Galaxy Morphology Classification with Deep Neural Networks

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Abstract. *The large-scale analysis of astronomical data requires automated and reliable methods for interpreting visual information. In this work, we propose a deep learning-based approach for galaxy morphological classification using Convolutional Neural Networks (CNNs). Two architectures are evaluated: AlexNet and ResNet152. The models are trained and tested on a balanced subset of the Galaxy Zoo 2 dataset, considering nine morphological classes. Data augmentation and class balancing techniques are employed to address dataset limitations. Experimental results show that ResNet152 significantly outperforms AlexNet, achieving an accuracy of 91.96% against 76.48%. The results demonstrate the effectiveness of deep CNNs in extracting complex visual patterns from astronomical images, even under constrained datasets.*

1. Introduction

Galaxies are fundamental components of the universe, and their morphology provides essential insights into cosmic formation and evolution processes. The shape and structure of galaxies are closely related to physical properties such as star formation, dynamics, and interactions [Cao et al. 2024, He et al. 2023]. Since the classical classification proposed by Hubble [Hubble 1926], galaxies have been categorized into types such as elliptical, spiral, and irregular, with further refinements capturing more detailed structural features [Reza 2021].

With the rapid growth of astronomical data from large-scale surveys such as the Sloan Digital Sky Survey (SDSS), the number of observed galaxies has increased dramatically, reaching billions of objects [Conselice et al. 2016]. This rapid data expansion makes manual classification infeasible, even with the support of citizen science initiatives such as Galaxy Zoo[1]. As a result, automated methods have become important allied for processing and analyzing this vast scenario of astronomical images [Rafsanjani et al. 2019].

In this context, deep learning techniques, particularly Convolutional Neural Networks (CNNs), have shown great potential for image-based classification tasks. CNNs are capable of automatically learning hierarchical features from raw data, enabling robust and scalable analysis of complex visual patterns [Chen et al. 2021, LeCun et al. 1998]. In astronomy, these models have achieved good performance in galaxy classification [Cao et al. 2024, Sadasivam et al. 2024].

[1]https://www.zooniverse.org/projects/zookeeper/galaxy-zoo

Despite these advances, important challenges remain. Many studies focus on a limited number of classes, simplifying the classification problem, while real-world galaxy morphology involves a broader range of categories with subtle visual differences. Additionally, issues such as class imbalance and ambiguity in certain morphologies, especially irregular and merging galaxies, continue to affect model performance.

To address these challenges, this work proposes a deep learning-based approach for galaxy morphology classification using two CNNs architectures: AlexNet and ResNet152. The models are evaluated on a balanced subset of the Galaxy Zoo 2 dataset[2], considering nine morphological classes and incorporating data augmentation techniques to improve generalization. The main contributions of this work are: (i) a comparative evaluation of CNN architectures for galaxy classification; (ii) the use of a balanced dataset with nine morphological classes; and (iii) A detailed analysis of classification performance across different galaxy types.

2. Background and Related Work

2.1. Galaxy Morphology Classification

Galaxy morphology plays a central role in understanding the formation and evolutionary history of the universe. Since the pioneering work of Hubble [Hubble 1926], galaxies have been broadly categorized into elliptical, spiral, and irregular types, with further subdivisions capturing refined structural details such as bars, rings, and edge-on perspectives. These morphological distinctions are linked to physical properties such as stellar population, star formation rate, and dynamical processes [Cao et al. 2024, He et al. 2023].

Traditionally, galaxy classification has relied on visual inspection by experts, a process that is inherently subjective and difficult to scale. With the advent of large-scale sky surveys, such as the Sloan Digital Sky Survey (SDSS), the volume of available astronomical images has grown exponentially, making manual classification impractical [Rafsanjani et al. 2019]. Citizen science initiatives, such as Galaxy Zoo, have attempted to mitigate this issue by leveraging human volunteers, but even these approaches face scalability and consistency challenges.

Moreover, certain galaxy classes, such as irregular or merging systems, present significant ambiguity due to their lack of well-defined structures. As noted by [Reza 2021], these complexities require more sophisticated approaches capable of capturing subtle visual patterns. Consequently, there has been a growing interest in automated classification systems based on machine learning and deep learning, which can process large volumes of data, while maintaining high accuracy.

2.2. Deep Learning in Astronomy

The application of artificial intelligence, particularly deep learning, has transformed the field of astronomical image analysis. CNNs, originally introduced by [LeCun et al. 1998], are especially well-suited for visual data due to their ability to learn hierarchical feature representations directly from raw images.

In astronomy, CNNs have been successfully applied to tasks such as galaxy classification, anomaly detection, and object segmentation [de Almeida and Teixeira 2024].

[2] https://data.galaxyzoo.org/\#section-7

Their ability to automatically extract complex features, such as edges, textures, and spatial patterns, makes them particularly effective for distinguishing between different galaxy morphologies.

Several studies have demonstrated the effectiveness of deep learning models in this domain. For instance, [Sadasivam et al. 2024] employed a ResNet50V2-based classifier to distinguish between astronomical objects, achieving accuracies above 90%. Similarly, [Misra et al. 2020] combined CNNs with traditional classifiers such as SVM and Naive Bayes, reaching accuracies of 97.39% for galaxy classification into three major categories (i.e., elliptical, spiral, and irregular).

More recent approaches have explored hybrid and advanced architectures. The use of Vision Transformers combined with convolutional layers, as proposed by [Cao et al. 2024], has shown promising results, achieving accuracy levels exceeding 98% in five-class classification tasks. Additionally, multi-channel deep residual networks, such as the ResNet-Core model proposed by [He et al. 2023], incorporate multiple sources of information to improve classification performance, particularly in challenging and imbalanced datasets.

Despite these advances, the performance of deep learning models is highly dependent on factors such as dataset quality, class balance, and architectural design. This reinforces the importance of carefully designed experimental setups when comparing different models.

2.3. Related Work

A wide range of machine learning approaches has been explored for galaxy morphology classification. Early methods relied on handcrafted feature extraction combined with traditional classifiers. For example, [Rafsanjani et al. 2019] proposed a multi-stage approach involving preprocessing, extraction of hundreds of visual features, and classification using a multilayer perceptron. Their study considered five classes (disk, spiral, elliptical, round, and other), achieving an accuracy of 67.10%, highlighting both the feasibility and limitations of manual feature engineering.

More recent works have shifted toward automated feature extraction using deep learning. [Reza 2021] applied Artificial Neural Networks (ANN) and ExtraTrees (ET) to SDSS data, achieving 98.40% accuracy. However, their approach is limited to a binary classification problem (star vs. galaxy), which simplifies the task compared to multi-class morphological classification.

Deep convolutional architectures have further improved performance. [Sadasivam et al. 2024] utilized a ResNet-based classifier trained on Galaxy Zoo 2 data, achieving 93.20% accuracy in a three-class problem (smooth, featured/spiral, and artifact). Similarly, [Dere et al. 2021] explored the use of InceptionV3 and Fast R-CNN for classification and anomaly detection, focusing on three morphological classes (elliptical, spiral, and irregular), reaching an accuracy of 90.12%.

In addition to CNN-based approaches, hybrid and optimization-based methods have also been investigated. [Şenel 2023] combined CNNs with metaheuristic optimization (Grey Wolf Optimizer), addressing a more complex scenario with ten classes (including disk variations, smooth shapes, spiral structures, disturbed, and merging galax-

ies), achieving 85.21% accuracy. Further, [Cao et al. 2024] introduced a Convolutional Vision Transformer (CvT), combining CNN feature extraction with transformer-based attention mechanisms, achieving 95.73% accuracy in a five-class problem (elliptical, spiral, edge-on, cigar-shaped, and dissimilar galaxies).

Despite these advances, many existing works focus on a limited number of classes (typically 2–5) or rely on highly specialized datasets. Furthermore, class imbalance and visual ambiguity remain persistent challenges, particularly for categories such as irregular and merging galaxies. Table 1 summarize the number of classes and accuracy achieved by the related work.

In contrast, this work aims to provide a more comprehensive evaluation by: (i) addressing a broader classification problem with nine morphological classes; (ii) comparing architectures with significantly different depths and representational capacities (AlexNet vs. ResNet152); (iii) incorporating explicit dataset balancing and data augmentation strategies; and (iv) providing a detailed class-level and error analysis to better understand model limitations.

Table 1. Comparison of related works in galaxy classification.

Work	Classes	Accuracy (%)
[Rafsanjani et al. 2019]	Disk, Spiral, Elliptical, Round, Other	67.10
[Reza 2021]	Star, Galaxy	98.40
[Sadasivam et al. 2024]	Smooth, Featured/Spiral, Artifact	93.20
[Dere et al. 2021]	Elliptical, Spiral, Irregular	90.12
[Şenel 2023]	Disk (Face-on/Edge-on), Smooth, Bulge, Spiral, Disturbed, Merging	85.21
[Cao et al. 2024]	Elliptical, Spiral, Edge-on, Cigar-shaped, Dissimilar	95.73

3. Deep-Learning Galaxy Morphology Classifier

The objective of this work is to automatically classify galaxy images into nine morphological categories: elliptical, spiral, spiral with bar, spiral with ring, edge-on, lenticular, irregular, merger, and disturbed. This task is particularly challenging due to the visual similarity between certain classes and the intrinsic variability of galaxy structures [Kalvankar et al. 2020].

To address this problem, two CNN architectures with distinct characteristics were evaluated: AlexNet, representing a shallower and computationally efficient model, and ResNet152, a deep architecture designed to capture complex visual patterns through residual learning [He et al. 2016]. Both models were trained and tested under the same experimental conditions to ensure a fair comparison. Figure 1 provides an overview of the methodological pipeline.

3.1. Dataset

The dataset used in this work is Galaxy Zoo 2, a large-scale collection of galaxy images obtained from the Sloan Digital Sky Survey (SDSS). The dataset contains more than 300,000 images labeled through a crowdsourcing approach [Reza 2021, Cao et al. 2024].

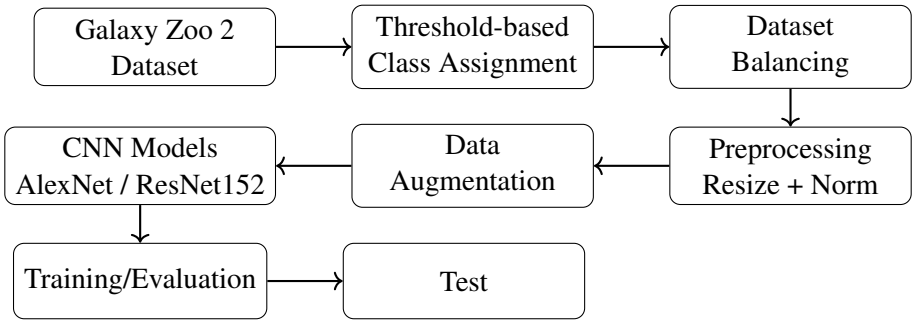


Figure 1. Compact and sequential methodology pipeline.

Each galaxy in the Galaxy Zoo 2 dataset is associated with probabilistic labels derived from the aggregated responses of multiple volunteers. Instead of assigning a single deterministic label, the dataset encodes the degree of agreement among participants regarding specific visual features, such as whether a galaxy is elliptical, spiral, contains a bar, or exhibits ring structures. These responses are converted into probabilities representing the fraction of volunteers that identified each characteristic.

Table 2. Criteria for Galaxy Classification.

Class	Type	Criteria	Threshold
0	Elliptical	$f_{elliptical}$	≥ 0.70
1	Spiral Bar	f_{spiral}, f_{bar}	$\geq 0.70, \geq 0.50$
2	Spiral	f_{spiral}	≥ 0.70
3	Spiral Ring	f_{spiral}, f_{ring}	$\geq 0.70, \geq 0.40$
4	Edge-on	f_{edgeon}	≥ 0.70
5	Lenticular	f_{lens}	≥ 0.50
6	Irregular	$f_{irregular}$	≥ 0.50
7	Merger	f_{merger}	≥ 0.50
8	Disturbed	$f_{disturbed}$	≥ 0.40

Based on these probabilities, threshold-based criteria are applied to assign each image to one of the nine morphological classes. Specifically, a galaxy is included in a given class only if the corresponding feature probabilities exceed predefined thresholds, typically ranging from 60% to 70%, depending on the morphological attribute. For example, a galaxy is classified as elliptical (class 0) if the probability associated with elliptical morphology is greater than or equal to the defined threshold. Similarly, spiral galaxies with bars (class 1) require high confidence in both spiral structure and the presence of a central bar.

This thresholding strategy ensures that only galaxies with sufficiently strong consensus are included in each category, reducing label noise and improving dataset reliability. Galaxies that do not meet any of the specified criteria are excluded from the classification process, further contributing to the quality of the training data. This approach enables the efficient organization of large-scale datasets using objective criteria derived from collective human annotations. To provide a visual understanding of the diversity of these morphological categories, Figure 2 presents representative examples of each of the nine classes considered in this work.

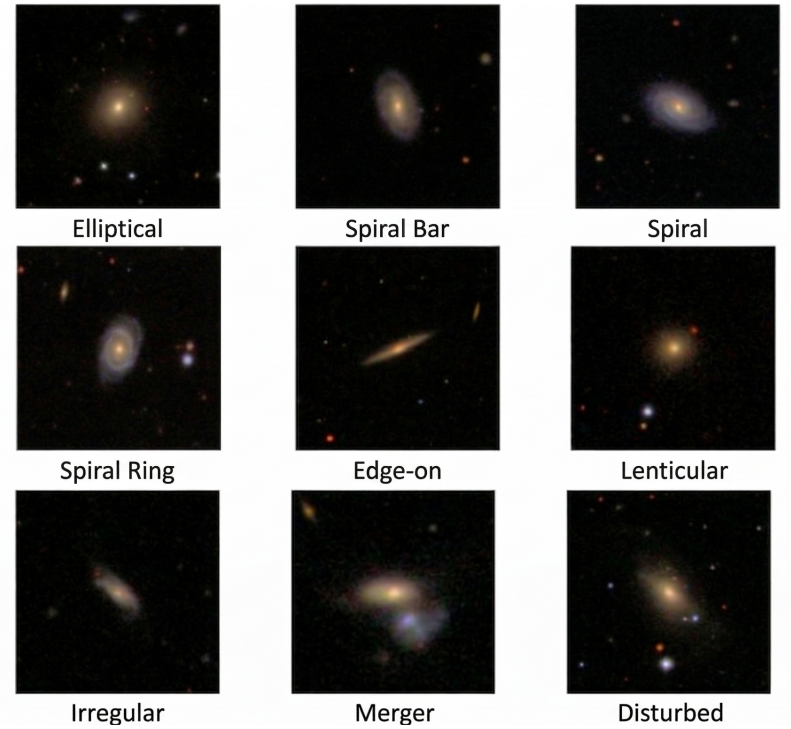


Figure 2. Morphologic Classes

The original dataset presents a highly imbalanced distribution across classes, with elliptical galaxies dominating the samples. This imbalance can bias the learning process, leading the model to favor majority classes [Buda et al. 2018]. To mitigate this issue, a balanced subset was constructed: 1000 images per class for training; and 300 images per class for testing. For classes with fewer samples, oversampling combined with data augmentation was applied. For classes with excess samples, random undersampling was performed. This strategy ensures equal representation of all classes during training.

Table 3. Dataset distribution by morphological class.

Class	Galaxy Type	Samples	Proportion (%)
0	Elliptical	86423	33.0
1	Spiral Bar	39239	15.0
2	Spiral	37864	14.5
3	Spiral Ring	24193	9.2
4	Edge-on	16126	6.2
5	Lenticular	867	0.3
6	Irregular	3600	1.4
7	Merger	1102	0.4
8	Disturbed	4409	1.7
Total		261695	100.0

The distribution of the original dataset is presented in Table 3. It can be observed that the majority of galaxies belong to the elliptical class (class 0), accounting for 33% of the total samples. This is followed by spiral galaxies with bar (class 1) and spiral galaxies without bar (class 2), representing 15.0% and 14.5% of the dataset, respectively. In contrast, the remaining classes, such as spiral with ring, edge-on, and disturbed galax-

ies, appear with significantly lower frequencies. Some categories, including lenticular, merger, and irregular galaxies, are particularly underrepresented, comprising less than 2% of the dataset each.

This distribution highlights a natural class imbalance, which is a common characteristic of astronomical datasets. Such imbalance can negatively impact the performance of machine learning models, as they tend to bias predictions toward the majority classes, potentially reducing the ability to correctly identify rare or complex morphologies. Therefore, addressing this imbalance is an important step to ensure robust and generalizable classification models.

All images were resized to 224×224 pixels to match the input requirements of both CNNs architectures used. Pixel normalization was applied using ImageNet statistics, ensuring compatibility with pre-trained weights. To improve generalization and reduce overfitting, data augmentation techniques were applied during training [Kumar et al. 2024, Amarù et al. 2023], including random rotations (up to 30°); horizontal flipping; brightness and contrast adjustments; and random cropping. These transformations simulate variations in galaxy orientation and imaging conditions, increasing the robustness of the models.

3.2. Model Architectures and Training

Two CNN architectures were evaluated: (i) **AlexNet**: A classical CNN composed of five convolutional layers followed by three fully connected layers [Krizhevsky et al. 2017]. Its relatively simple structure makes it suitable as a baseline model; and (ii) **ResNet152**: A deep residual network with 152 layers that employs skip connections to mitigate the vanishing gradient problem [He et al. 2016]. This architecture enables the extraction of more complex and abstract features. Both models were initialized with ImageNet pretrained weights and adapted to the classification task by replacing the final fully connected layer with a 9-class output layer.

The training process was conducted under identical conditions for both models, using: Optimizer AdamW; Learning rate of 1×10^{-4}; Weight decay of 0.01; Loss function CrossEntropy with label smoothing; Learning rate scheduler using ReduceLROnPlateau; Early stopping by patience of 5 epochs. Fine-tuning was applied to all layers, allowing the networks to adapt fully to the galaxy classification task.

4. Evaluation and Results

To assess the performance of the models, standard classification metrics were employed: (i) **accuracy** measures the proportion of correctly classified instances over the total number of samples. It provides a general overview of model performance; (ii) **precision** evaluates the proportion of correctly predicted samples within a given class, indicating how reliable the predictions are; (iii) **recall** (or sensitivity) measures the proportion of actual samples correctly identified by the model, reflecting its ability to detect each class; and (iv) **loss** represents the error between predicted and true labels during training, guiding the optimization process.

These metrics were monitored at each epoch to analyze both convergence behavior and generalization capability [Brownlee 2018, Chollet 2017, Goodfellow et al. 2016].

Figure 3 (left) shows the evolution of accuracy during training of the **AlexNet** architecture. Both training and validation curves exhibit a similar increase, indicating that the model successfully learned relevant features without significant overfitting. The loss curve, presented in Figure 3 (center), shows a consistent decrease over epochs, reinforcing the stability of the learning process.

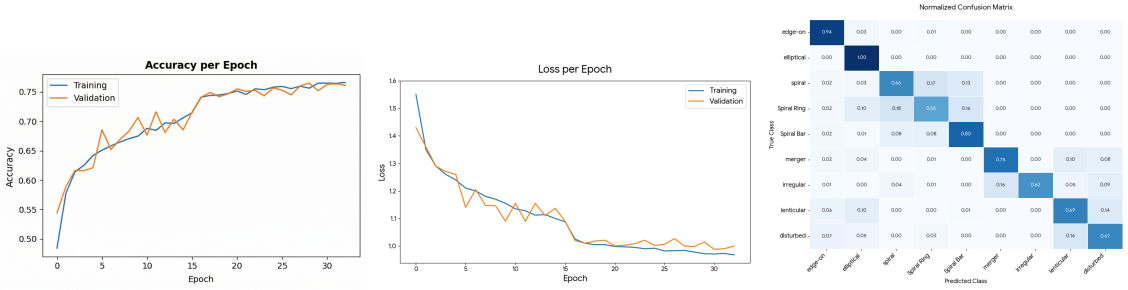


Figure 3. Accuracy and Loss curves, and Confusion matrix for AlexNet.

The **ResNet152** model demonstrates a more significant improvement during training. As shown in Figure 4 (left), the accuracy rapidly increases and stabilizes at a higher level compared to AlexNet. Similarly, the loss curve in Figure 4 (center) shows faster convergence and lower final error values, indicating more efficient learning. The proximity between training and validation curves in both accuracy and loss suggests that overfitting was controlled.

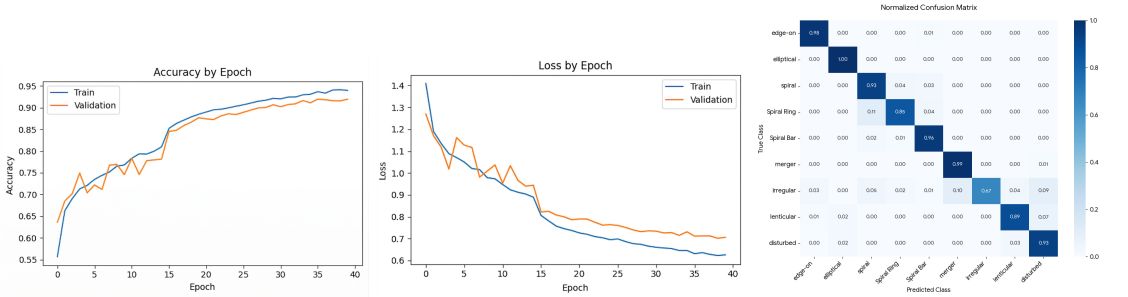


Figure 4. Accuracy and Loss curves, and Confusion Matrix for ResNet152.

The overall accuracy achieved by AlexNet was 76.48%, while the accuracy achieved by ResNet152 was 91.96%. The results show a significant improvement when using ResNet152, highlighting the impact of deeper architectures in capturing complex morphological patterns.

A detailed analysis of classification accuracy per class reveals important differences between galaxy types. For AlexNet, high accuracy was observed in well-defined classes such as elliptical (100%) and edge-on (96.67%). However, the performance dropped in more complex categories such as spiral ring (58.33%) and irregular (65.67%). ResNet152 improved performance across nearly all classes, particularly in spiral-related categories. For example, spiral galaxies reached 92.00% accuracy, and spiral with bar achieved 95.00%. The most challenging class remained irregular galaxies, with 68.67% accuracy. These results indicate that deeper networks are better suited for distinguishing subtle structural differences.

The confusion matrices provide further insight into model behavior. The AlexNet confusion matrix in Figure 3 (right) shows significant misclassification among spiral sub-

Table 4. Per-class Precision, Recall, and F1-score for the AlexNet model.

Class	Precision	Recall	F1-score
Edge-on	0.81	0.94	0.87
Elliptical	0.74	1.00	0.85
Spiral	0.68	0.66	0.67
Spiral Ring	0.58	0.55	0.56
Spiral Bar	0.73	0.80	0.76
Merger	0.82	0.75	0.78
Irregular	1.00	0.62	0.77
Lenticular	0.65	0.69	0.67
Disturbed	0.61	0.67	0.64
Macro Avg	**0.74**	**0.74**	**0.73**

classes (spiral, ring, and bar). Additionally, irregular and disturbed galaxies are often confused with spiral classes, reflecting the difficulty of capturing subtle differences. As shown in Table 4, high recall is achieved for classes with well-defined structures, such as elliptical (1.00) and edge-on (0.94) galaxies. However, their precision values are considerably lower, indicating that these classes attract a significant number of false positives from other categories.

Spiral-related classes exhibit the most significant performance degradation. In particular, spiral and spiral ring categories show both low precision and recall, with F1-scores below 0.70. This behavior reflects strong confusion between subclasses, as also observed in the confusion matrix, where spiral galaxies are frequently misclassified as spiral ring or spiral bar variants.

The irregular class again presents a characteristic imbalance between precision and recall. While precision remains very high (1.00), recall drops to 0.62, indicating that the model is conservative when predicting this class and fails to identify many true irregular galaxies. This suggests that AlexNet struggles to generalize patterns for visually ambiguous morphologies.

Overall, the macro-average F1-score of 0.73 highlights the limitations of AlexNet in capturing fine-grained morphological differences. The results confirm that shallower architectures have reduced capacity to distinguish subtle structural variations, leading to increased confusion among similar classes.

The ResNet152 confusion matrix in Figure 4 (right) demonstrates a clear improvement. As shown in Table 5, the model achieves high performance for well-defined morphological classes such as elliptical, edge-on, and merger galaxies, all presenting F1-scores above 0.95. These results indicate that the model is highly effective in identifying galaxy types with clear and distinctive structural patterns.

In contrast, spiral-related classes exhibit slightly lower precision values, particularly for the generic spiral category. This behavior is mainly due to confusion between visually similar subclasses, such as spiral, spiral with ring, and spiral with bar. Although recall remains high for these classes, the reduced precision indicates that misclassifications occur among them, reflecting the subtle differences in their morphological features.

Table 5. Per-class Precision, Recall, and F1-score for the ResNet152 model.

Class	Precision	Recall	F1-score
Edge-on	0.96	0.98	0.97
Elliptical	0.96	1.00	0.98
Spiral	0.84	0.93	0.88
Spiral Ring	0.92	0.85	0.88
Spiral Bar	0.92	0.96	0.94
Merger	0.91	0.99	0.95
Irregular	1.00	0.67	0.80
Lenticular	0.93	0.89	0.91
Disturbed	0.85	0.93	0.89
Macro Avg	**0.92**	**0.91**	**0.91**

The irregular class presents a distinct pattern, with perfect precision but relevant lower recall. This indicates that predictions labeled as irregular are highly reliable; however, a substantial number of true irregular galaxies are incorrectly classified into other categories. This behavior highlights the intrinsic difficulty of modeling irregular morphologies, which lack well-defined visual structures.

Overall, the results show that classification errors are concentrated among morphologically similar classes, while well-structured galaxies are consistently identified with high confidence. These findings reinforce the importance of deeper architectures, such as ResNet152, in capturing fine-grained visual distinctions in astronomical images.

In general, the experimental results demonstrate that model depth plays a critical role in galaxy morphology classification. While AlexNet provides a reasonable baseline, its limited depth restricts its ability to distinguish complex patterns. ResNet152, with its residual connections and increased representational capacity, significantly improves both overall accuracy and class-level performance. The results also highlight that certain classes, particularly irregular galaxies, remain difficult due to their inherent variability and lack of well-defined structure. Overall, our findings confirm that deep convolutional architectures are effective for automated analysis of astronomical images, especially when combined with balanced datasets and appropriate preprocessing strategies.

5. Conclusion

This work presented a deep learning-based approach for galaxy morphology classification, evaluating the performance of two convolutional neural network architectures: AlexNet and ResNet152. The models were trained and tested on a balanced subset of the Galaxy Zoo 2 dataset, considering nine distinct morphological classes and incorporating data augmentation techniques to improve generalization.

The experimental results demonstrated the benefits of deeper architectures. While AlexNet achieved a reasonable baseline accuracy of 76.48%, the ResNet152 model significantly outperformed it, reaching 91.96% accuracy. This improvement highlights the importance of network depth and residual learning in capturing complex and subtle visual patterns present in astronomical images.

A detailed analysis of class-level performance revealed that well-defined mor-

phologies, such as elliptical and edge-on galaxies, are consistently easier to classify, which is also evidenced in the discussed literature. In contrast, irregular and morphologically ambiguous classes remain challenging, even for deeper models. The confusion matrix analysis further showed that most classification errors occur between visually similar categories, particularly among spiral subclasses.

These findings confirm that CNNs are effective tools for large-scale automated analysis of galaxy images, especially when combined with balanced datasets and appropriate preprocessing strategies. However, they also indicate that certain limitations persist, particularly in handling highly variable or poorly defined structures.

In future work, we intend to explore the use of more advanced architectures, such as vision transformers or hybrid models, as well as the integration of multi-modal data (e.g., spectral information) to improve classification performance. Additionally, alternative strategies for handling class ambiguity and improving robustness in underrepresented categories should be further investigated.

Overall, this study contributes to the advancement of automated methods in astronomy, demonstrating the potential of deep learning techniques to support the analysis of increasingly large and complex astronomical datasets.

References

Amarù, S., Marelli, D., Ciocca, G., and Schettini, R. (2023). Dalib: A curated repository of libraries for data augmentation in computer vision. *Journal of Imaging*, 9(10):232.

Brownlee, J. (2018). Metrics to evaluate machine learning algorithms in python. `https://machinelearningmastery.com/metrics-evaluate-machine-learning-algorithms-python/`. Acesso em: 5 jun. 2025.

Buda, M., Maki, A., and Mazurowski, M. A. (2018). A systematic study of the class imbalance problem in convolutional neural networks. *Neural Networks*, 106:249–259.

Cao, J., Xu, T., Deng, Y., Deng, L., Yang, M., Liu, Z., and Zhou, W. (2024). Galaxy morphology classification based on convolutional vision transformer (cvt). *Astronomy & Astrophysics*, 683:A42.

Chen, L., Li, S., Bai, Q., Yang, J., Jiang, S., and Miao, Y. (2021). Review of image classification algorithms based on convolutional neural networks. *Remote Sensing*, 13(22):4712.

Chollet, F. (2017). *Deep Learning with Python*. Manning Publications.

Conselice, C. J., Wilkinson, A., Duncan, K., and Mortlock, A. (2016). The evolution of galaxy number density at z¡ 8 and its implications. *The Astrophysical Journal*, 830(2):83.

de Almeida, T. A. and Teixeira, R. R. P. (2024). Explorando a fronteira entre inteligência artificial e astronomia na educação. *Informática na educação: teoria & prática*, 27(1).

Dere, S., Fatima, M., Jagtap, R., Inamdar, U., and Shardoor, N. B. (2021). Anomaly detection in astronomical objects of galaxies using deep learning. In *2021 7th International Conference on Advanced Computing and Communication Systems (ICACCS)*, volume 1, pages 702–706. IEEE.

Goodfellow, I., Bengio, Y., and Courville, A. (2016). *Deep Learning*. MIT Press.

He, K., Zhang, X., Ren, S., and Sun, J. (2016). Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 770–778.

He, Y., Zhang, Y., Chen, S., and Hu, Y. (2023). Classification of galaxy morphology based on multi-channel deep residual networks. In *2023 IEEE 6th Information Technology, Networking, Electronic and Automation Control Conference (ITNEC)*, volume 6, pages 1648–1653. IEEE.

Hubble, E. P. (1926). Extra-galactic nebulae. Astrophysical Journal, 64, 321–369.

Kalvankar, S., Pandit, H., and Parwate, P. (2020). Galaxy morphology classification using efficientnet architectures. *arXiv preprint arXiv:2008.13611*.

Krizhevsky, A., Sutskever, I., and Hinton, G. E. (2017). Imagenet classification with deep convolutional neural networks. *Communications of the ACM*, 60(6):84–90.

Kumar, T., Brennan, R., Mileo, A., and Bendechache, M. (2024). Image data augmentation approaches: A comprehensive survey and future directions. *IEEE Access*.

LeCun, Y., Bottou, L., Bengio, Y., and Haffner, P. (1998). Gradient-based learning applied to document recognition. *Proceedings of the IEEE*, 86(11):2278–2324.

Misra, D., Mohanty, S. N., Agarwal, M., and Gupta, S. K. (2020). Convoluted cosmos: classifying galaxy images using deep learning. In *Data Management, Analytics and Innovation: Proceedings of ICDMAI 2019, Volume 1*, pages 569–579. Springer.

Rafsanjani, M. K., Bagherinezhad, H., and Batth, R. S. (2019). The classification of galaxy images using neural network algorithm. In *2019 International Conference on Computing, Power and Communication Technologies (GUCON)*, pages 127–131. IEEE.

Reza, M. (2021). Galaxy morphology classification using automated machine learning. *Astronomy and Computing*, 37:100492.

Sadasivam, T., Serrao, R. T., Bansod, A. P., Singh, T., and Bharathi, R. (2024). Celestlearn ai: Astronomical image generator and classifier. In *2024 Asia Pacific Conference on Innovation in Technology (APCIT)*, pages 1–6. IEEE.

Şenel, F. A. (2023). A hyperparameter optimization for galaxy classification. *Computers, Materials & Continua*, 74(2).