Deep-Learning Approach for Visual-Binary Source Detection in Stamp Images from Multiple Surveys

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Abstarct

We introduce a cutting-edge deep-learning methodology designed to detect visual-binary sources within stamp images downloaded from various astronomical surveys. Our primary objective is to develop a robust model that accurately identifies the presence or absence of visual-binary sources within 2.5 arcseconds. This includes the following stages; data preparation, model selection, training, evaluation, and deployment.

1. Data Preparation and Annotation

- We downloaded stamp images from 27,730 sources in our Orion catalog. All-sky surveys like 2MASS and WISE have images for every source, while partial-sky surveys like Spitzer cover only observed regions.

- We stacked images with identical name prefixes but different filter prefixes for each survey. For instance, in 2MASS, we stacked 'J', 'H', and 'K' filter images, and in PanSTARRS, 'g', 'i', 'r', 'y', and 'z' filters. If only one stamp image existed, we did not stack it.

- Fig. 1 shows stacked images for visual binary source 00022 from different surveys, revealing varied details. Fig. 2 shows stacked images for binary source 22466. High-resolution surveys like Hubble (HST) and James Webb (JWST) resolve two sources within a 2.5 arcsecond radius, unlike lower-resolution surveys.

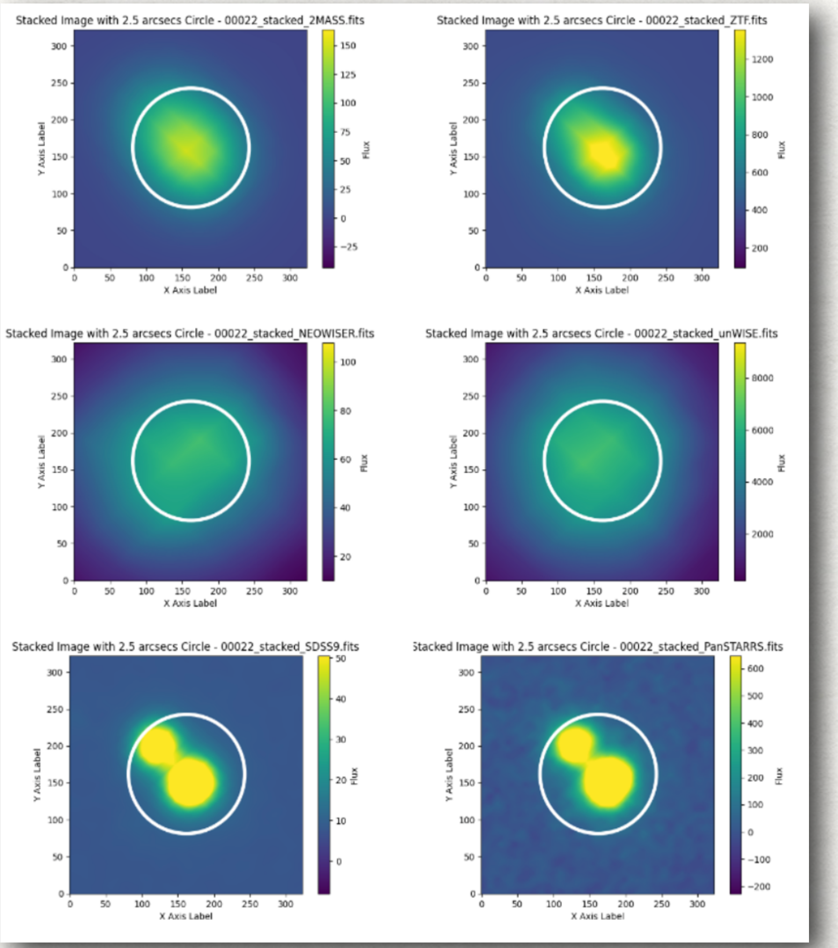

Fig. 1 Stacked images of 00222 from different surveys are displayed. From upper left to bottom right stacked images of 2MASS, ZTF, neoWISER, unWISE, SDSS9, and PanSTARRS, respectively.

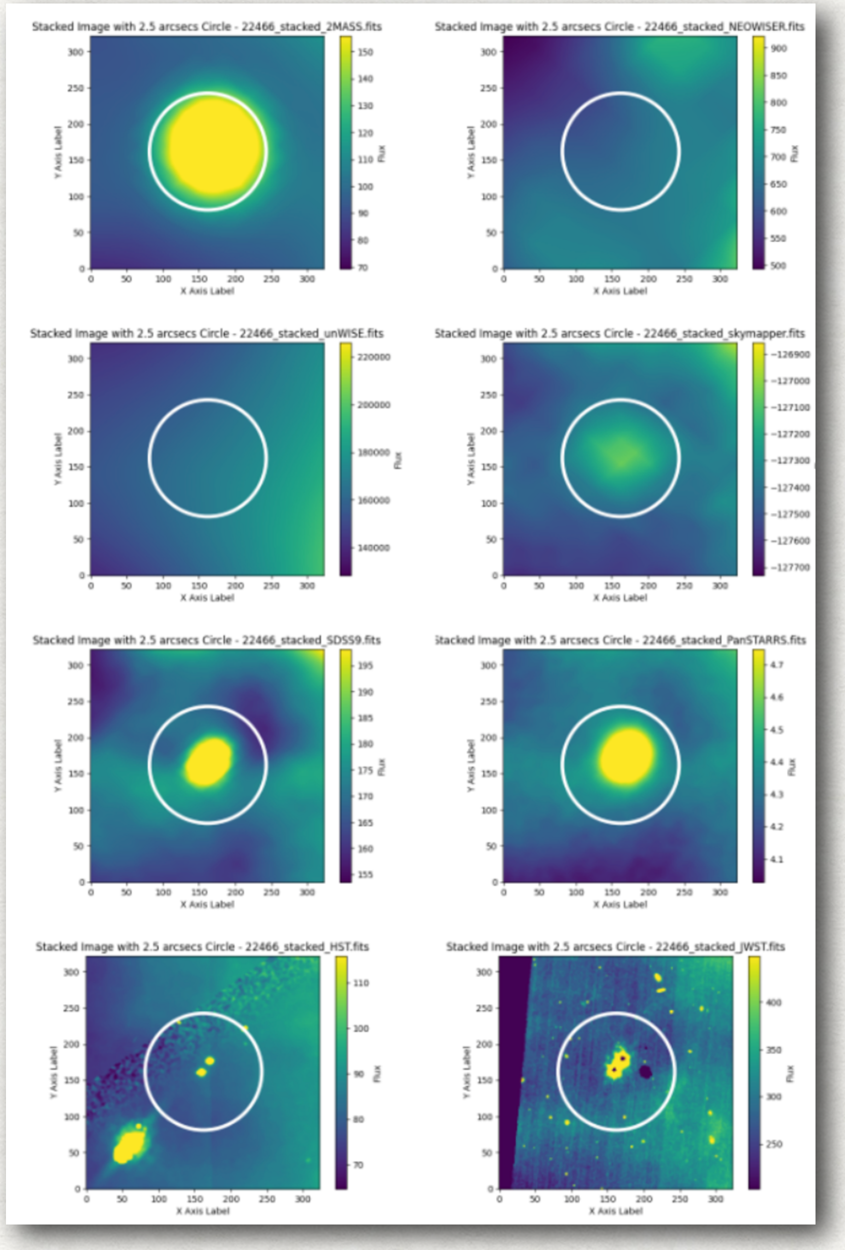

Fig. 2 Stacked images of 22466 from different surveys are displayed. From upper left to bottom right stacked images of 2MASS, neoWISER, unWISE, skymapper, SDSS9, PanSTARRS, HST, and JWST, respectively.

1. Data Preparation and Annotation

Table 1 lists survey telescopes and their aperture sizes. Fig. 3 displays stacked images and a 2D peak plot of object 00222 from 2MASS and ZTF surveys, while Fig. 4 shows the same for Pan-STARRS and SDSS9. 2MASS and ZTF do not resolve the binary source, whereas Pan-STARRS and SDSS9 do.
Telescope resolution, determined by following Rayleigh's law, depends on aperture size, categorizing surveys by their resolutions.

$$\theta = \frac{1.22\lambda}{D}$$

θ represents the angular resolution, λ represents the wavelength of light and D represents the diameter of the telescope's aperture

Telescope	Aperture Size (m)
DECaLS	0.1
UnWISE	0.4
NEOWISER	0.4
2MASS	1.3
ZTF	1.2
SkyMapper	1.35
Pan-STARRS	1.8
SDSS9	2.5
HST	2.4
JWST	6.5
HSCLA	8.2

Table 1. Aperture sizes of various survey telescopes used for downloading stamped images, sorted in ascending order.

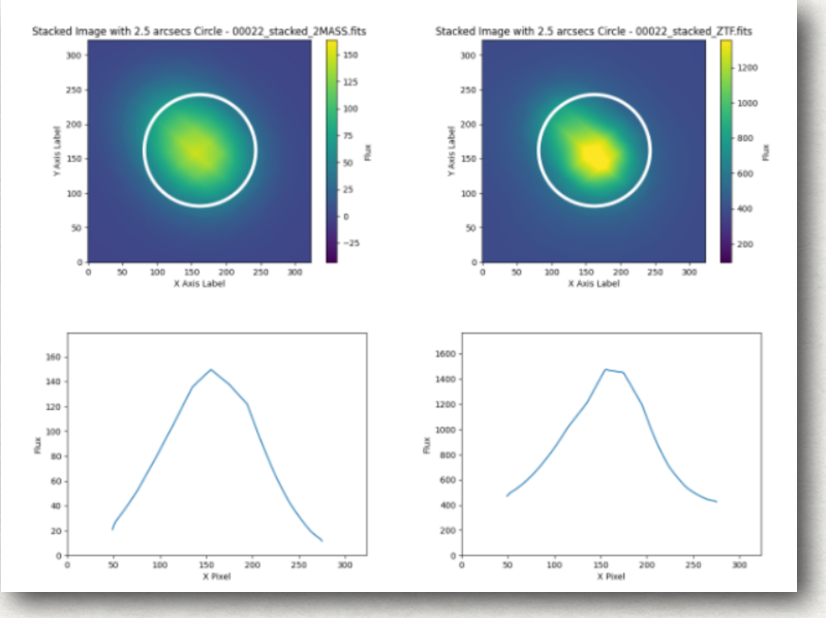

Fig. 3 In the upper panel, the right image shows the stacked images of 00222 from 2MASS and the left image shows the stacked image of 00022 from the ZTF survey. The bottom panel shows their 2D peak plots for the 00022 source from 2MASS and ZTF, respectively.

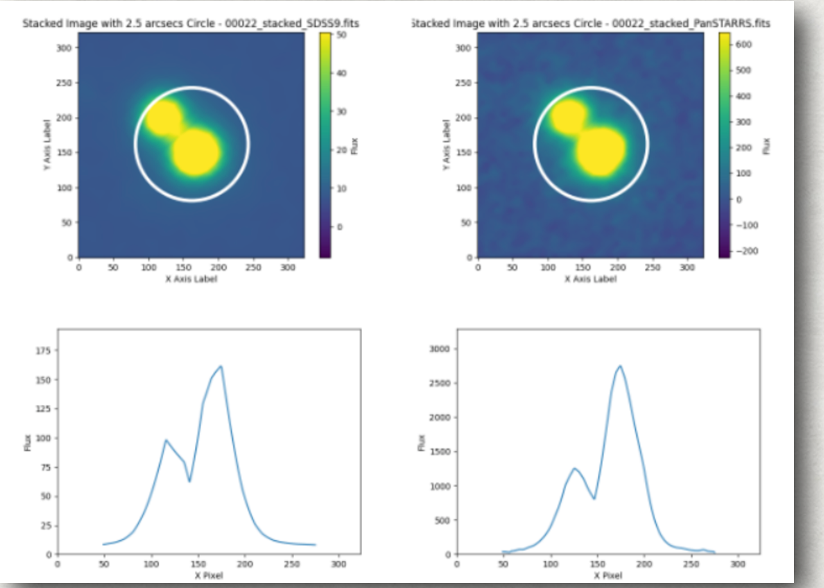

Fig. 4 In the upper panel, the right image shows the stacked images of 00222 from SDSS9 and the left image shows the stacked image of 00022 from the PanSTARRS survey. The bottom panel shows their 2D peak plots for the 00022 source from SDSS9 and PanSTARRS, respectively.

2. Model Selection and Training

We built training samples by visually inspecting stamp images from each survey group and annotating them with binary labels, indicating the presence or absence of visual-binary sources within 2.5 arcseconds. This process resulted in a balanced training dataset comprising about 150 binary and 150 else sources for the third group, and 40 binary and 40 else sources for the fourth group.

PyTorch is employed to train a convolutional neural network (CNN) with the ResNet34 for binary classification. The ResNet model is loaded without pre-trained weights and adapted for the specific task. Additional convolutional layers are added to enhance feature extraction, while the output layer is adjusted to generate two output channels for binary classification. To facilitate training, a loss function, optimizer, and learning rate scheduler are defined. GPU acceleration is utilized for efficient computation. The number of training epochs is set to 40.

3. Evaluation and Deployment

The model is rigorously evaluated on an independent testing dataset to assess its ability to detect visual-binary sources across diverse survey datasets. Using a split of 70% for training, 15% for testing, and 15% for validation, the model's performance is thoroughly assessed. The classification report in Table 2 summarizes its performance on the training sample from the third group, which includes Pan-STARRS, SDSS9, and HST. Upon successful evaluation, the model is deployed for operational use. This deployed model efficiently detects binary sources in stamp images obtained from Pan-STARRS, SDSS9, and HST simultaneously.

Class	Precision	Recall	F1-Score
0	0.98	0.96	0.97
1	0.96	0.98	0.97
Accuracy			0.97
Macro Average	0.97	0.97	0.97
Weighted Average	0.97	0.97	0.97

Table 2. Detailed classification report for visual binary classification

4. Conclusion

We constructed two distinct training samples and trained separate models accordingly.

- The first sample consisted of stacked FITS images from Pan-STARRS, SDSS9, and HST surveys.
- The second sample focused on high-resolution surveys, specifically JWST and HSCLA.
- The first model classified approximately 50,000 stacked FITS images from Pan-STARRS, SDSS9, and HST surveys, while the second model classified about 6,500 images from HSCLA and JWST surveys.
- Combined, the models identified 575 visual binary sources across the survey dataset.

Our approach integrates deep-learning techniques to offer a reliable and efficient solution for visual-binary source detection, supporting scientific exploration in astronomy and related fields.

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