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Transferability exploration of weight based on ImageNet for galaxy classification

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Abstract. The accurate classification of galaxies is essential for understanding the structure of the cosmos and establishing connections with host haloes. Manual classification methods are time-consuming, subjective, and prone to errors. This study investigates the efficiency of automated galaxy categorization utilising transfer learning with pre-trained models from ImageNet by utilising deep learning techniques. The Galaxy10 DECals Dataset is used in the study, and the DenseNet-121 network architecture is used for transfer learning. Experiments are used to assess the effects of various ImageNet weight configurations on the performance of the model. The findings reveal that the model trained with 20% ImageNet data achieves the highest classification accuracy of 79% for galaxies. Grad-CAM visualisation further highlights the impact of weight initialization on categorisation by displaying the different focal points of models trained with various ImageNet weights. The results indicate that using higher weights from ImageNet transfers advanced features, whereas using fewer weights transfers basic features, potentially producing inaccurate results. Prior to transfer learning, the study emphasises the significance of choosing the best weights from ImageNet. The knowledge acquired aids in the classification of galaxies and offers direction for further study.

Keywords: galaxy classification, transfer learning, deep learning, ImageNet weights.

1. Introduction

Galaxy classification is the process that involves the systematic grouping of galaxies based on their properties, such as morphology, size, color, and stellar mass. The classification process holds significance in understanding the structure of the universe on a large scale and establishing connections between the properties of galaxies and host halos. Historically, galaxy classification was performed manually by astronomers using visual inspection of galaxy images. However, this procedure is time-consuming, subjective, and prone to inconsistency and inaccuracies due to varying opinions among astronomers. However, the emergence of deep learning techniques, notably convolutional neural networks (CNNs), has revolutionized across numerous domains, including computer vision. Therefore, by leveraging deep learning techniques, galaxy classification stands to benefit from automated and improved analytical capabilities [1].

The utilization of deep learning methods for automated galaxy classification presents a promising avenue for accelerating the analysis of expansive astronomical datasets, while ensuring objectivity and reliability in the obtained results. It facilitates the effective management of large-scale datasets,

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expediting astronomical discoveries [2]. Moreover, deep learning possesses the potential to unveil latent patterns and reveal valuable insights pertaining to galaxy formation and behavior, thereby contributing to the advancement of the understanding in this field.

Transfer learning is a commonly employed technique in galaxy classification [3], pre-training on ImageNet can still be useful in improving the performance of machine learning techniques in setups with small amounts of labeled data available [4, 5]. This is because pre-training on ImageNet allows the network to learn general features that can be useful for other tasks, including galaxy image classification. However, the assessment of pre-trained models from ImageNet, considering the substantial dissimilarities between the dataset and galaxy images, becomes imperative in determining their contribution to galaxy classification.

According to the current studies, the performance of transfer learning in galaxy classification can be impacted by the pre-trained CNN model that is selected. For instance, a study used transfer learning to examine the results of pre-trained CNN models' classification of galaxy morphology using the Galaxy10 DECals Dataset [6]. According to the study, DenseNet121 performed better than other models and obtained 89% accuracy on the testing dataset. EfficientNetV2S, the second-best model, requires twice as much time but achieves a test set accuracy that is 2.43% lower. Pre-trained CNN models from ImageNet have been widely used for galaxy classification, other methods such as self-supervised learning and designing new lightweight deep learning frameworks can also achieve high accuracy and efficiency [7, 8].

Despite the effectiveness of transfer learning in galaxy classification, there has been a notable absence of research exploring the utilization of pre-trained models from ImageNet. This study aims is to explore the effectiveness of ImageNet in transfer learning for galaxy classification. Despite the inherent differences between ImageNet and galaxy images, the pre-trained models exhibit promising performance. Unravelling the optimal utilization of ImageNet to enhance transfer learning outcomes in galaxy classification is considered in this study. Moreover, this study aims to determine the ideal proportion of ImageNet integration by evaluating various transfer learning ratios. The insights gained from this research will shed light on the role and significance of ImageNet in galaxy classification, providing valuable guidance for future studies.

2. Method

2.1. Dataset description and preprocessing

The Galaxy10 DECals Dataset employed in this study is sourced from the DECam Legacy Survey (DECaLS) [9], which is part of the larger Dark Energy Spectroscopic Instrument (DESI) Legacy Imaging Surveys. DECaLS is an astronomical survey that utilizes the Dark Energy Camera (DECam) on the Blanco 4-meter telescope located at the Cerro Tololo Inter-American Observatory (CTIO) in Child. The Galaxy 10 DECals dataset contains 17,736, 256x256 pixel color images of galaxies (g, r, and z-bands) divided into 10 categories as shown in Figure 1.

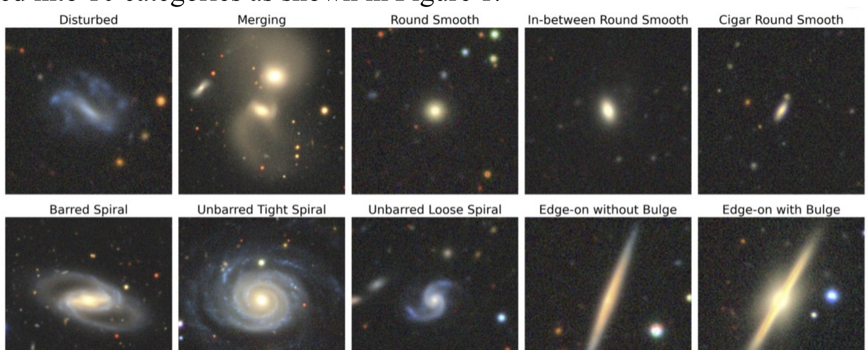

Figure 1. Example images of each class from Galaxy10 DECals [9].

Sample balancing is a crucial issue in machine learning and deep learning due to the inherent risk of bias and compromised model accuracy stemming from imbalanced sample sizes across different categories. Due to the significant difference in the number of galaxies in each category, the sample equilibrium problem must be taken into consideration when performing the task of classifying galaxies. Some categories in the Galaxy 10 DECals dataset have a significantly larger sample size than others. This class imbalance can lead to a skewed emphasis of the model towards categories characterized by a substantial sample size, subsequently resulting in the inadvertent neglect of other classes, which has an negative impact on model training.

In order to address the problem of sample imbalance, this work employed the random oversampling method as shown in Figure 2 to balance a number of dataset categories. Random oversampling method is a technique used to address the issue of imbalanced data in machine learning models. The method involves generating new instances of minority class samples by randomly duplicating the existing data, thus increasing the number of minority class samples [10]. This strategy is uncomplicated, easy to implement, and has produced successful results in research.

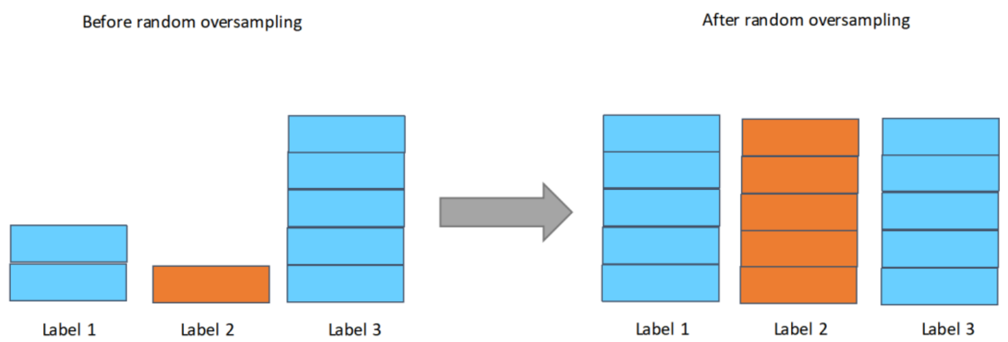

Figure 2. The schematic diagram of the random oversampling [10].

ImageDataGenerator is a data augmentation tool in the Keras library that can be used for image data augmentation in machine learning models. The tool provides several methods for augmenting images, such as rotation, shifting, and flipping, to create new images for training models [11]. Due of their distinct qualities, the aspect ratio of galaxy photographs will affect the identification of galaxy species. To ensure the constancy of image proportions, this study exclusively focuses on applying data augmentation techniques to color channels while incorporating translation and rotation operations. Using ImageDataGenerator to expand the data channel will increase the dataset's diversity, thereby improving the model's classification capability.

2.2. CNN model

CNN utilizes convolutional layers and pooling layers to extract features and reduce spatial dimensions of galaxy images. By learning local patterns and spatial structures, CNNs are effective in recognizing and categorizing different types of galaxies, providing powerful tools for astronomical research and exploration of the universe. One study demonstrated the CNN can achieve 97.272% in testing accuracy and outperformed other related works in terms of testing accuracy [12].

A deep learning model called Densenet shown in Figure 3 was constructed specifically for galaxy classification tasks. It introduces a dense connectivity pattern wherein each layer receives direct input from all preceding layers. The network's information flow is improved, and feature reuse is encouraged by this dense connectivity. The compactness, parameter efficiency, and superior performance of densenet models in capturing fine details in galaxy images are well known. Densenet demonstrates to be a useful method for precise and efficient galaxy classification by taking advantage of the dense connection, enabling breakthroughs in astronomical research and comprehension of the cosmos.

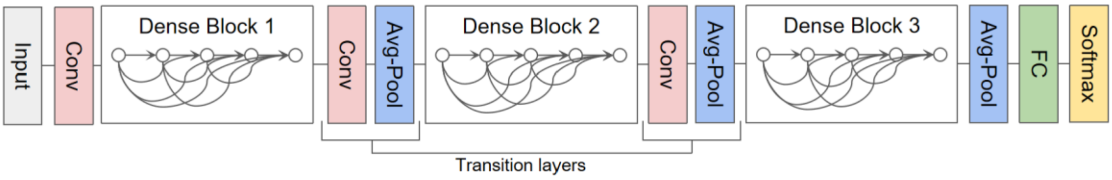

Figure 3. The schematic diagram of DenseNet with three dense blocks (Photo/Picture credit: Original).

In this study, the DenseNet-121 network architecture was employed for transfer learning to train a galaxy classification model. The pretrained model was initially trained on the ImageNet dataset. To investigate the impact of different ImageNet weight configurations on the performance of the galaxy classification model, a series of six comparative experiments were conducted. These experiments evaluated the accuracy and generalization ability of the model at ImageNet weight percentages of 0%, 20%, 40%, 60%, 80%, and 100%. The training layer proportions were modified to incorporate different ImageNet weights. Only Global Average Pooling and a Dense output layer were added to the DenseNet architecture. Apart from adjusting the training layer proportions, all other experimental conditions remained consistent.

2.3. Implementation details

In terms of the setting of hyperparameters, the optimizer and the corresponding learning rate was set to Adam and 0.0005, respectively. To enable the model to iteratively learn from the data, 10 epochs of training were completed. The categorical cross-entropy, was employed for the loss function.

The accuracy measure from test dataset was utilised to evaluate the model's performance. This statistic gives a broad indication of how well the model can categorise galaxies. Grad-CAM, a visualisation technique, was also used to comprehend the model's attention and focus on various areas of the input photos. The effect of various Imagenet weights on the model's performance in galaxy categorization might be seen by viewing the Grad-CAM maps.

3. Result and discussion

3.1. Classification performance of the model based on various ImageNet weights

A series of experiments consisting of six sets of trials were conducted to test the performance of the model on the dataset by adjusting the ImageNet weights and incorporating various chunks of ImageNet into Densenet121. According to the experimental findings, the model with ImageNet=20% training performed the best in classifying galaxies, with an accuracy of 79% shown in Table 1. The models that were trained with ImageNet=60% and 40% also demonstrated encouraging results, obtaining accuracies of 76% and 73%, respectively.

Table 1. The performance of the model based on various ImageNet weights in the galaxy dataset

ImageNet	Performance			
	Training Loss	Training Accuracy	Testing Loss	Testing Accuracy
0%	0.62	0.78	0.91	0.65
20%	0.36	0.87	0.60	0.79
40%	0.42	0.85	0.68	0.73
60%	0.41	0.85	0.66	0.76
80%	0.63	0.77	0.87	0.67
100%	1.22	0.56	1.26	0.48

These results highlight the significant influence of ImageNet proportions on the model's efficacy.

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For transfer learning tasks to be completed with the highest level of accuracy, it is essential to choose the right percentage of pre-trained weight.

3.2. Model interpretability at different Imagenet scales

In order to further analyze the influence of different ImageNet weight settings on the attention allocation of the model during the image prediction process, a comprehensive investigation was conducted. The Table 2 below uses the Grad-CAM visualization method to show the different concerns of different Imagenet scales on galaxy pictures.

Table 2. Grad-Cam diagram of galaxies under different ImageNet weights.

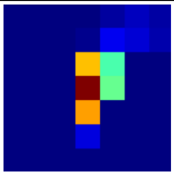
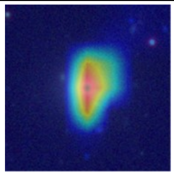
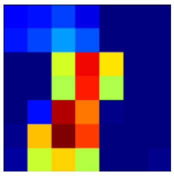
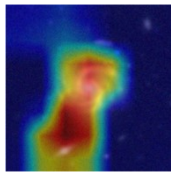
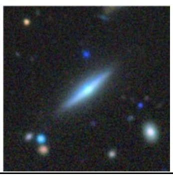
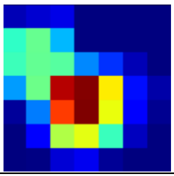
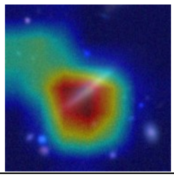
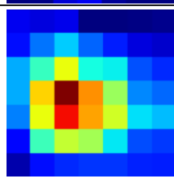
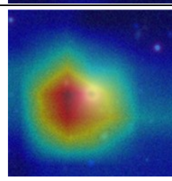
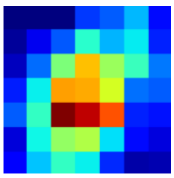
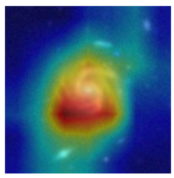
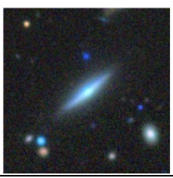
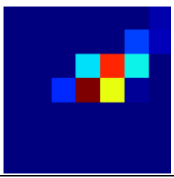
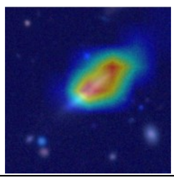
ImageNet		Performance	
0%	Origin Gradient diffusion	Heatmap Gradient diffusion	superimposing Gradient diffusion
20%			
			
			
40%			
			
			
ImageNet		Performance	
	Origin Gradient diffusion	Heatmap Gradient diffusion	superimposing Gradient diffusion

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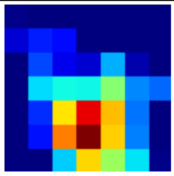
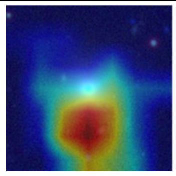
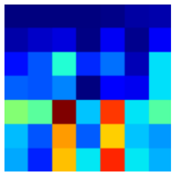
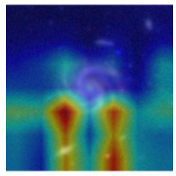
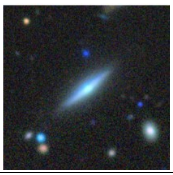
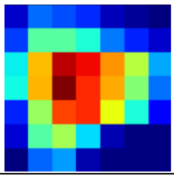
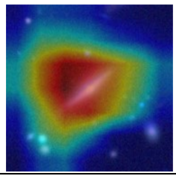
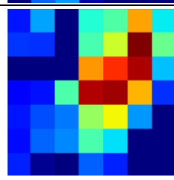
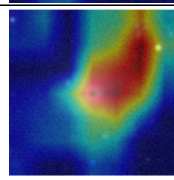
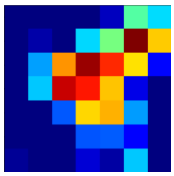
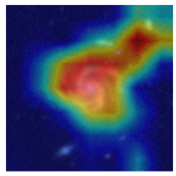
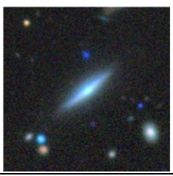
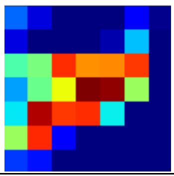
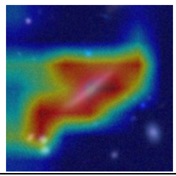
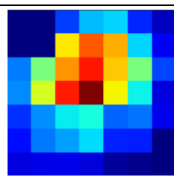
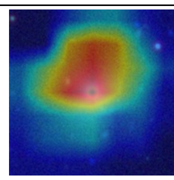
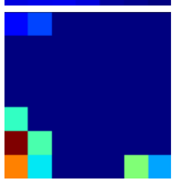
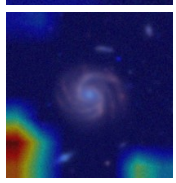
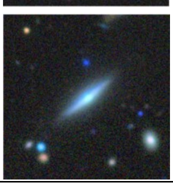
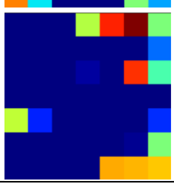
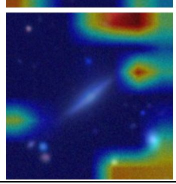
Table 2. (continued)

60%			
			
			
80%			
			
			
ImageNet		Performance	
	Origin Gradient diffusion	Heatmap Gradient diffusion	superimposing Gradient diffusion
100%			
			
			

The experiment shows that when identifying galaxy images, models trained with various ImageNet weights exhibit noticeably varied focal points. This suggests that the focal points established by the ImageNet weights have a significant influence on the models' capacity for categorization. Gradient diffusion occurred during the gradient propagation process, as shown in the Table 2 above, with 0% weight, making it impossible to capture the final Grad-Cam image. With 20% weight, the model was able to focus on the galaxies' regions with accuracy, and the targeted area's size matched the galaxies' well. The model still correctly recognised the target area with 40% weight, which was not noticeably different from 20% weight. 60% of the weight, the model could have a tiny focus range divergence and focus on the region near the galaxy's position. Even though the model concentrated on the galaxy's location, the focus region was too wide with 80% weight, making it difficult to determine the galaxy's precise location. The model had trouble locating the galaxy with 100% weight and frequently ended up focusing in the wrong places. The identical experimental setting served as the setting for the aforementioned tests.

The experimental results demonstrate the influence of different ImageNet weights on the classification capability of the models for galaxy image classification. When utilizing 0% weight, the occurrence of gradient diffusion in the model during propagation led to poor interpretability. Conversely, employing appropriate proportions of ImageNet weights (e.g., 20% or 40%) enabled the models to accurately focus on the relevant regions of the galaxy images. However, relying entirely on ImageNet weights (100%) resulted in decreased classification performance, as the models struggled to precisely identify the target regions within the galaxy images. These findings suggest that the selection of ImageNet weights significantly impacts the model's classification ability. Using suitable weight proportions allows for proper focus on the relevant areas, thereby improving performance. Nevertheless, complete dependence on ImageNet weights can hinder the model's effectiveness in transfer learning for galaxy classification tasks. These insights enhance the understanding of the role of weight initialization in achieving optimal transfer learning outcomes. Through experiments, it has been observed that when using fewer weights from ImageNet, some basic features within the ImageNet images can be transferred, such as the contours and shapes of objects. However, when using a larger number of weights from ImageNet, many advanced features from the ImageNet images are transferred, which can lead to inaccurate focus. This finding demonstrates that the current practice of using all weights from ImageNet in research is unreasonable. Prior to transfer learning, it is essential to confirm the optimal weights from ImageNet.

4. Conclusion

In conclusion, this work investigated the influence of transfer learning using various ImageNet weights on the categorization of galaxies. It was discovered that galaxies might be classified differently by models that had been trained using various ImageNet weights. Different impacts from various ImageNet weights could be obtained by varying the percentage of trained layers. The study also represented the attention patterns of these models, illuminating the regions of focus in galaxy images. In order to find patterns and choose the best weights, future study will examine the precise effects of various ImageNet weights on various elements of galaxy images. This study demonstrates the value of ImageNet weights in transfer learning for classifying galaxies and lays the groundwork for future research in this area.

References

[1] Sarvesh G Yogesh D et al 2022 Galaxy classification: a deep learning approach for classifying Sloan Digital Sky Survey images MNRAS 511 5120-5124

[2] Nour E M et al 2017 Deep Galaxy: Classification of Galaxies based on Deep Convolutional Neural Networks Computer Vision and Pattern Recognition (cs.CV)

[3] Singh S P et al. 2022 Classification of Galaxies using Transfer Learning 2022 4th International Conference on Advances in Computing, Communication Control and Networking (ICAC3N) 1541-1545

[4] Cadrin C A 2022 Moving from ImageNet to RadImageNet for improved transfer learning and generalizability Radiology: Artificial Intelligence 4(5): e220126
[5] Yu Q et al 2019 Semantic segmentation of intracranial hemorrhages in head CT scans 2019 IEEE 10th International Conference on Software Engineering and Service Science (ICSESS) IEEE 112-115
[6] Hui W Y et al 2022 Galaxy Morphology Classification with DenseNet Journal of Physics: Conference Series 2402
[7] Ana M et al 2020 Self-supervised Learning for Astronomical Image Classification cs.CV arXiv 2004.11336
[8] Wu D D et al 2022 A Lightweight Deep Learning Framework for Galaxy Morphology Classification Research in Astronomy and Astrophysics 22
[9] AstroNN 2017 Galaxy10 DECals Dataset — astroNN 1.2.dev0 documentation https://astronn.readthedocs.io/en/latest/galaxy10.html
[10] Sridhar S and Kalaivani A 2021 Performance Analysis of Two-Stage Iterative Ensemble Method over Random Oversampling Methods on Multiclass Imbalanced Datasets Int. J. Image Graph. 22 2250025:1-2250025:18
[11] Mittal A et al 2019 Data augmentation based morphological classification of galaxies using deep convolutional neural network Earth Science Informatics 13 601 - 617
[12] Nour E et al 2017 Deep Galaxy: Classification of Galaxies based on Deep Convolutional Neural Networks arXiv cs.CV 1709.02245