Proceedings of the 5th International Conference on Computing and Data Science
DOI: 10.54254/2755-2721/21/20231156

Denoising convolutional autoencoder for improving the classification performance based on noisy galaxy images

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Abstract. Images of galaxy objects are of great importance to the work of astronomers. Nowadays, the task of galaxy classification has been aided by Neural-Network-based classification models, who are powerful yet vulnerable to the attack of noisy images. In this research, RGB noises and bright spots simulating stars were generated, and a Convolutional-Neural-Network (CNN) based lightweight denoising image autoencoder was proposed. Firstly, a benchmark CNN classifier using DenseNet structure was trained on the Galaxy 10 DECals dataset, which consists of over 17, 000 RGB color galaxy images. Then, noisy images were generated by adding bright spots of different size and color simulating stars and applying gaussian RGB noises over the original images. The CNN autoencoder that consists of Convolutional layer in its encoder and Convolution Transpose layers in decoder was trained on the raw and noisy training data to learn effective galaxy image denoising. Finally, the effect of the autoencoder was evaluated by contrasting the performance of the CNN classifier over the noisy and denoised images. In contrast with being evaluated on the raw testing set, the CNN classifier's accuracy dropped by 0.41 when tested on the generated noisy testing images, indicating the effectiveness of the attack of image noises. While after denoising with the proposed autoencoder, the classifier's accuracy increased significantly by 0.37. Output denoised images also suggest that the autoencoder can effectively remove the applied bright spot and gaussian RGB noise, recreating the original shape of the galaxy.

Keywords: galaxy classification, image denoising autoencoder, convolutional neural network.

1. Introduction

Galaxies are systems of stars that are bounded by gravity and visible in space as entities. These celestial structures can be furthered separated into various subcategories according to their morphological features. The classification of galaxies is also fundamental to the discovery of unknown entities, by enabling researchers to learn about a new galaxy object just by observing its morphological features and relating to a previously known and well-studied objects of the same category. The pursuit of galaxy exploration relies highly on the support of graphics retrieved from telescopes and satellites, as the visual appearance of celestial objects carries valuable information about their structure, shape, and internal dynamics. Among which, classification of celestial objects by their visual features is of vital importance. It provides a systematic approach for researchers to study the properties and behaviors of individual objects, and enables astronomers to identify patterns, commonalities, and differences among distinct ones. The limitations of the traditional method.

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In recent years, the field of computer vision witnessed great progresses. As machine-learning/deep-learning-based models continue to evolve and manifest great capabilities on handling image classification tasks. In response to growing demand for automated classification of newly surveyed galaxy objects, some studies looked to implement computer vision models into the field of Astronomy and on the task of celestial object classifications. For instance, Kalvankar et al. implemented EfficientNet [1], a scaling-up convolutional neural network to classify over 80, 000 galaxy images from Galaxy Zoo 2 dataset into 7 classes and managed to achieve 94% accuracy [2]. Cavanagh et al. experimented involving multiple convolutional neural network structures, comparing their performance on 3-ways and 4-ways morphological galaxy classification tasks [3].

More recently, Shaiakhmetov et al. proposed SpiralNet [4], a novel framework that effectively reduced computational costs while achieving an 82% accuracy on a 10-class task on Galaxy Zoo dataset. R. Dagli set a new state-of-the-art baseline with Astroformer [5], a transformer-convolutional hybrid model on Galaxy 10 DECals dataset that provides a 10-class classification task. Y. Andrew experimented under multiple settings utilizing pretrained Convolutional Neural Network (CNN) models including ResNet, VGG, DenseNet, and Xception to test out the influence of choices of color channels on the performances of transfer learning models [6].

However, it is noteworthy to highlight that several of the aforementioned studies did not explicitly address the challenges associated with noisy data, which could potentially compromise the performance of neural network-based classifiers. Paranhos da Costa et al. demonstrated that random gaussian and Poisson noise can significantly reduce the accuracy of image classifiers trained on clean images [7]. Unfortunately, this could always be the case during implementation of classification models in real settings, as the observation of the target object could be interfered by unrelated bright cosmic objects and disturbed by inevitable noises due to limitations of astronomic instruments.

To address this problem, denoising algorithms could be implemented to reduce noise level and remove irrelevant bright spots in the image of celestial objects. Specifically, denoising autoencoders are suitable to work with neural-network-based classifiers. Autoencoders are sets of neural networks that is used to learn efficient coding in unsupervised context. A Denoising Autoencoder (DAE) is a kind of autoencoders that is trained to effectively remove noise of input, while retaining useful information contained in the original input. L. Gondara has shown a CNN based DAE trained on a relatively small dataset can effectively remove gaussian and Poisson noise applied to medical images [8]. Bajaj et al. proposed a deep CNN DAE that outperforms traditional image processing methods in terms of dealing with gaussian noise on STL-10 dataset of color images [9]. Tun et al. also implemented CNN DAE on facial images to remove different kinds of noises [10].

The preceding researches implied the effectiveness of CNN based autoencoders on processing images of various types. Nonetheless, the application of DAEs to galaxy images, which exhibit substantial dissimilarities from everyday life images, has received limited attention within the existing body of research. This research aims to fill this gap by implementing an unsupervised CNN-based Denoising Autoencoder trained on galaxy image data and examine its performance when working with NN-based galaxy image classifiers.

2. Methodology

2.1. Dataset introduction

The dataset employed in this research is Galaxy 10 DECals [11], which consists of 17, 736 256×256 RGB images of galaxy objects corresponding to 10 categories as shown in **Figure 1**. The images of the dataset are from DESI Legacy Imaging Surveys [12], and its corresponding labels from Galaxy Zoo Dataset [2].

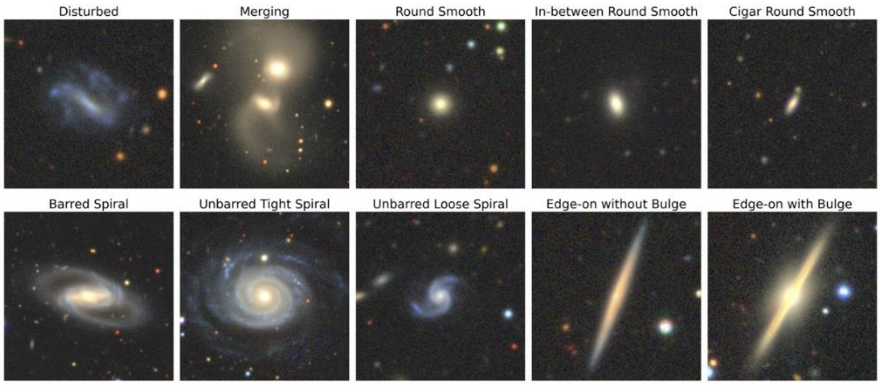

Figure 1. The sample images of Galaxy 10 DECals dataset.

In terms of the data preprocessing, images are first read from the dataset as a h5 file, and then written into jpg format image files locally for saving RAM space. When loading the image file, tensorflow.keras.ImageDataGenerator is used to reshape original images to 128x128, and rescale it on 3 color channels, transforming the original range of 0-255 to a standardized range between 0 and 1.

To generate the noise needed for training the autoencoder, a two-step noise-adding method using OpenCV was designed to work with the ImageDataGenerator. Specifically, the first step is to add random bright spots that simulate irrelevant celestial objects around the observed galaxy. The random range for size, brightness, RGB values, and blurring kernel size are carefully designed to simulate white, blue, and red stars with a proportion of 2:1:1.

The second step simulates an RGB noise that is always present in astronomical images, a random gaussian noise was added after of the original image and randomly simulated stars were merged. Sample noisy images and their corresponding raw images are shown in Figure 2.

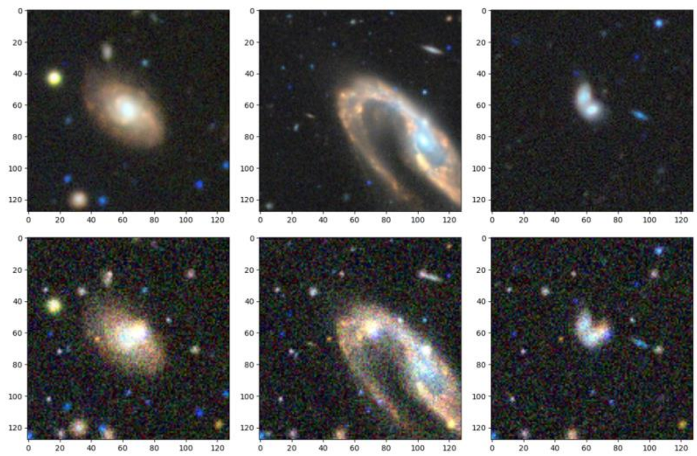

Figure 2. Sample training images before and after adding noise.

The dataset is then partitioned into training and testing data with a 8:2 ratio, and the training set is further split into training and validation set with a 8:2 ratio for hyperparameter tuning.

2.2. Convolutional neural networks

CNN represents a prominent category of neural networks that are frequently used for analyzing images. It typically consists of convolutional layers, pooling layers and fully connected layers. Convolutional layers can convolve the input with kernels to extract feature maps and feed to the next layer. Pooling layers can effectively reduce the dimension of output of convolution layer by combining outputs of several neurons into one input for the next layer, which is conductive to reducing the number of trainable weights involved in the fully connected layers. The fully connected layers produce the final output based on the extracted features from previous layers.

In this research, a variation of CNN, DenseNet as shown in Figure 3 [13], is trained on Galaxy10 DECals dataset as classifier. A DenseNet is a CNN that utilizes dense connection between layers through Dense Blocks. Under this structure, each layer obtains and concatenates additional inputs from all preceding layers and feed its output to all succeeding layers. This allows the model to have fewer channels in all of its convolutional layers and can effectively reduce computational and memory expenses during training.

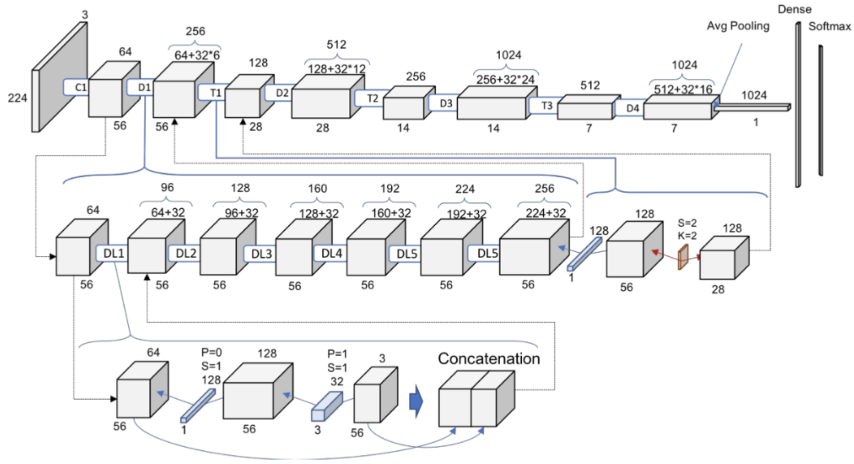

Figure 3. Model architecture of DenseNet121 [14].

Specifically, the structure of DenseNet 121 that consists of ReLU activation and batch normalization in between convolutional layers provided by tensorflow.keras.applications was implemented and an additional classification head that consists of 2 fully connected dense layers was added. The output layer consists of 10 neurons with softmax activation, outputting the posterior possibility of an observation belonging to one of the ten classes.

2.3. *Autoencoder*

An autoencoder (AE) represents a type of neural network that is specifically designed to learn representation of unlabeled data through unsupervised learning. An autoencoder consists of an encoder that transforms the input data into a lower dimensional representation, and a decoder that recreates the data that has the same shape as the input from the learned representation. A DAE is one that aims to reduce noise of the input image by learning a representation and then recreating the image.

In this research, a light-weight CNN-based DAE was proposed to deal with galaxy denoising task, with its architecture shown below. The Encoder consists of 4 convolution – batch normalization blocks, and the decoder consists of 4 convolution transpose layers that corresponds to the encoder. The final output layer is a convolutional layer with 3 kernels, returning a 128×128 image with three channels identical to the input image. The structure is shown in Figure 4.

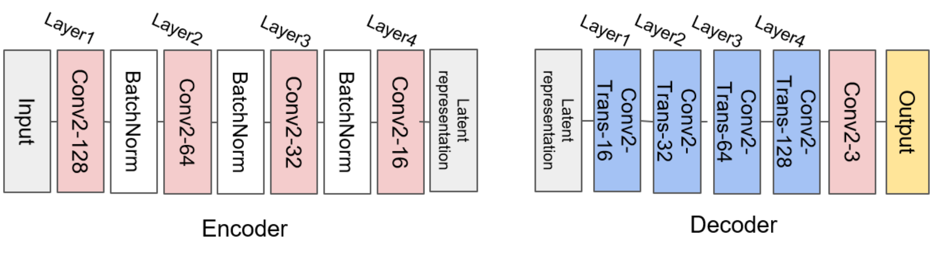

Figure 4. Architecture of the CNN denoising autoencoder (Photo/Picture credit: Original).

2.4. Training details
Both trainings of CNN classifier and Autoencoder are conducted with a NVIDIA RTX-3060 graphics card.

2.4.1. CNN classifier. The DenseNet121 classifier was trained on the training set and evaluated on the validation set for 18 epochs before stopping on an early stopping callback. An Adam optimizer with a learning rate of 0.001 was used.

2.4.2. Autoencoder. The training of the autoencoder based on the training set consists of two parts. Initially, the raw training image was given to the autoencoder as both input and target and the autoencoder was trained for 20 epochs using Adam optimizer with learning rate of 0.001. This is for the autoencoder to learn basic representations of the galaxy image. Furthermore, noisy image was fed as the input while the raw image was given as the target, the model is trained on this setting for 60 epochs for it to learn how to perform effective denoising.

3. Results and discussion

3.1. CNN classifier baseline
On the original Galaxy10 DECals testing set, the trained CNN Classifier can achieve a 0.74 overall accuracy, with the performance on each class shown in Table 1. The DenseNet121-based CNN classifier exhibits the capability to acquire significant and interpretable representations of the galaxy images for the majority of the classes.

Table 1. Performance of the CNN classifier on original Galaxy10 DECals testing set.

Class	Precision	Recall	F1-score	Support
0	0.38	0.53	0.44	204
1	0.79	0.79	0.79	373
2	0.94	0.76	0.84	529
3	0.76	0.89	0.82	408
4	0.58	0.79	0.67	71
5	0.92	0.65	0.76	436
6	0.54	0.84	0.66	365
7	0.66	0.52	0.58	516
8	0.82	0.94	0.88	283
9	0.96	0.75	0.84	363
Overall Accuracy			**0.74**	3548
Macro avg	0.73	0.74	**0.73**	3548
Weighted avg	0.77	0.74	**0.74**	3548

3.2. CNN performance on noisy images
In the presence of noise introduced to the testing set, the performance of the CNN classifier deteriorates significantly, the performance on the noisy testing set is shown in Table 2. The overall accuracy drops from 0.74 to 0.33, and the classifiers' performance on each class degraded.

Table 2. Performance of the CNN classifier on testing set with noises applied.

Class	Precision	Recall	F1-score	Support
0	0.16	0.39	0.23	204
1	0.43	0.73	0.54	373
2	0.00	0.00	0.00	529
3	0.30	0.02	0.04	408
4	0.16	0.11	0.13	71

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Table 2. (continued).

5	0.29	0.55	0.38	436
6	0.47	0.29	0.36	365
7	0.25	0.46	0.32	516
8	0.64	0.46	0.54	283
9	0.81	0.20	0.32	363
Overall Accuracy			**0.33**	3548
Macro avg	0.35	0.32	**0.29**	3548
Weighted avg	0.35	0.33	**0.28**	3548

3.3. CNN performance on the denoised images

The CNN classifier was then evaluated on noisy images processed by the denoising autoencoder, the performance significantly improved in comparison with the result evaluated directly on the noisy images, and was comparable with its performance on the raw testing set. The classifier's performance on the denoised testing set is shown in Table 3.

Table 3. Performance of the CNN classifier on the denoised testing set.

Class	Precision	Recall	F1-score	Support
0	0.40	0.48	0.43	204
1	0.80	0.74	0.77	373
2	0.93	0.73	0.82	529
3	0.77	0.80	0.78	408
4	0.49	0.82	0.61	71
5	0.84	0.61	0.71	436
6	0.46	0.86	0.60	365
7	0.59	0.47	0.52	516
8	0.79	0.93	0.85	283
9	0.96	0.68	0.79	363
Overall Accuracy			**0.70**	3548
Macro avg	0.70	0.71	**0.69**	3548
Weighted avg	0.74	0.70	**0.70**	3548

3.4. Denoised sample images

Samples of the output of the denoising autoencoder, i.e., the denoised testing images, are shown in Figure 5. The DAE effectively removed gaussian RGB noises and some of the added bright spots in the noisy image, recreating the original shape of the galaxy object. However, the processed images are blurred noticeably in comparison with the raw image.

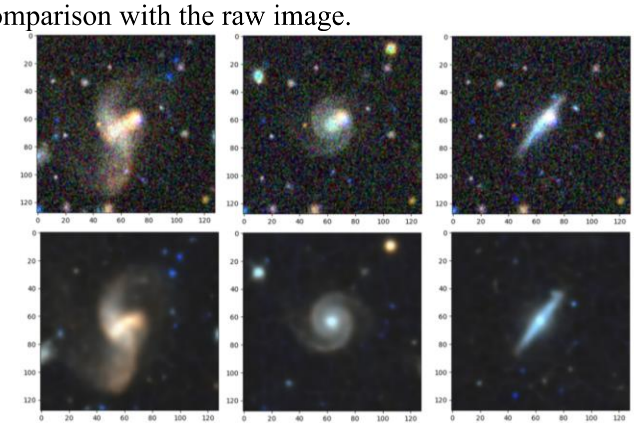

Figure 5. Sample noisy and denoised testing images.

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3.5. Discussion

The experiments suggested that added RGB noises and bright spots simulating irrelevant celestial objects can significantly perturb the decision of the classification model, suggesting the vulnerability of a CNN classifier trained on clean images to the attack of noises. The denoising autoencoder, on the other hand, can effectively remove the added noise and reconstruct the original shape of the galaxy, although blurred. The experiments demonstrated that a light-weight CNN DAE could already in some sense defend against the attack of noisy images and facilitating the receipt of input images that closely resemble the corresponding training data, and therefore boost the performance of the model when dealing with noisy images.

It is noticeable, however, the autoencoder exhibited limitations in effectively removing some of the irrelevant stars that are originally in the raw image. An explanation could be that the morphological and color distribution of these stars are slightly different than the generated bright spots, making the autoencoder distinguish them during training. Future experiments can focus on simulating with a distribution extracted from the original images, or try to quantify the morphological and color feature of the stars originally in the raw image more precisely. Furthermore, it should also be acknowledged that the denoised images produced by CNN-based autoencoders inherently suffer from blurring. A more intricated model such as Generative Adversarial Network could potentially output a clearer denoised image, while being more computationally expensive and requires more training data for better results should be considered in the future.

4. Conclusion

In this research, a light-weight CNN autoencoder was proposed for denoising galaxy image data. Initially, a baseline CNN classifier on galaxy image data was trained. Subsequently, noisy image data with RGB noises and bright spots simulating stars were generated. A light-weight CNN based autoencoder was trained to learn effective denoising for galaxy images. Additionally, the effectiveness of denoising was evaluated by contrasting the performance of the CNN classifier on noisy and denoised testing images. The denoising autoencoder managed to boost the overall accuracy of the classifier on noisy testing set by 0.37, by effectively removing both types of noises applied. This research demonstrated the effectiveness of light-weight CNN denoising autoencoder on dealing with galaxy images, which are significantly different than images in daily life. A limitation of this study is that the simulated stars are still not identical in distribution compared with the stars captured in the original astronomical images, and the denoised images being slightly blurred. Future investigations can focus on simulating stars with a more finessed distribution, or exploring more complicated models for more effective denoising.

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