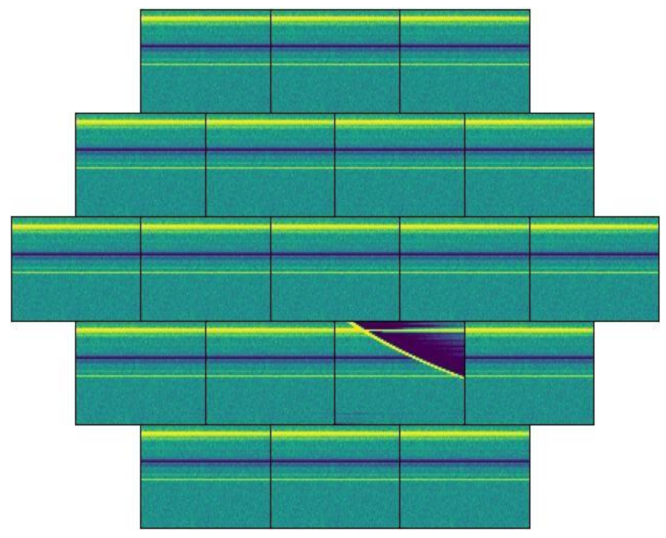

Figure 3: The training data used for the FRB blind search under FAST 19-beam observations, which have included noise and RFI. In this plot, a bright simulated FRB can be observed at one of the 19 beams.

Given system parameters for the FAST 19-beam receiver, we can simulate a large number of FRBs by setting up their positions, arrival time, flux, width and dispersion measure. Using these as the training sample, we train the model based on EfficientNet to achieve the performance we expected. Taking Stochastic Gradient Descent (SGD) as examples, we plot the loss line chart and accuracy line chart of the two respectively as Figure 4. From these two diagrams, we can see that the loss function continues to decrease, showing a convergence trend, and the accuracy gradually stabilizes after continuous training. The accuracy of the final model recognition sample validation has reached 99.1%.

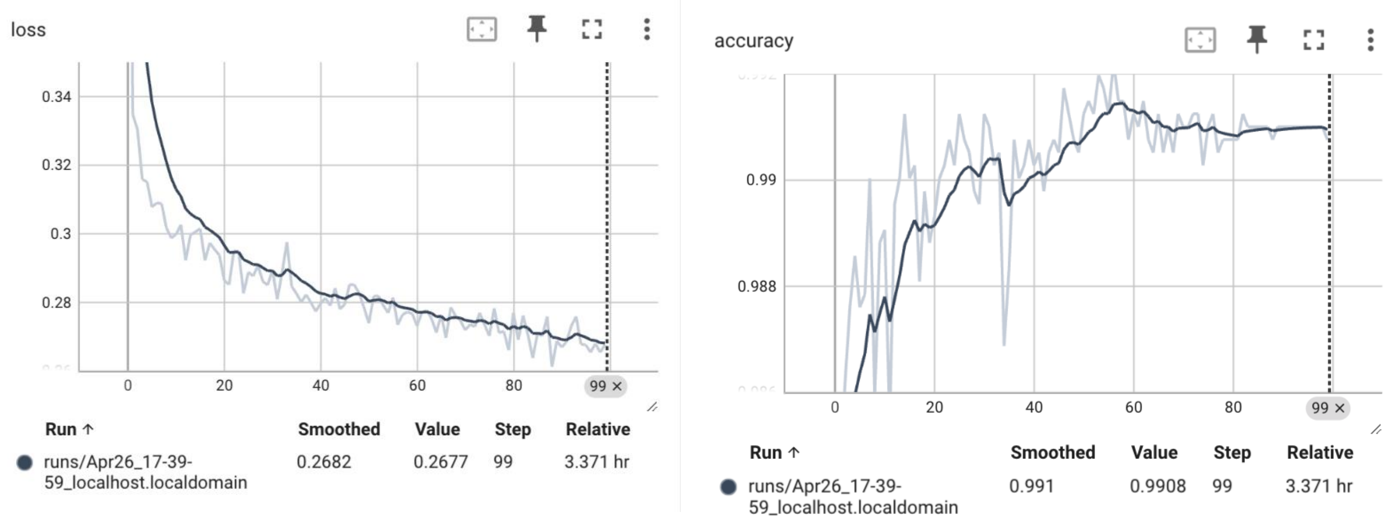

Figure 4: Based on the SGD optimizer, we train the model for 100 epochs and obtain two diagrams through the running log. The left panel shows the change of model validation set accuracy with the number of training times, and the right panel shows the change of the cross-entropy loss function with the number of training times.

Discussion and Outlook:

We have simulated and selected almost 20,000 samples using *simulateSearch*, out of which about 8,000 samples containing FRB signals. The signals in these samples are randomly generated within a given parameter range and are very close to real data. We have trained the model using these samples and obtained some validation results, as shown in Figures 3 and 4. According to the current results, we observe that the loss function of the model continues to decrease and has a convergence trend during the training processes, and the model accuracy can reach 99.1%.

Next, we will apply the model to multi-class training and even real-world data of simulated FRBs at different DM ranges to benchmark the performance of traditional algorithms and machine learning methods. At the same time, we will use this model to further train on single-beam data, compare the possibility of eliminating interference between single-beam and multi-beam models, and conduct further analyses. We hope that multi-beam image recognition will aid in the initial screening search for FRB candidates in the actual data of FAST 19-beam surveys. Machine learning can identify FRB candidates significantly faster than traditional discrete methods and greatly improve people's work efficiency.

References

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ychen@e.gzhu.edu.cn