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Enhancing Galaxy Morphology Classification using Ensemble Learning

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ABSTRACT

In recent decades, due to progress made in the field of astronomy and the development of specialized equipment, large-scale sky surveys have generated immense amounts of data. To address this issue, astronomers have utilized the power of crowdsourcing provided by the Galaxy Zoo project for the morphological classification of galaxies. However, with the upcoming generation of surveys, relying on crowdsourcing is not optimal, and the adoption of automated strategies for the morphological classification of galaxies is essential. The aim in this work is to design a model focused on the classification of galaxies, exploring average weighted ensemble learning, and comparing the outcomes with baseline models using a dataset from the astronomical DESI Legacy Imaging Surveys (DESI), which consists of approximately 18,000 images from 10 broad galaxy types. The results reveal that employing ensemble learning outperforms the baseline models and produces better results compared to them. In this work, models such as ResNet-50, EfficientNetV2S, and DenseNet-121 are employed to create the ensemble, with the ensemble achieving a test-set accuracy of 89%, compared to ResNet-50, DenseNet-121 and EfficientNetV2S achieving 86%, 87% and 88%, respectively.

1. Introduction

Galaxies are intricate systems bound by gravitational forces, composed of matter such as dust, gas, star particles, and black holes [1]. In our observable universe, there are approximately more than 2 trillion galaxies. These galaxies display a wide range of morphological traits such as rings, bars, and arms. These morphological traits aid us in understanding the evolutionary history of the universe [2]. Different morphological types suggest different formations and evolutionary processes. By studying morphology, astronomers can trace the development of galaxies over cosmic time [3]. In 1926, Edwin Hubble performed a visual inspection of fewer than 400 images of galaxies and proposed a classification system called "The Hubble sequence," based on their shape observed from Earth, the Hubble classification system. It divides galaxies into different types depending on their morphological traits. The Hubble classification system includes two main categories: early type (elliptical galaxies)

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and late type (spiral galaxies). Elliptical galaxies are distinguished by their smooth and featureless appearance, while spiral galaxies have spiral arms and a disk-like structure [4].

Precise morphological classifications are needed to help us understand the development of the universe. The process of galaxy classification has always been performed by astronomers or scientists. However, state-of-the-art sky surveys have been capturing more and more detailed images that astronomers can't manually classify [5]. The Galaxy Zoo tried to solve this by asking volunteers to help with the classification via a web interface. Through the interface, volunteers were shown an image of the sky with a galaxy in the center and given a set of questions based on decision trees. The volunteers submitted the classification results [6]. Other projects including Galaxy Zoo Hubble (GZH) [7] and the CANDELS project [8] have found success in exploiting volunteers to visually classify galaxies. However, despite the success of these projects, with the amount of surveys and the data deluge they bring, approaches that rely on humans will require time and effort to be valuable, meaning projects that rely on volunteers to visually classify morphology will not be sustainable with the next generation of surveys [9]. This work proposes a framework based on ensemble learning using models such as ResNet-50, EfficientNet-v2S, and DenseNet-121 for the galaxy morphology classification task. Also, we assess the performance of the Ensemble model against the baseline models and others from the literature. The remainder of this paper is presented as follows, Section 2 relays the literature survey, Section 3 provides the methodology used in this work, Section 4 demonstrates our results, then Section 5 provides a discussion, and Section 6 presents the conclusion & future work.

2. Literature Survey

After studying and analysing various machine learning techniques, Mittal *et al.*, [10] proposed a model named daMCOGCNN for the task of galaxy morphology classification. They utilized various datasets such as SDSS, Galaxy Zoo, and the Hubble image gallery, dividing galaxies into three classes: elliptical, spiral, and irregular. Due to the small size of the dataset, which comprises approximately 4614 samples, the authors relied on augmentation. Although the model achieved a test-set accuracy of 97%, it was only trained with three distinct classes.

The focus of Eassa *et al.*, [11] was on the illumination of galaxies. Utilizing both illumination intensity and Euclidean gap from the centre, their proposed model classifies the dataset into three classes: elliptical, spherical, and miscellaneous. To isolate the raw illumination of galaxies from background interference caused by stars and other objects, the authors subtracted the background illumination, they applied methods such as k-means clustering to categorize galaxies into three classes. Cheng *et al.*, [12] conducted a comparative study where they employed different traditional learning algorithms such as KNN, logistic regression (LR), SVM, Random Forest (RF), and deep learning algorithms such as Multi-Layer Perceptron Classifier (MLPC) and convolutional neural networks using sample of images consists of 2800 galaxies coming from the GZ dataset. The results showed higher performance of models based on deep learning compared to traditional learning algorithms regarding training time and accuracy. Cavanagh *et al.*, [13] proposed a model named C2, and reimplemented other models from the literature such as Dielman model and AlexNet, the model was trained binary classification (elliptical and spiral), on 3-way classification (elliptical, spirals, Lenticular and irregular), and 4-way classification (elliptical, spiral, Lenticular, irregular and miscellaneous), The authors resorted to using augmentation techniques to combat overfitting and generate more data. They achieved accuracies of 92%, 82%, and 77% for two, three, and four classes, respectively.

Mazzeo *et al.*, [14] presented an original CNN architecture which have been trained to classify galaxies into twenty-six classes based on the Hubble-DeVaucouleurs system for the first time. In this

work, the authors used the Galaxy Zoo dataset challenge from Kaggle and relied on corresponding decision trees (DT) to extract labelled examples. The proposed model achieved an accuracy of 78%. Jimenez *et al.*, [15] experimented with two strategies first, the traditional approach using a feature-extractor coupled with a classifier, and end to end CNN. The dataset in this study comes from The GZ1 dataset and consists of approximately 670k samples. Jesse *et al.*, [16] work focuses on the comparative performance of pretrained and non-pretrained versions of AlexNet when applied to images from the SDSS release 4. their findings reveal that the pretrained Alex-Net consistently outperforms the non-pretrained Alex-Net, achieving an average test accuracy of 84.2% compared to 82.4%. Additionally, the pretrained model attains peak accuracy more efficiently, requiring only 155 epochs on average versus 367 epochs for the non-pretrained Alex-Net. When considering the 200 epochs, the pretrained model's accuracy advantage increases to 4.6%. with Goyal *et al.*, [17] the goal was to analyse the different machine learning methods used for the task of galaxies classification and to design CNN based classification model with cerin data augmentation techniques, in this work the authors utilized the galaxy zoo dataset achieving 88%.

All these studies have contributed significantly to the classification of photometric galaxy images. To the best of our knowledge, there hasn't been a comparative study done between ensembled models and baseline models in the context of galaxy morphology. Therefore, the goal of this work is to develop a deep learning model based on ensemble learning and compare it with the baseline models.

3. Methodology

3.1 Baseline Models

In this work, after a thorough experimentation with various architectures we opted to use ResNet-50, DenseNet-121, and EfficientNetV2S based on their performance in related tasks in the literature [18]. ResNet-50 is a deep learning model designed for image classification tasks. ResNet-50 introduces skip connections, which allow the network to skip certain layers. This helps in addressing the vanishing gradient problem when training deep networks, ResNet-50 model consists of 50 layers, hence the name. It comprises several convolutional layers followed by residual blocks, with a global average pooling layer (GAP) and a fully connected layer at the for classification. DenseNet-121 is another deep learning model that belongs to a family of densely connected convolutional networks. DenseNet-121 builds upon the idea of residual connections introduced in ResNet but it feeds each layer to every other layer in a feedforward manner. This connectivity pattern allows the features to be reused throughout the network, which leads to an improved gradient flow, feature propagation, and parameter efficiency. EfficientNetV2S is an improved version of the original EfficientNet, which incorporates a new novel of convolutional layer called Fused MBConv as well as a unique scaling technique.

3.2 Ensemble Learning

Ensemble learning methods are often considered a solution to various deep learning problems. By training a diverse set of models and combining their predictions, these methods can significantly improve overall prediction accuracy compared to relying on a single model alone [19]. The process involves training multiple base models and then combining their outputs to form a collective prediction. In this study, we employ an average weighted ensemble approach. Each model in the ensemble is assigned a weight between 0 and 1, which defines its contribution to the final prediction. These weights are determined based on the performance of each model during experimentation.

Generally, models that perform better are assigned higher weights. After experimenting with different weights, we found that [0.1, 0.7, 0.2] provided the best results for ResNet-50, EfficientNetV2, and DenseNet-121, respectively, based on their performance. The prediction of the ensemble \hat{y} for a given input image x can be given in Eq 1. Where "N" represents the models in the ensemble, w_i is the weight given to the i^{th} . Model, \hat{y}_i is the output of the i^{th} . model for input x . The structure of the ensemble system is given in Fig. 1.

$$\hat{y} = \sum_{i=1}^N w_i \cdot \hat{y}_i \tag{1}$$

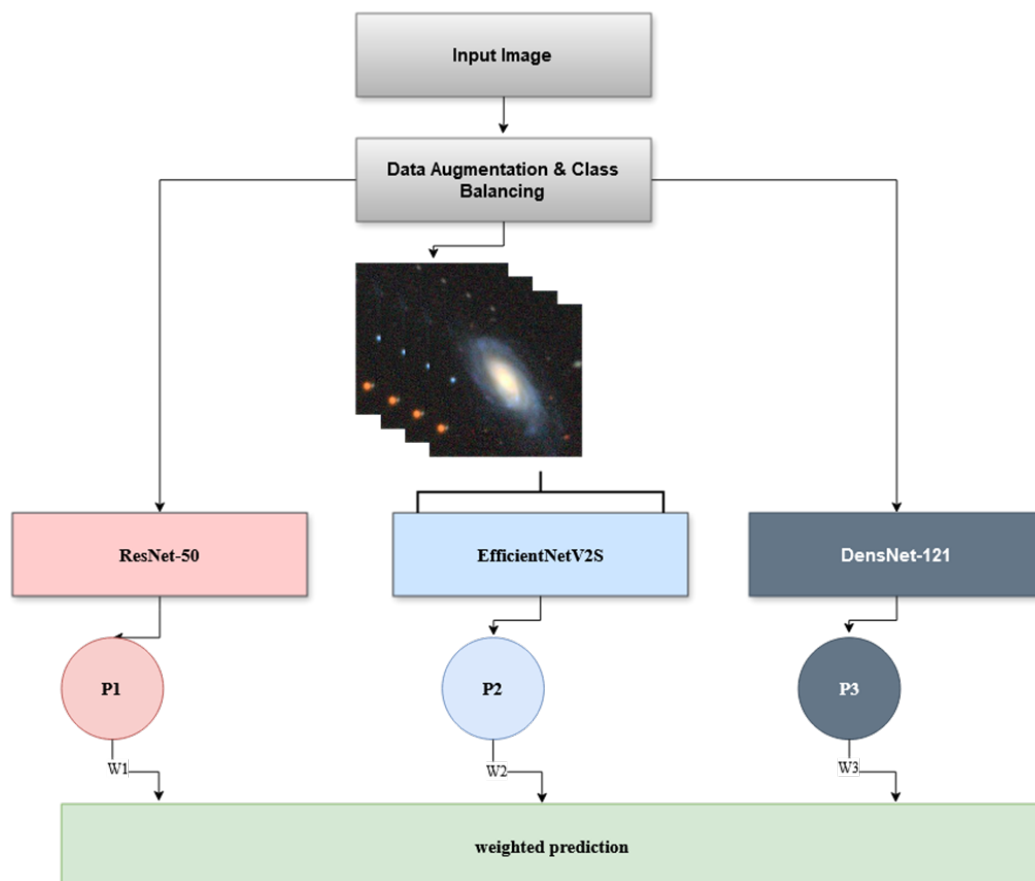


Fig. 1. The structure of our proposed model

3.3 Data Set Description

The Galaxy DECals dataset used in this work is introduced by [20], it consists of approximately 18,000 labeled images which are coming from GZD 2 where the public classify approximately 270k of galaxy samples. Galaxy zoo then combined the GZ, DR2, with DECals where 18k of the images were selected using the votes. In this work the DECals dataset is used due to its broadness, it includes 10 broad classes in addition to the high resolution that it provides so that CNNs can extract useful information. Table 1 shows the 10 classes and their distribution, while Fig. 2 displays and examples of raw images for each class.

Table 1
 The DECals dataset image distribution

Class number	Class name	Number of samples
0	Disturbed Galaxies	1081
1	Merging Galaxies	1853
2	round smooth Galaxies	2645
3	In-between rounds and smooth Galaxies	
4	Cigar-Shaped Smooth Galaxies	2027
5	Barred Spiral	334
6	Unbarred-Tight Spiral Galaxies	2043
7	Unbarred-Loose Spiral Galaxies	1829
8	Edge-on without Bulge Galaxies	2628
9	Edge-on with Bulge Galaxies	1423

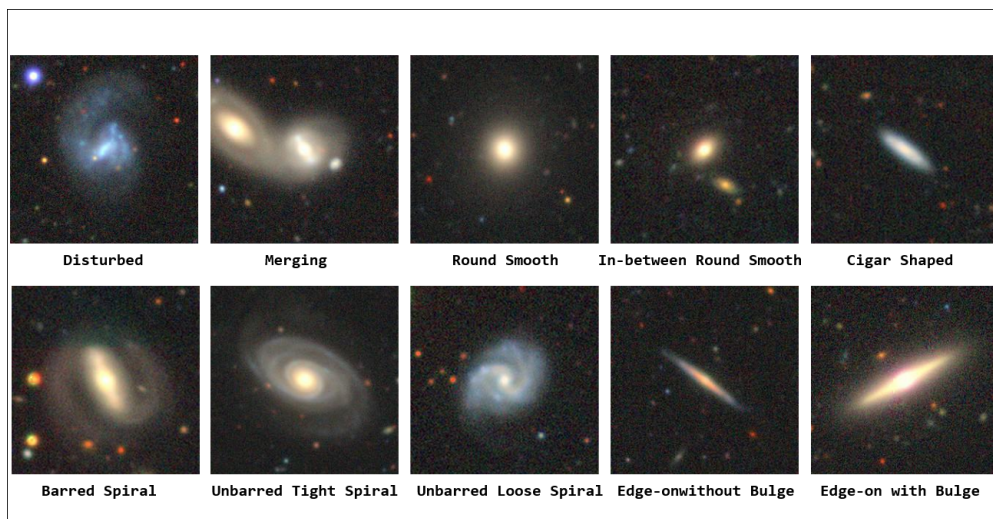


Fig. 2. Example images for the 10 classes in the DECals dataset

3.4 Class Balancing

According to the data presented in Table 1 the dataset used in this study is highly imbalanced, hence it will introduce a severe bias when training and it will influence the model's performance. In this study we use class weights where we calculate class weights based on class frequencies and assign high class weight to the minority classes and low class weight to the majority classes making use of the torch-sampler provided by the PyTorch library.

3.5 Data Augmentation and Preparation

In this work we split the dataset to 70%, 15%, 15% training, validation and testing respectively, for the training subset all the images are resized to 224 x 224 to accommodate to the input dimensions of the base models, also giving the models complexity, to prevent overfitting and improve

the generalization we used data augmentation. We used random rotation angle 0-90, horizontal/vertical flip of 0.7 with center crop of 224.

3.6 Implementation Details

First, for each model in the ensemble we removed the last dense fully connected layer from the pre-trained models and added an GPA layer on top alongside a dense layer that has 2048,1280 and 1024 for the ResNet-50, EfficientNetV2 and DensNet-121 respectively ReLU and final layer with 10 neurons corresponding to the 10 classes alongside a Softmax activation and batch size of 64. The performance of any deep learning model is always effected by hyper-parameters such as learning rate, activation functions and optimization algorithms. Finding the best set of hyper-parameters is a crucial step for creating a well calibrated model. We repeatedly trained each of the base models with a different set of hyperparameters. First, we experimented with different trainable layers to fine tune the model. We found that the models perform poorly when trained with small number of layers, so we chose to fully train the models using ImageNet weights and had desirable results. The Adam optimization with momentum algorithm was used for all the models. Learning rate is crucial hyper parameters to tune because it influences the model performance and convergence. Finding the optimal learning rate is considered a time consuming and challenging task, after we experimented with different set of values, we opted to use a learning rate scheduler in our training approach, we applied Lr of 0.0010 and multiplying it by a factor of 0.1 after every 10 epochs. This adjustment helps accelerate the learning process, enabling the model to converge.

3.7 Evaluation Metrics and Setup

The ensemble model is built using PyTorch framework [21]. The model was trained on a laptop with NVIDIA RTX 3070 GPU. The dataset was divided into training-set, validation-set, and testing-set. Here we used the validation set for hyperparameter tuning to avoid bias, the training process was done over 50 epochs and a batch size of 64, we also employed a method called early stopping to stop the training process when there is no positive convergence in the training. Early stopping is a technique used while training deep learning models to stop overfitting of the model. It consists of monitoring the model performance on the validation dataset while training and halting the training process once the performance of the model stops improving. We also use categorical cross entropy function. To validate the models, we used metrics such as accuracy, precision, recall, F1, confusion matrix (CM), AUC & ROC

- Accuracy: The percentage of images classified correctly; the formula is given in Equation (2):

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \times 100\% \quad (2)$$

- Precision: the ratio of accurately predicted positive images of all images. The calculation is as follows:

$$Precision = \frac{TP}{TP+FP} \quad (3)$$

- Recall: the correct positive images predictions out of all positive predictions.

$$Recall = \frac{TP}{TP+FN} \quad (4)$$

- F1-Score: a harmonic mean of the precision and recall together, the formula is given in Equation (5):

$$F1 - Score = \frac{2 \times precision \times recall}{precision + recall} \quad (5)$$

4. Results

The precision, recall F1-score and accuracy of the base and the ensemble models are given in Table 2, the highest achieving metrics are displayed in bold. The high performance of the ensemble compared to the baseline models is apparent. In Table 3, we validate the performance of the ensemble with others from the literature, since various models trained with a different datasets and different classes, we opted to include models that uses the same datasets as ours for more righteous comparison.

Table 2

The precision, recall, F1 score and accuracy of the baseline and the ensemble

Model	Precision	Recall	F1 Score	Accuracy
ResNet50	86.3%	86.4%	86.2%	86.4%
EfficientNetV2	87.7%	88.0%	87.7%	88.0%
Densnet121	87.5%	87.8%	87.5%	87.8%
Ensemble Model	88.8%	89.0%	88.8%	89.0%

Table 3

Comparison of the proposed model with other different models from the literature

Model	Data	Accuracy
Radhamani <i>et al.</i> , [22]	Galaxy DECals	73.4%
Ciprijanovic <i>et al.</i> , [23]	Galaxy DECals	79.0%
Ghadekar <i>et al.</i> , [24]	Galaxy DECals	84.4%
HOLANDA <i>et al.</i> , [25]	Galaxy DECals	86.2%
Ensemble Model (Ours)	Galaxy DECals	89.0%

In Table 4 we report the results for each class for the ensemble model. These results were extracted from the confusion matrix, which is reported in Fig. 3.

Table 4

Reports the class, F1-score, precision, recall for each class

CLASS NO	CLASS	PRECISION	RECALL	F1 SCORE
0	Disturbed	67.3%	58.7%	62.8%
1	Merging	93.3%	90.8%	91.9%
2	round smooth	94.7%	95.8%	95.2%
3	In-between rounds and smooth	93.9%	98.0%	95.9%
4	Cigar Shaped Smooth	79.4%	91.1%	84.9%
5	Barred Spiral	89.5%	91.7%	90.0%
6	Unbarred Tight Spiral	89.5%	91.7%	90.5%
7	unbarred Loose Spiral	80.3%	89.1%	84.0%
8	Edge-on without Bulge	94.5%	96.5%	95.5%
9	Edge-on with Bulge	94.3%	98.4%	96.3%

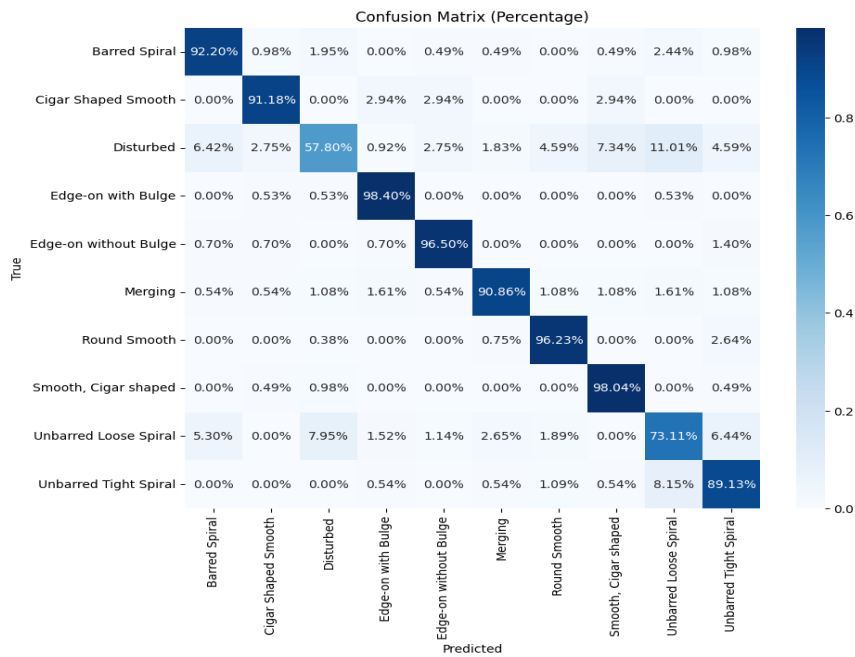


Fig. 3. The confusion matrix for the ensemble model

5. Discussion

The goal of this work is to propose an ensemble learning model for the task of galaxy morphology classification. All of the base models and the ensemble classification results are given in Table 2. It compares all the models with various evaluations metrics. The EfficientNetV2 scored excellent recall and it contributed to the ensemble, although it is computationally expensive and required almost 1 hour of training. The Densenet121 scored a good recall and accuracy. Compared to the EfficientNetV2 the model is not computationally expensive with approximately 7 million trainable parameters. The Resnet-50 model performed the least in comparison with the other 2 models, like the EfficientNetV2, the model required almost 1 hour of training due to the number of parameters. The average weighted ensemble model achieved superior results compared to the base models with precision of 88.8%, recall of 89.0% and accuracy of 89.0% without any further training. The model can be integrated into surveys pipeline. From the confusion matrix in Fig. 3 and the results for each class reported in Table 4. we can see the results of the ensemble model in detail. We found the ensemble performs well in all other classes except class 0 which represent disturbed galaxies. The model confuses disturbed galaxies with other classes and only classifying a small percentage of the data right, and that is due to the structure of disturbed galaxies. Unlike other classes disturbed galaxies can exhibit a wide range of complex morphologies, such as irregular shapes, tidal tails, and asymmetric features. These diverse structures can make it difficult for the CNNs to correctly classify them. To investigate and understand which features are most influential in our task we use Grad-CAM, which is a method used with CNNs to see which part of the input image is crucial to the network. as shown in Fig 4. The model focuses on the part of interest instead of the noise around it. Although the ensemble gave us the desirable results, the model still has its limitations. Ensemble learning can be inherently computably expensive. Training and maintaining different models in the ensemble can require significant computational resources, such as processing power, memory, and time. Also, in this experiment due to the limited resources we only used three pre-trained models from different architectural families adding other models could enhance the results.

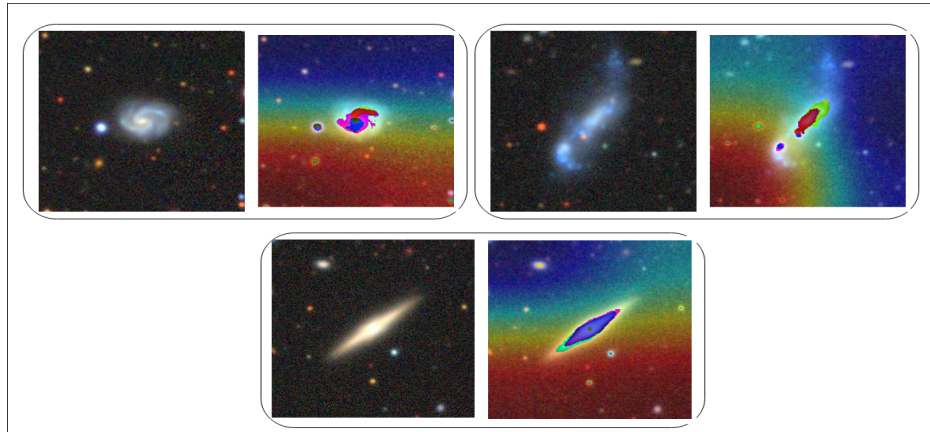


Fig. 4. Depicts the Grad-CAM for some of the classes

6. Conclusion

This research aimed to develop a deep learning model based on ensemble learning, and to compare the proposed model with the baseline and other models from the literature for the task of Galaxy morphology classification. We utilized DenseNet-121, ResNet-50 and EfficientNetV2S to create the ensemble. Furthermore, we used class balancing and data augmentation to address the imbalance in the dataset. All the models performed excellently, but the overall performance of Ensemble is better than others, achieving overall accuracy of 89%. For future work, we will explore attention-based convolutional neural networks (CNNs) as a potential approach to further improve classification performance. Attention mechanisms have the capability to highlight relevant features and patterns within the data, which can enhance the model's accuracy. By incorporating attention mechanisms into the model, we anticipate that the model's ability to identify differences in galaxy morphology could be greatly improved, leading to even higher accuracy rates and more robust classification results. This direction holds promise for advancing the state-of-the-art in galaxy morphology classification, pushing the boundaries of what is currently achievable with deep learning models.

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