HACETTEPE ÜNİVERSİTESİ

Enhancing Supernova Detection with Super Resolution

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1 Introduction

Supernovae are among the most powerful and luminous events in the universe. Accurate and timely detection of supernovae is crucial for astrophysical research, including studies of cosmic distances, dark energy, and stellar evolution. However, due to atmospheric distortion, sensor limitations, and the vast scale of astronomical data, images captured for supernova detection often suffer from reduced quality, making precise identification more challenging.

This project explores the application of super resolution techniques to enhance the quality of astronomical images, thereby improving the accuracy of computer vision-based supernova detection methods. By integrating super resolution models with object detection algorithms, we aim to determine whether image enhancement can yield measurable benefits in detecting supernovae. Our approach centers on combining Super-Resolution and Convolutional Neural Networks.

2 Dataset

Our experiments were grounded in two real-world astronomical datasets curated for the task of supernova detection: the Panoramic Survey Telescope and Rapid Response System (Pan-STARRS) [5] and the Popular Supernova Project (PSP) [6]. These datasets were introduced and benchmarked in the work of Yin et al. [4], where they were used to evaluate object detection algorithms in complex, real-sky scenarios.

We initially adopted the Pan-STARRS dataset, which offers 12,447 high-resolution, well-centered difference images collected from wide-field sky surveys. The dataset is notable for its consistency: most images are of uniform size (302 × 302), evenly exposed, and free of significant observational defects. This makes it an excellent testbed for standard detection pipelines. However, as previously noted by Yin et al., the dataset's relatively clean quality and high signal-to-noise ratio (SNR) reduce the potential benefits of super-resolution (SR) techniques. In other words, the Pan-STARRS images are already near-optimally resolved for most conventional CNN-based detectors, limiting the visible improvement SR can bring. We revisit this point in the Techniques section, where we present quantitative analysis on model performance with and without SR on Pan-STARRS.

To further test our hypothesis on the benefits of image enhancement and challenge our models under more realistic constraints, we turned to the PSP dataset. Unlike Pan-STARRS, the PSP dataset comprises only 716 real observation images, each suffering from common observational imperfections such as poor weather conditions, unaligned captures, tracking failures, and low SNR. These factors significantly increase detection complexity but better reflect the noisy conditions encountered in public sky survey pipelines. While more difficult to work with, this dataset proved especially valuable for evaluating super-resolution's role in improving detection robustness.

The shift from Pan-STARRS to PSP was essential for drawing meaningful conclusions about the limits and advantages of image enhancement in deep learning-based supernova detection. As confirmed by Yin et al. [4], models trained and evaluated on PSP tend to exhibit much lower performance out of the box, creating space for optimization through techniques like SR, attention mechanisms, and input scaling.

Below, we provide visual examples from both datasets to highlight the difference in image quality and challenge level:

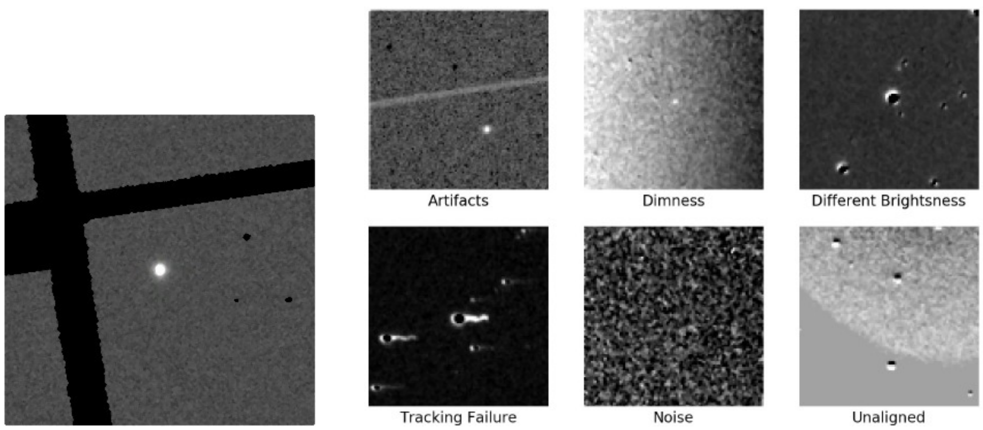


Figure 1: Left: Sample image from Pan-STARRS [5], showing a clean, high-resolution supernova candidate. Right: Sample from PSP [6], showing observational noise and reduced clarity.

3 Method

3.1 Supernova Detection Enhancement Pipeline

All experiments were conducted using a consistent object detection backbone—YOLOv8—across various preprocessing conditions to ensure fair and meaningful comparisons. Both datasets underwent initial cleaning and standardization steps before any super-resolution (SR) was applied.

For the **Pan-STARRS** dataset, all images were originally sized at 302×302 pixels. We experimented with two super-resolution models: **Residual Dense Network (RDN)** and **Residual in Residual Dense Network (RRDN)**, both known for their ability to reconstruct fine textures in astronomical imagery. These enhanced versions were benchmarked against the original images to assess any improvements in detection robustness.

The **PSP dataset** presented more challenges due to its heterogeneous resolutions, ranging from approximately 280×280 up to 580×580. To manage this variability, all images were rescaled and cleaned prior to model input. Similar to Pan-STARRS, we applied RDN and RRDN as enhancement methods, in addition to traditional interpolation baselines and ESRGAN.

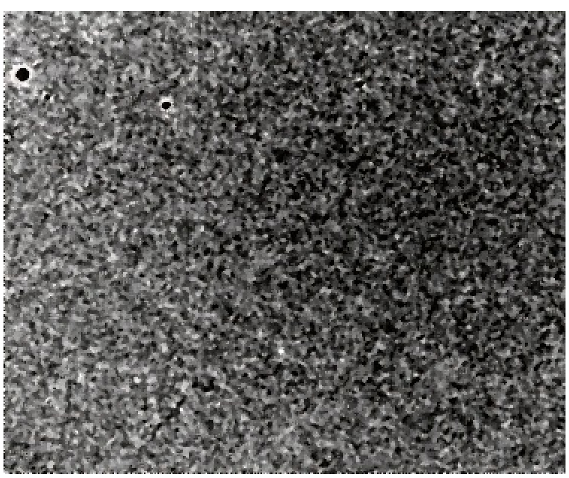
3.2 Evaluation Framework

For both datasets, the original unenhanced data served as our **baseline**. Subsequent SR-enhanced versions were evaluated using a standardized validation protocol on PSP, which included the following metrics:

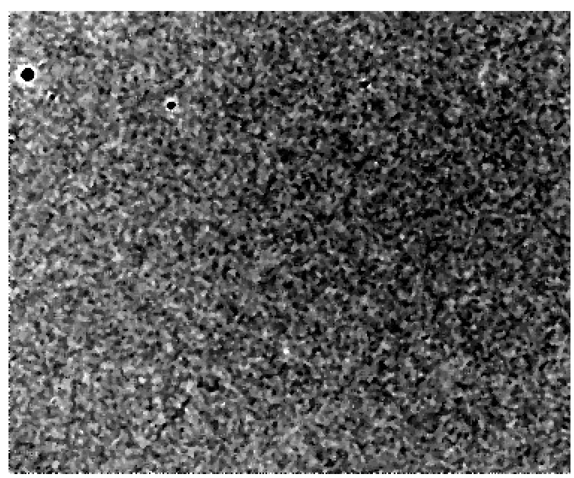
- **Precision** – How many of the predicted supernovae were correct.
- **Recall** – How many actual supernovae were detected.
- **mAP@50 and mAP@50-95** – Mean average precision at different IoU thresholds.
- **Preprocessing / Inference / Postprocessing Time** – Efficiency of the full pipeline.

3.3 Visual Illustration of Super Resolution Impact

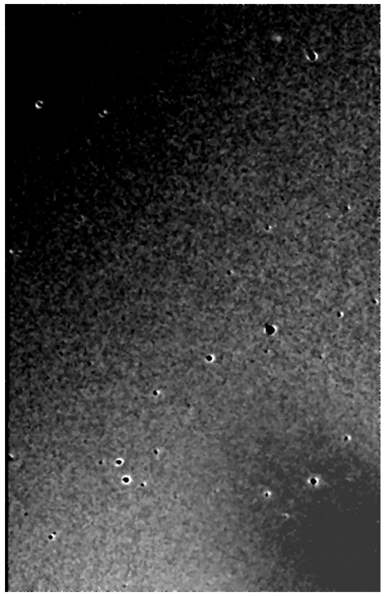
To visually highlight the effect of super resolution on astronomical imagery, we present two side-by-side comparisons using the Residual Dense Network (RDN) enhancement method. Figure 2 shows examples from both datasets—Pan-STARRS and PSP—before and after applying RDN.
In the Pan-STARRS example, although the original image is already relatively clean, the RDN-enhanced version reveals sharper contrast and more defined contours around the supernova candidate. In contrast, the PSP example demonstrates a more dramatic transformation: from a noisy, low-SNR input to a significantly clearer image with improved structure and signal separation. These enhancements are especially critical in challenging datasets like PSP, where detection accuracy is often constrained by observational noise.



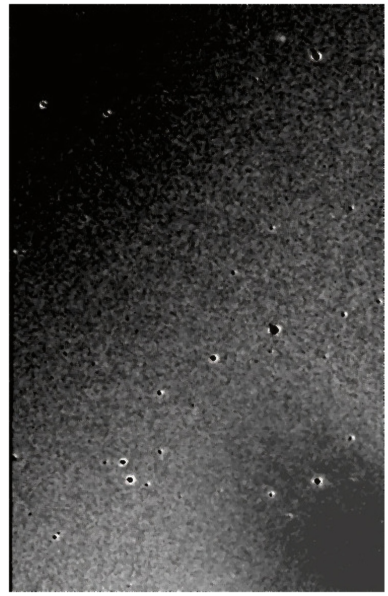
Pan-STARRS (Original)



Pan-STARRS (RDN Enhanced)



PSP (Original)



PSP (RDN Enhanced)

Figure 2: Examples of supernova regions before and after RDN super-resolution. Top row: Pan-STARRS. Bottom row: PSP. RDN improves clarity and contrast, aiding both visual interpretation and algorithmic detection.

3.4 Super Resolution Methods

We explored the following SR models:
RDN/RRDN: These methods leverage densely connected residual learning, well-suited for recovering fine astronomical textures.
ESRGAN: A generative approach for photo-realistic SR, evaluated particularly on PSP images with low SNR.
Each method's impact is analyzed relative to the original dataset performance, which serves as the benchmark in our ablation and comparative studies.

4 Experimental Settings

All experiments were conducted using Google Colab Pro, utilizing an NVIDIA L4 GPU. The models were implemented in PyTorch and trained using the YOLOv8 object detection architecture. To ensure consistency across all experiments, we used the same training setup:

- **Optimizer:** AdamW with a learning rate of 0.002 and momentum of 0.9
- **Epochs:** 100
- **Batch size:** 32
- **Input resolution:** 320×320 for baseline, 640×640 for all SR-enhanced experiments

Each model variant was trained independently under identical conditions. The following table summarizes the total training time for each configuration:
For performance evaluation, we used the following metrics:

Table 1: Training Time per Configuration (100 Epochs)

Configuration	**Training Time (hours)**
YOLOv8 Baseline (320×320)	0.083
YOLOv8 + RDN (640×640)	0.127
YOLOv8 + Real-ESRGAN	0.165
YOLOv8 + RRDN	0.133

- **Precision and Recall** – to evaluate classification performance
- **mAP@50 and mAP@50–95** – to assess object localization quality
- **Preprocessing, Inference, and Postprocessing Time** – to measure runtime performance and latency

All evaluations were performed on a held-out subset of the PSP dataset.

5 Results

This section presents the detection performance of our YOLOv8-based pipeline on both the Pan-STARRS and PSP datasets. All models were trained with the same configuration: **AdamW** optimizer with `lr=0.002`, `momentum=0.9`, and weight decay parameters following the YOLOv8 default grouping. The training was conducted for **100 epochs** with a **batch size of 32**. Input size was set to **320 for original datasets** and **640 for all super-resolution variants**.

5.1 Pan-STARRS Performance

As discussed in the Techniques section, Pan-STARRS is a relatively clean dataset with high-resolution images. The use of super-resolution techniques such as RDN or RRDN did not yield significant improvements in performance. In fact, detection metrics slightly declined after enhancement, indicating the original image quality was already optimal for this detection task.

Table 2: Detection Results on Pan-STARRS Dataset

Model	**Precision (P)**	**Recall (R)**	**mAP@50**	**mAP@50-95**
Original (YOLOv8)	0.972	0.865	0.929	0.657
Post-SR (RDN/YOLOv8)	0.944	0.877	0.918	0.575

5.2 PSP Performance

Unlike Pan-STARRS, the PSP dataset contains observational noise and variable resolution. Here, we evaluated several super-resolution strategies to determine their effect on YOLOv8 detection performance. Each experiment was conducted with the same training setup. All results are reported below:

5.3 Key Observations

- For Pan-STARRS, the original images outperformed the SR-enhanced versions, consistent with prior observations that the dataset is already optimized for detection tasks [4].

Table 3: Detection Results on PSP Dataset (YOLOv8)

Dataset	**P**	**R**	**mAP@50**	**mAP@50-95**	**Pre (ms)**	**Infer (ms)**	**Post (ms)**
PSP_aug_yolo	0.777	0.738	0.781	0.319	0.7	6.2	3.5
PSP_aug_yolo_sr	0.833	0.775	0.840	0.453	2.5	6.1	3.1
PSP_aug_esrgan	0.840	0.739	0.803	0.384	2.5	5.0	3.4
PSP_aug_yolo_RRDN	0.848	0.789	0.840	0.400	2.5	5.3	3.6

- On PSP, applying super-resolution—particularly RDN and ESRGAN—led to a clear boost in detection metrics, especially in mAP@50-95, indicating better bounding box precision.
- While super-resolution introduces a preprocessing overhead (from 0.7 ms to 2.5 ms), inference and postprocessing times remain comparable across variants, making these enhancements computationally feasible.

5.4 Qualitative Comparison of Detection Results

To further illustrate the impact of super resolution, Figure 3 shows the model predictions on a sample PSP image under different configurations. YOLOv8 with RDN enhancement yields the highest confidence prediction (0.84), while the baseline model and RealESRGAN versions show lower scores or minor localization shifts. These visual differences complement our quantitative findings, supporting the role of SR in boosting detection robustness.

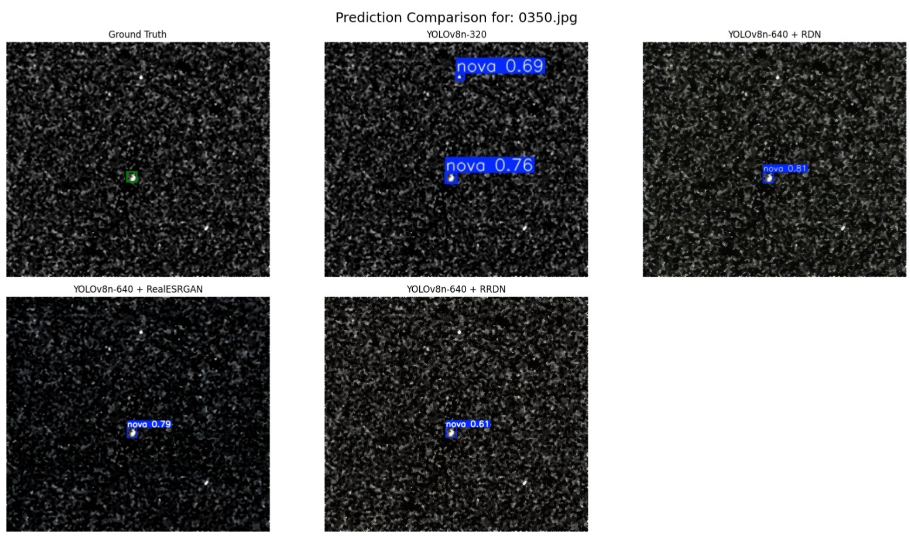


Figure 3: Prediction comparison on a single PSP image across different enhancement pipelines. Ground truth is shown at the top left; YOLOv8 results (with various SR methods) are shown with detection labels and confidence scores.

Super-Resolution Runtime

In addition to training time, we also recorded the time required to apply each super-resolution method on the PSP dataset. For 574 training images, 71 validation images, and 71 test images, the total preprocessing time was approximately:

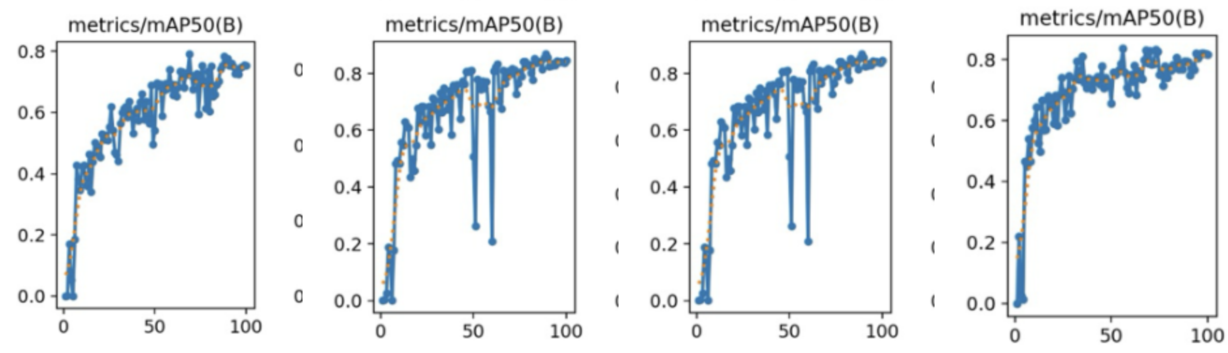
- **RDN:** 25 minutes

- **RRDN:** 14 minutes

These times reflect the **entire super-resolution step**, not training of the SR models, and were measured using pre-trained models applied via command-line tools. Given the relatively small dataset size, SR overhead was minimal in the full pipeline.

5.5 mAP Comparison Across SR Methods

As shown in Figure 4, both RDN and ESRGAN demonstrate noticeable improvements in detection performance compared to the baseline YOLO input, with sharper and more localized activations. RRDN, however, shows less consistent gains—potentially due to noise amplification—highlighting the importance of method selection in SR-enhanced detection pipelines.



YOLO (320x320) | RDN | ESRGAN | RRDN

Figure 4: Comparison of mAP performance across baseline YOLO and three SR-enhanced inputs.

6 Discussion and Conclusion

This project explored the impact of super-resolution (SR) on deep learning-based supernova detection. Experiments on Pan-STARRS and the more challenging PSP dataset showed that SR—particularly with RDN and ESRGAN—can significantly enhance detection performance in noisy, low-resolution astronomical imagery.

Key Strengths:

- SR improved mAP and recall on noisy PSP data with minimal computational overhead.
- The modular pipeline is adaptable to other detection tasks and datasets.

Limitations:

- SR had minimal or negative impact on already high-quality data like Pan-STARRS.
- Some methods (e.g., RRDN) introduced artifacts or amplified noise.

Challenges and Future Work:

- PSP data required careful preprocessing due to alignment and format issues.
- Future directions include noise-aware training, multi-band inputs (e.g., UV/IR), and SR models fine-tuned for astronomical domains.

Overall, SR is a valuable preprocessing step for enhancing astrophysical object detection in real-world, noisy imagery.

References

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