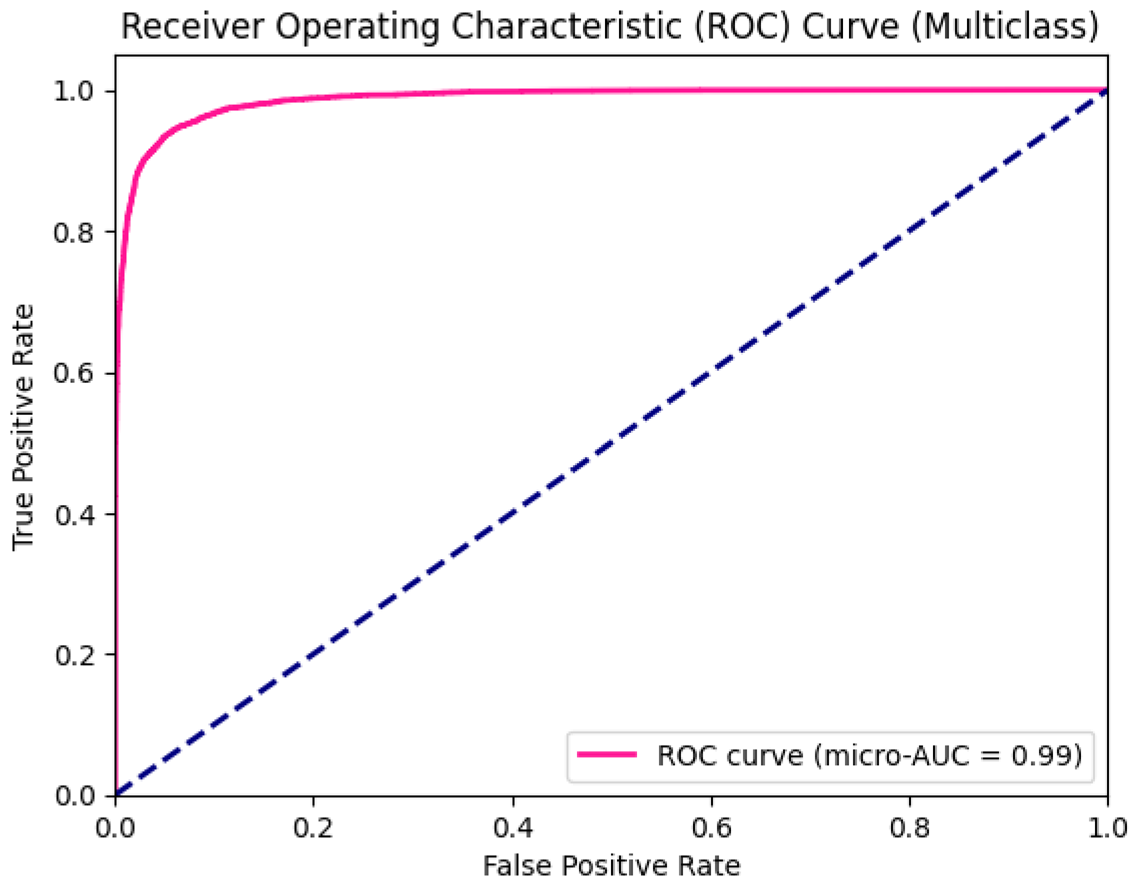
Common Test I. Multi-Class Classification

Task: Build a model for classifying the images into lenses using PyTorch or Keras. Pick the most appropriate approach and discuss your strategy.

Result(notebook):

Trained the ResNet-18 on the given dataset with a 5-fold cross-validation with each 5 epochs on 3*10k training images and used 3*2.5k for test

and reached the ROC-AUC score of 0.99 on test data.



I used ResNet-18 as it can capture more intricate patterns and features in the data, leading to better generalization and higher accuracy. And the model should not be much deep as it will overfit for grayscale images. The ability of ResNets to carry many useful features make ResNet-18 most appropriate choice. Also from various research papers ResNet-18 make the best results for lens classification.

Specific Test V. Physics-Guided ML

Task: Build a model for classifying the images into lenses using PyTorch or Keras. Your architecture should take the form of a physics-informed neural network (PINN). In this case, use the gravitational lensing equation in your architecture to improve network performance over your Common Test result.

Approach1(notebook):

For classifying gravitational lenses into three types (no lensing, vortex, and halo substructure) using a PINN, we primarily be interested in the lens equation, which describes how light is bent by the gravitational field of a massive object. The lens equation can be expressed as:

$$\beta = \theta - \alpha$$

Where:

- β is the apparent position of the source in the absence of lensing.
- θ is the observed position of the source.
- α is the deflection angle, which depends on the mass distribution of the lensing object.

Now, the mass distribution of the lensing object is due to galaxies and dark matter between the source and the observer.
φ_{galaxy} be the gravitational potential of the galaxy and
X be the mass distribution of dark matter.

Given that we don't know the profile of the galaxy, **we will assume a Singular Isothermal Sphere (SIS) model**, with a proportionality parameter **k** to correct potential distortions.

$$\Psi_{Galaxy}(x_i, y_i) \approx k \cdot \sqrt{x_i^2 + y_i^2}$$

Now, $\sqrt{x^2 + y^2}$ = r2

Therefore, $\beta = \theta - c.(\varphi_{galaxy} + X)$

$$\beta + c.X = \theta - (k.r2)$$

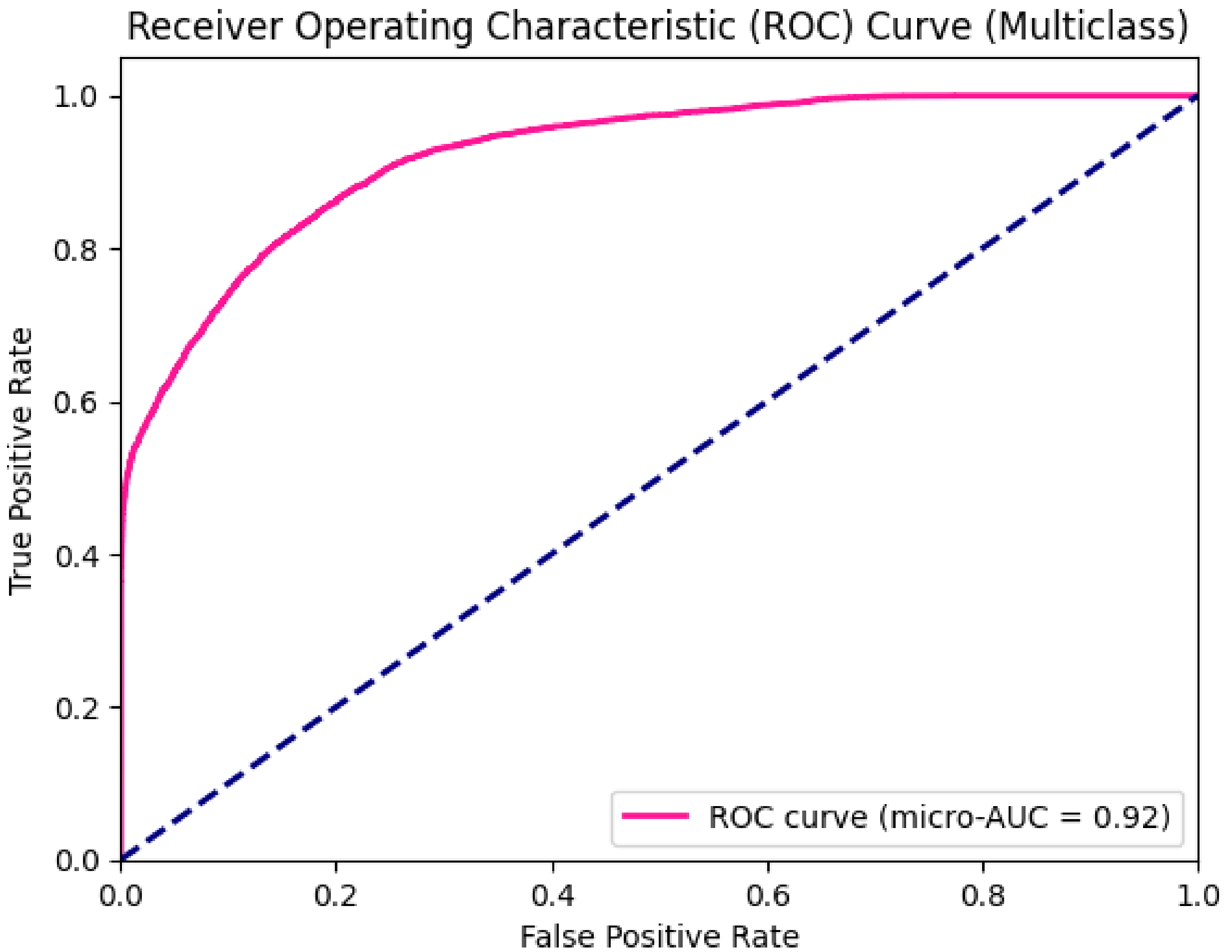
Now, we have β +c.X = C term which consist the information of dark matter distribution.

θ = A_features which is the feature vector from the ResNet-18.

K = B_features which is the feature vector from another ResNet-18.

So that, C = A_features - B_features*r2

Then I have applied three neural layers on C to extract features to classify lenses.



In this approach, I have trained this model using 5-fold cross-validation with each 5 epochs on 3*10k training images and used 3*2.5k for test and reached the ROC-AUC score of 0.92 on test data.

Approach2(notebook):

In the above derived equation,

$$C = \beta + c.X = \theta - (k.r2)$$

I have used original image vector(I) to represent θ.

And k = B_features (from ResNet-18)

$$\text{Therefore, } C = I - (B\_features * r2)$$

Computed another A_features from another ResNet-18 to represent some useful source features.

$$D = \text{concatenate}(A\_features, C)$$

Then, applied three neural layers on D to classify into lenses.