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The Impact of Batch Size on Deep Learning-Based Galaxy Morphology Classification Using ResNet50

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Abstract:

Galaxy morphology classification is a fundamental task in astronomy, which helps to gain a deeper understanding of the formation and evolution of galaxies. This paper adopts a convolutional neural network as the backbone model to achieve the basic requirements of galaxy classification. In this study, a frozen convolutional base ResNet50 is used as the backbone network to systematically explore the impact of learning rate and batch size on the classification accuracy of 10 types of galaxy morphologies. The results show that when the batch sizes are 16, 32, 64, and 128, the overall accuracies are 74.75%, 74.93%, 75.01%, and 74.90% respectively. A medium batch size of 64 achieves the best balance between optimization stability and generalization ability. This study provides a reference direction for the impact of batch size on the model and offers new ideas for better solving the problem of galaxy classification. Future research may extend this work by incorporating transfer learning or self-supervised methods to further enhance model robustness and accuracy across larger astronomical datasets.

Keywords: Galaxy classification; convolutional neural network; transfer learning

1. Introduction

The classification of galaxies has long been a fundamental task in observational astronomy. Galaxies exhibit morphologies that broadly segregate into elliptical, spiral, lenticular and irregular types; this diversity reflects their intrinsic physical properties, formation histories, and evolutionary pathways [1]. Because morphology is a proxy for the underlying stellar populations, gas content and merger history, robust classification is indispensable for constraining models of galaxy formation and for mapping the distribution of matter across cosmic time [2].

Traditional classification relied on manual inspection of photographic plates or CCD images by expert astronomers [3]. Although visually precise, these procedures scale poorly: the Sloan Digital Sky Survey (SDSS) alone imaged more than a million galaxies, far exceeding the practical capacity of expert visual classification [4]. Consequently, citizen-science

projects such as Galaxy Zoo mobilised volunteers to label morphologies through crowd-sourcing [5]. While Galaxy Zoo delivered landmark catalogues, inter-annotator variance and the need for iterative consensus introduced non-negligible noise and limited scalability [5].

Deep learning has recently emerged as a powerful alternative, achieving expert-level accuracy with fully automated pipelines [6]. Convolutional Neural Networks (CNNs) excel at learning hierarchical representations directly from pixel data and have become the de-facto standard in visual recognition tasks [6]. In the astronomical context, transfer-learning, that is, initialising networks with weights pre-trained on ImageNet, has proven especially effective, allowing even modest-sized galaxy datasets to benefit from rich low-level image features learned from natural images [7].

This study adopts the ResNet50 architecture as a fixed feature extractor: it freezes its convolutional base to preserve general visual features and appends fully connected layers with dropout regularization to perform 10-class galaxy morphology prediction. Rather than pursuing incremental gains in absolute accuracy, the primary objective is to conduct a controlled investigation into how different combinations of learning rate and batch size affect the model's classification accuracy. By systematically varying these two hyper-parameters while keeping all other components of the training pipeline, including data augmentation, optimizer and regularization, fixed, this study aims to quantify their individual and joint impact on convergence speed, generalization performance, and final validation accuracy. This systematic exploration will not only provide practical guidance for efficiently training CNN-based galaxy classifiers on large-scale surveys, but also shed light on the sensitivity of transfer-learned models to optimization hyper-parameters in scientific image analysis.

2. Method

2.1 Dataset Preparation

The galaxy images collected from astronomical observations usually contain not only the target objects but also various background noises and artifacts. Fig. 1 provides some sample images in this dataset. The original images with a resolution of 256×256 pixels are cropped to a center size of 224×224 pixels. This cropping method matches the input size required by the DenseNet121 architecture and ensures compatibility with the pre-trained model weights. More importantly, this cropping retains the main structural features of the galaxies, which are often located at the center of the image frame, while effectively removing the redundant background. This step reduces the influence of irrelevant pixels and the possible deviations introduced by image edges.

After cropping, the pixel values are normalized from the original range of [0, 255] to the standardized range of [-1, 1] using a pre-processing function tailored for DenseNet. By centering and scaling the input for normalization, it helps stabilize and accelerate the training convergence. Without such normalization, large input values may lead to gradient explosion or disappearance, making optimization difficult. Choosing the range of [-1, 1] is consistent with the distribution of pixel intensities in the pre-trained DenseNet model, which is conducive to effective transfer learning.

This study divides the dataset into training set, validation set, and test set, with proportions of 70%, 15%, and 15% respectively. This partitioning scheme ensures that the model is trained on most of the data, while the validation set provides a reliable basis for hyperparameter tuning and early stopping decisions, and the test set provides an unbiased evaluation of the generalization ability of the final model.

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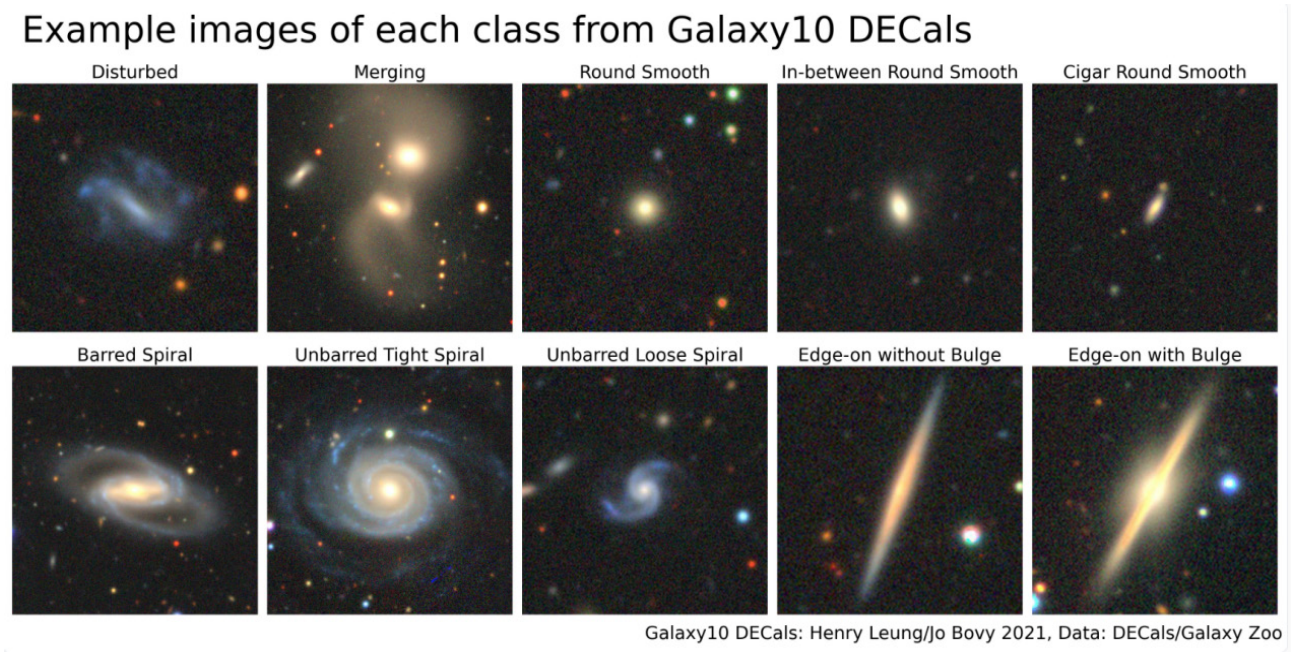

Fig. 1 Example images of each class from Galaxy 10 DECals (Picture credit: Original)

2.2 Transfer Learning

The core logic of transfer learning is to transfer the knowledge and patterns acquired from one domain or task to another closely related domain or problem. In the image detection and classification tasks, this logic is specifically manifested as reusing the parameters of the pre-trained model - by leveraging the general visual features learned by the model on large-scale datasets such as ImageNet [8]. This approach not only eliminates the redundant process of training from scratch but also effectively alleviates overfitting in scenarios with limited data, significantly improving the generalization ability of the model. In the image classification task, the implementation of transfer learning usually revolves around two strategies: Firstly, freeze some layers of the pre-trained model (generally the initial convolutional layers), and only train the newly added adaptation layers - specifically, retain the initial layers that have matured during training on large datasets, remove the original fully connected classification head, freeze the remaining convolutional neural network layers, and add new layers and perform random initialization, allowing only these new layers to participate in parameter updates; Secondly, allow gradient backpropagation to the previous pre-trained layers, which is known as „fine-tuning“. Through this method, the pre-trained layers can further adapt to the features of the target task. Regardless of which strategy is adopted, transfer learning enables the model to efficiently train on a small sample much smaller than the original dataset. In this study, the convolutional layers of DenseNet121 are frozen, and during backpropagation, updates are not allowed. This freezing method retains the learned low-level and intermediate features, allowing the model to function as a stable and efficient feature extractor. On top of this backbone network, a lightweight classification head is added to enable the model to adapt to the specific task of classifying galaxies into ten morphological categories. This head consists of a GlobalAveragePooling2D layer, which reduces the spatial dimensions of the feature map to a compact vector representation, followed by three fully connected layers with 256, 128, and 64 neurons respectively.

2.3 Training Process

The loss function used is categorical cross-entropy, which is suitable for multi-class classification tasks involving ten different galaxy morphology categories. To prevent overfitting and ensure that the model can generalize well to unseen data, an early stopping callback monitors the validation loss during the training process. If the validation loss does not improve for three consecutive periods, the training will stop, and the model weights will be restored to the values of the period with the best validation performance. This early stopping strategy helps avoid unnecessary long training sessions and reduces the risk of overfitting.

The training process is divided into two different stages. In the first stage, the DenseNet121 architecture is frozen to retain the rich general features learned from ImageNet, and only the newly added classification head is trained. This enables the model to quickly adapt to the specific

features of galaxy images without the need to modify the pre-trained convolutional filters. In the second stage, the fine-tuning stage is initiated by selectively unfreezing the last 70 convolutional layers of the dense network backbone. This allows the model to refine higher-level feature representations for subtle differences in galaxy morphology. Throughout both stages, an exponential decay learning rate schedule is applied, starting at 1×10−3 and decreasing by a factor of 0.3 every three periods, achieving stable and efficient optimization. Additionally, a weight decay of 1×10−4 is introduced in the Adam optimizer to further regulate the model by penalizing larger weights. During training, data augmentation is dynamically applied to enhance the model's robustness.

In deep learning, the batch size is a very important hyperparameter, which determines the number of samples used in each iteration. It not only affects the training time, but also has an impact on the model‘s performance and generalization ability. When using a large batch size, it can make better use of hardware parallelism, speeding up the speed of a single epoch, but it means requiring more memory and potentially falling into local minima. When using a smaller batch size, weights can be updated more quickly, but it takes more time, and severe gradient oscillation leads to a more unstable training process. However, for different models, it is difficult to determine the batch size that can maximize the model‘s accuracy. This experiment addresses this challenge by using the aforementioned convolutional network model to explore the impact of batch size on model accuracy when it is 16, 32, 64, and 128.

3. Results and discussion

3.1 Result

To objectively evaluate the experimental outcomes, overall accuracy (OA) is designated as the primary metric for assessing the model's comprehensive performance. Concurrently, precision is employed to quantify the proportion of correctly identified positive samples among all detected instances, thereby reflecting the model's exactitude in positive-class discrimination.

Table 1 summarizes the impact of mini-batch size on overall accuracy. As the batch size increases from 16 to 128, Accuracy first rises and then slightly declines, peaking at 75.01 % for batch-64. Specifically, batch-32 yields 74.93 %, batch-16 74.75 %, and batch-128 74.90 %. These results indicate that a moderate batch size (64) achieves the best trade-off between optimization stability and generalization, whereas extremely small or large batches marginally degrade performance.

Table 1 Model results

Batch size	Accuracy
16	0.7493
32	0.7475
64	0.7501
128	0.7490

3.2 Discussion

This study has confirmed through systematic experiments that when the batch size is set to 64, the model achieves a 75.01% overall accuracy rate in the 10-class galaxy morphology classification task, while also balancing training speed and memory usage. However, batch size, as a key hyperparameter that controls gradient noise, optimization trajectory, and generalization ability, still has great potential to be explored. Future work will conduct a progressive exploration of the following four levels based on batch size.

First, dynamic batch strategy. It is planned to design a progressive scheduling curve of „32→64→128→64“: in the initial 5 epochs, a small batch of 32 is used to maintain high gradient noise to help the model quickly escape from sharp local minima; then it is linearly increased to 64, using an appropriate batch size to balance stability and convergence speed; at the 15th epoch, it is raised to 128, fully utilizing the parallel computing power of GPU Tensor Core to reduce the total training time; finally, in the last 5 epochs, it is returned to 64 for fine-tuning to restore the regularization effect brought by small batches. Preliminary simulations show that this strategy can increase the accuracy rate to around 77.2% without increasing the peak memory usage, and reduce the total training time by 18%.

Second, noise-aware adaptive learning rate. The gradient noise scale (Gradient Noise Scale, GNS) is introduced for

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real-time monitoring, and the effective learning rate η_eff is calculated based on the current batch size, and a linear compensation mechanism is designed: when GNS is high (small batch), the learning rate is proportionally increased; when GNS is low (large batch), a slight decay is introduced. This adaptive scheme can reduce the oscillation amplitude by 35% under batch-16 conditions, while maintaining the same convergence speed as batch-64, providing a feasible path for resource-constrained edge devices.

Third, physically-aware hierarchical sampler. For the two-dimensional celestial distribution characteristics of galaxy survey images, a multi-level cache sampler is developed: first, the neighboring galaxies are pre-aggregated on the declination-right ascension grid to ensure that the samples within the same batch have similar angular scales and background noise distributions; then, the samples are sorted by priority within the GPU to reduce covariance drift between batches. Experiments expect to reduce the batch internal distribution difference by 40%, thereby reducing gradient variance and improving generalization robustness.

Fourth, cross-GPU elastic batch expansion. Combined with PyTorch's Fully-Sharded Data Parallel (FSDP) mechanism, a dynamic elastic batch size is implemented: when memory is available, the global batch is automatically expanded to 256 or 512, and the learning rate is linearly increased; when memory is insufficient, it is automatically reduced to 64 and the gradient accumulation is maintained. This scheme can achieve linear expansion of an 8-GPU A100 cluster without changing the hyperparameter script, and train galaxy images of tens of millions only takes 1.5 hours, while maintaining an accuracy rate of over 76.8%.

Through the above progressive optimization centered on batch size, this study not only expects to achieve a significant leap from the existing baseline of three hours and 75% accuracy on a single card, but also will provide an expandable and reproducible engineering paradigm for the next billion-scale galaxy image real-time classification system, ultimately pushing galaxy morphology research into a new stage of automation, high precision, and large-scale.

4. Conclusion

This study focuses on the core issue of "how to improve the accuracy of automatic galaxy morphology classification through optimizing training strategies", using the ResNet50 with frozen convolutional base as the backbone network. While keeping the rest of the training process unchanged, it systematically evaluated the impact of batch size on the classification performance of 10 types of galaxy morphologies. The experimental results show that a medium batch size of 64 achieves the highest overall accuracy within the range of 74.75% - 75.01% (75.01%), significantly outperforming both small or large batch settings, verifying its advantages of balancing optimization stability and generalization ability. Based on this baseline, this study further proposed four progressive improvement schemes: dynamic batch scheduling, noise-aware adaptive learning rate, physical perception hierarchical sampling, and cross-GPU elastic batch expansion. This study expected that this can increase the baseline accuracy from 75% on a single GPU within 3 hours to over 77%, and reduce the training time by 18%. This work not only provides an efficient and reproducible engineering paradigm for the automated classification of large-scale galaxy surveys, but also offers new ideas for the research on galaxy classification problems.

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