Morphological Classification of Galaxies using Vision Transformer Models

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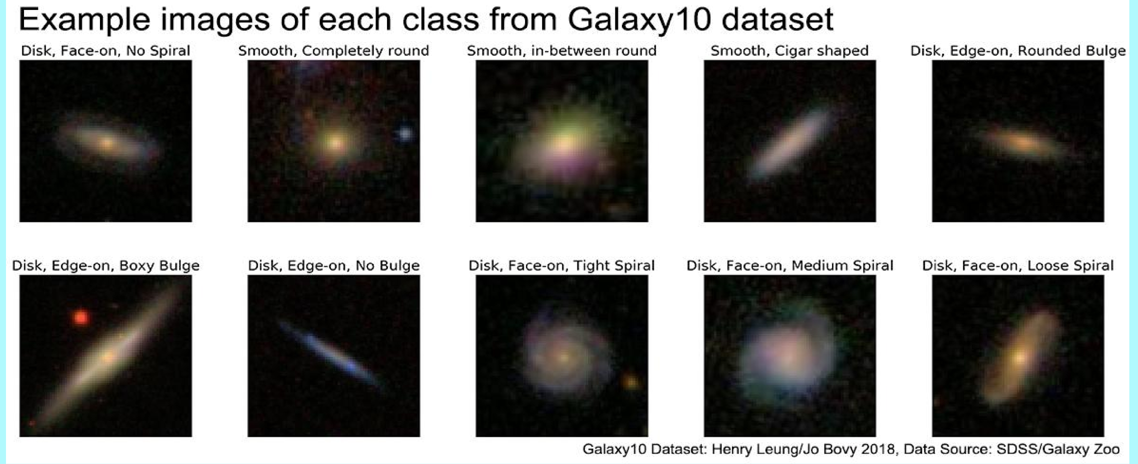
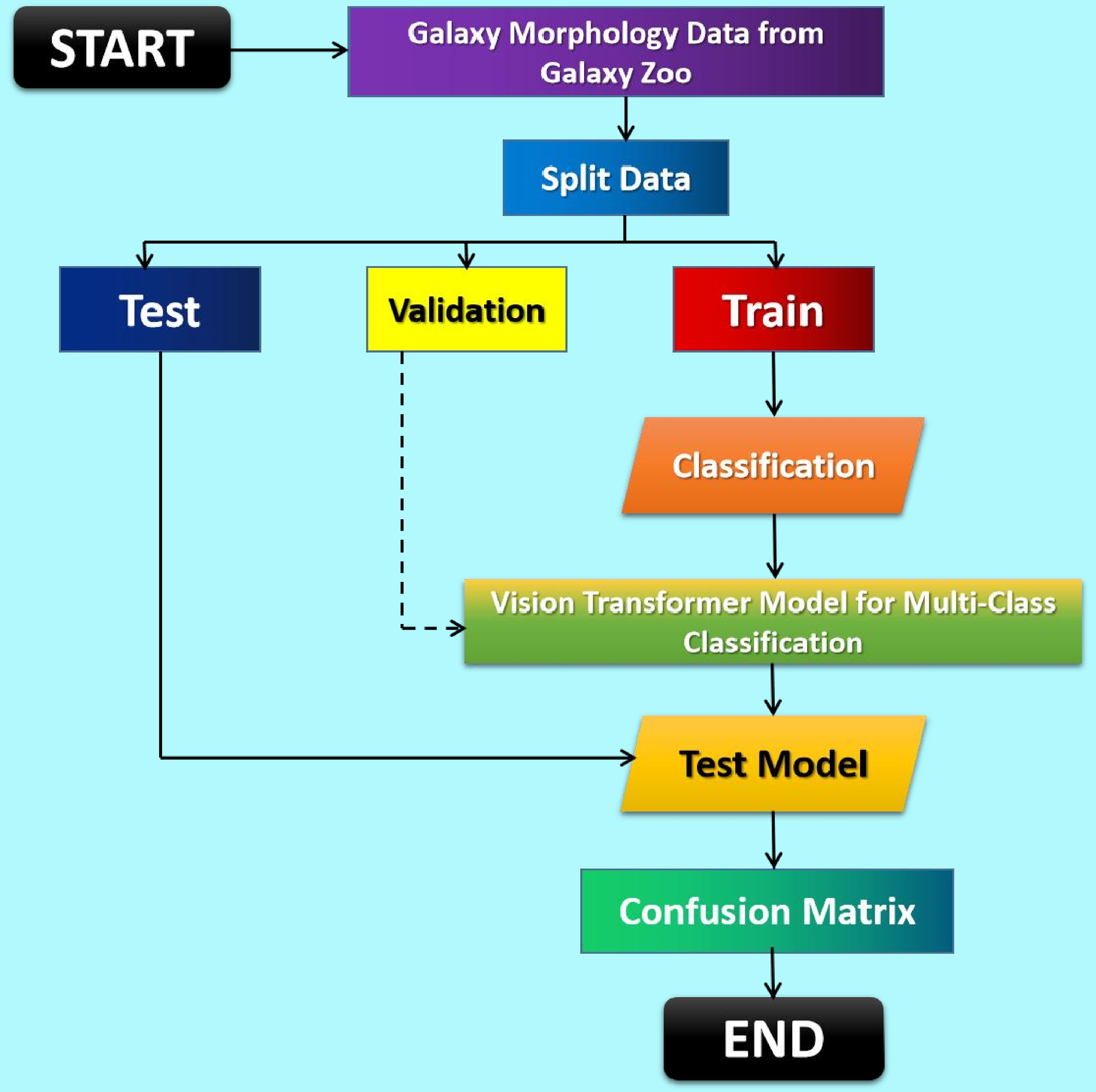
GALAXY MORPHOLOGY & DATASET

Morphology is a fundamental property of galaxies. They aid in understanding galaxies' structure, evolution, interaction, star formation, and environmental properties. What started as a simple three-class classification by Hubble in 1936 has transformed rapidly due to the copious amounts of data generated from numerous ongoing surveys and missions - thus calling for many and more extensive methods of classifying galaxies based on morphology.

Galaxy10 SDSS is a dataset containing 69x69 pixels colored galaxy images (g, r, and i band) separated into classes. These images are from Sloan Digital Sky Survey, and labels come from Galaxy Zoo, a Citizen Science project. In this endeavor, we use the highly efficient Vision Transformer Model (ViT) for Galaxy Morphology Classification with Galaxy10 SDSS images as our dataset.



METHODOLOGY



VISION TRANSFORMER & BINARY CLASSIFICATION

A Transformer in machine learning is a deep learning model that uses parallelizable attention mechanisms, differentially weighing the significance of each part of the input data. Vision Transformer (ViT) models are viable replacements for the generic CNN (Convolutional Neural Network) based Deep Learning, primarily due to their image classification capabilities. These capabilities arise due to their architecture, as discussed here.

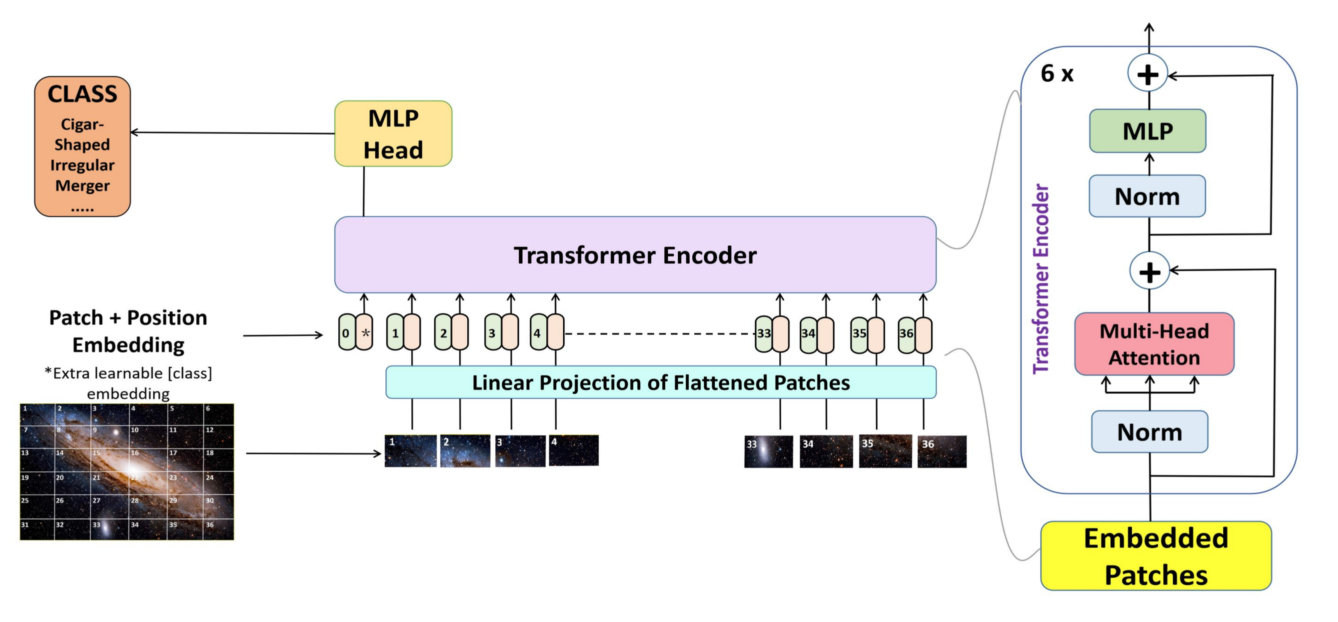
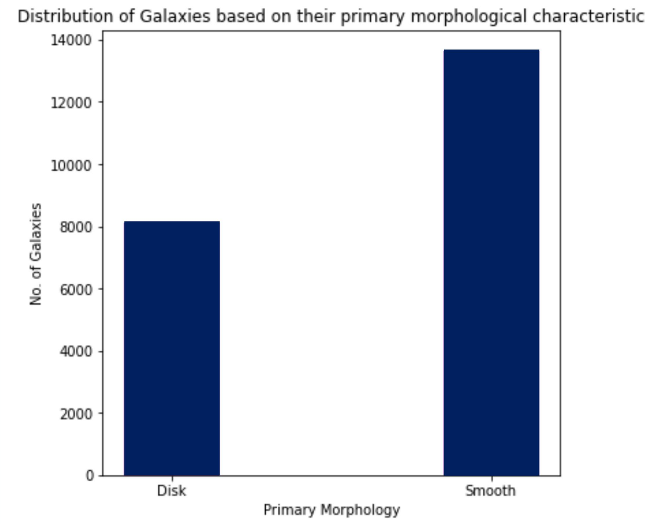
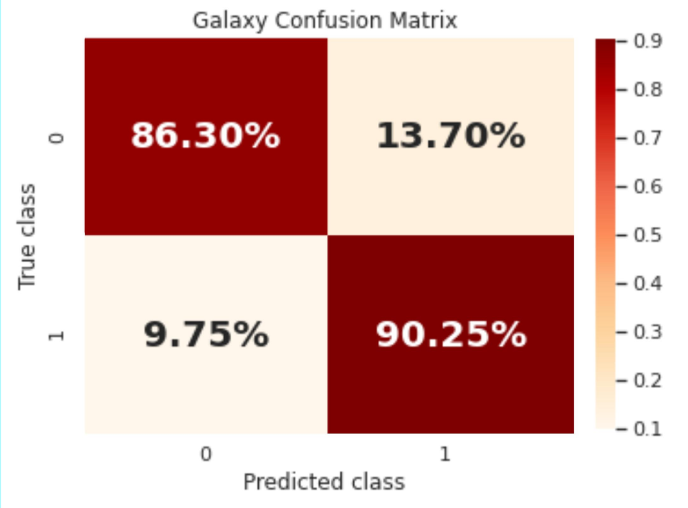


Fig : Vision Transformer Architecture. An overview adapted from the origin paper

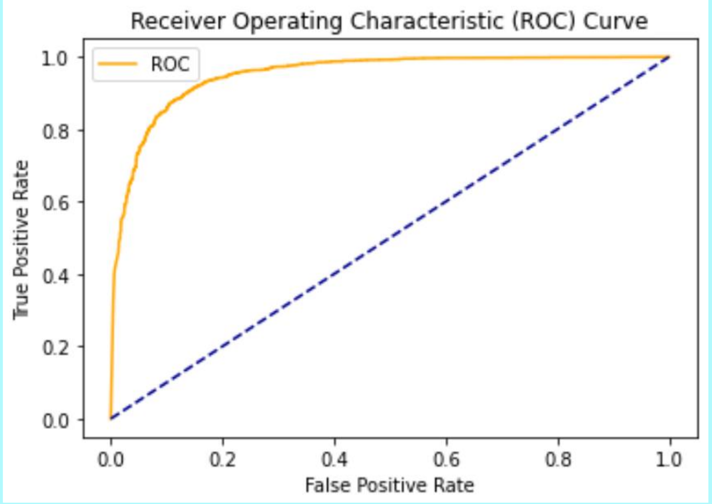
To begin with, we classify our Galaxy10 dataset into two image classes based on the galaxies' primary morphology - 'Disk' and 'Smooth' Shape. Out of a total of 21768 samples, there are 8130 Disk-shaped Galaxies and 13638 Smooth-shaped galaxies.

Upon training the model for 2000 epochs, a Confusion Matrix that visualizes and summarizes the predictive performance of the ViT Model is plotted. With the hyperparameters optimized over several iterations, it is noteworthy that the model predicts exceedingly well over its regular CNN counterparts, as evident by its diagonal elements.





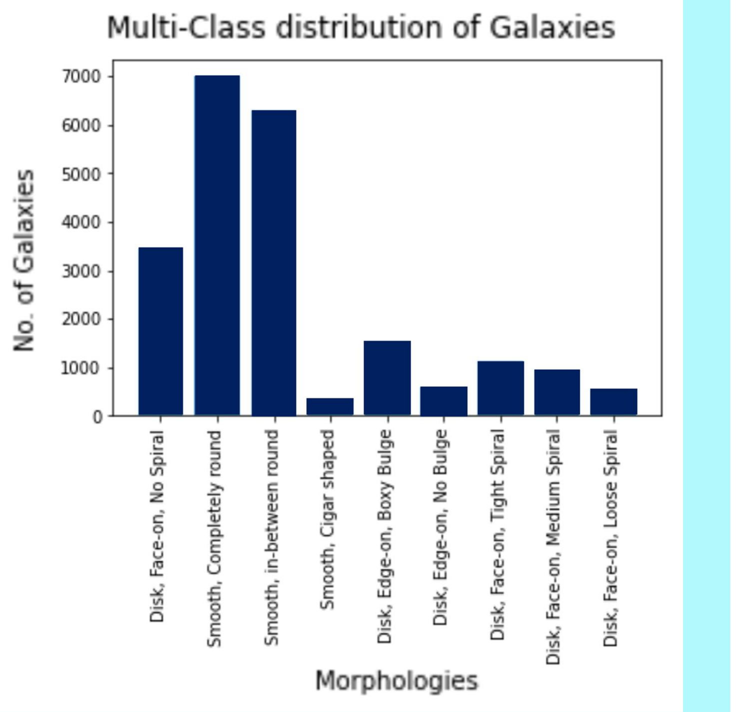
To gain an understanding, the confusion matrix below indicates that 86.30% of the Disk galaxy images and 90.25% of the Smooth galaxy images have been identified by the model correctly.

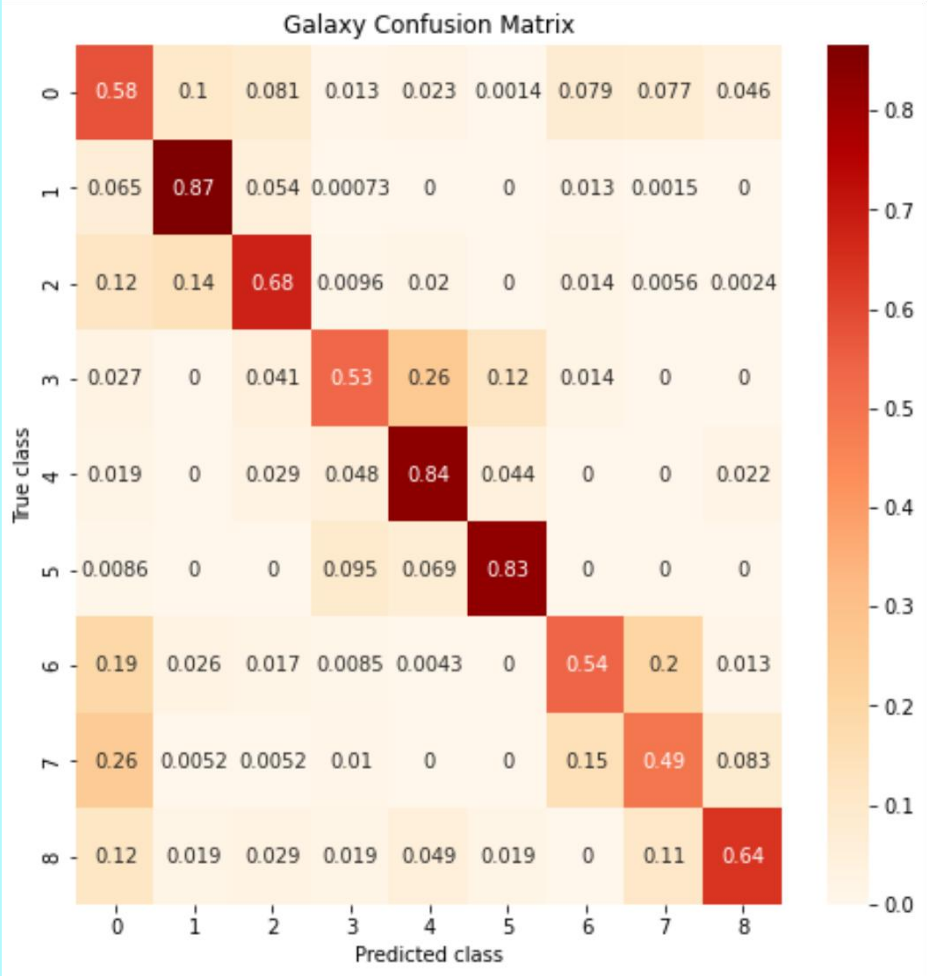


ROC AUC Curves aid immensely in understanding the performance of a binary classifier well beyond the accuracy metric. Here,we obtained a ROC AUC Score of 95.21% with a very good characteristic ROC Curve.

MULTI-CLASS CLASSIFICATION

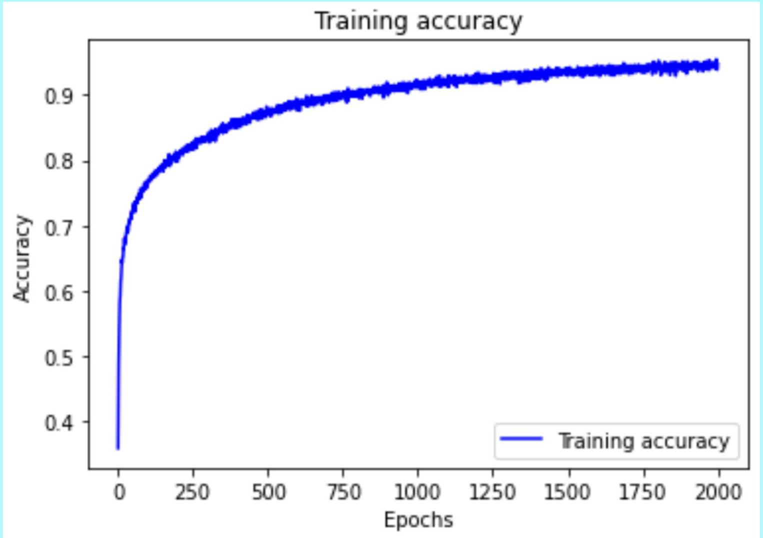
The main aim of this work is to classify our Galaxy10 dataset images into the nine classes they belong to. Each class is depicted as (a,b,c) with the grouping based on one broad category of 'Disk' or 'Smooth' as discussed before, and two other features like the bulge, compactness, eccentricity, etc. Among the 21768 samples used for training the ViT model, the distribution among each class is as in the histogram on the right. This labeling is obtained from Galaxy Zoo itself.





Upon training the model for 2000 epochs, the Confusion Matrix is obtained. The high level of accuracy provided by the model even in multi-class classification cases is evident, with the model identifying as high as 87% of the smooth and completely round galaxies samples. We can also infer from this trend that a higher number of class samples yields better and more accurate predictions.

Hence, it is observed that the model classifies the multi-class data at very high accuracy (99-99.5%) with the progression of epochs.



MODEL PARAMETERS AND METRICS

Hyperparameters are detrimental to a Deep-Learning model's learning process and are iterated until optimal values are achieved. The table below encapsulates the optimized values used in the training process.

OPTIMIZED HYPERPARAMETERS

Sl. No.	Hyperparameter	Optimized Value
1	Test-Train Split Ratio	0.2 : 0.8
2	Optimizer	Adam
3	Activation Function	GELU
4	Learning rate	0.0007
5	Image Size	32 X 32
6	Patch Size	4 X 4
7	Batch Size	32
8	Projection Dimension	64
9	Drop-Out Rate	0
10	MLP Head Units	[32, 32]
11	No. of Multi-Attention Heads	1
12	No. of Transformer Layers	6
13	No. of Epochs	2000
14	Drop-Out Rate	0

The 'efficiency' or success of a model is measured not just by accuracy but by other metrics as well. The ViT model classified the morphologies of galaxies with a high accuracy of 99.48%, among the other metrics listed in the table.

EVALUATION METRICS

Sl. No.	Evaluation Metric	Value
1	Accuracy	99.48%
2	Precision	0.89180
3	Recall	0.89090
4	F1 Score	0.89122
5	Mathews Correlation Coefficient (MCC)	0.76967
6	ROC AUC Score	0.95210

WAY AHEAD

As understood before,the Morphology of a galaxy is crucial to understanding the Universe's existence as it is today. The ViT model has performed extensively well on not just accuracy parameters but also in classifying small, faint galaxies as well. It shows a lot of potential in image recognition, something that is a crucial cornerstone in Astronomy. With JWST in action and other upcoming surveys like LSST & TMT, Deep Learning models like ViT will evolve into the norm. We hope to further this work into larger datasets, higher accuracy outcomes and least human intervention requirements.