Cosmic-CoNN: A Cosmic-Ray Detection Deep-learning Framework, Data Set, and Toolkit

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Abstract

Rejecting cosmic rays (CRs) is essential for the scientific interpretation of CCD-captured data, but detecting CRs in single-exposure images has remained challenging. Conventional CR detectors require experimental parameter tuning for different instruments, and recent deep-learning methods only produce instrument-specific models that suffer from performance loss on telescopes not included in the training data. We present Cosmic-CoNN, a generic CR detector deployed for 24 telescopes at the Las Cumbres Observatory, which has been made possible by the three contributions in this work: (1) We build a large and diverse ground-based CR data set leveraging thousands of images from a global telescope network. (2) We propose a novel loss function and a neural network optimized for telescope imaging data to train generic CR-detection models. At 95% recall, our model achieves a precision of 93.70% on Las Cumbres imaging data and maintains a consistent performance on new ground-based instruments never used for training. Specifically, the Cosmic-CoNN model trained on the Las Cumbres CR data set maintains high precisions of 92.03% and 96.69% on Gemini GMOS-N/S 1 × 1 and 2 × 2 binning images, respectively. (3) We build a suite of tools including an interactive CR mask visualization and editing interface, console commands, and Python APIs to make automatic, robust CR detection widely accessible by the community of astronomers. Our data set, open-source code base, and trained models are available at https://github.com/cy-xu/cosmic-conn.

Unified Astronomy Thesaurus concepts: Astronomy data reduction (1861); CCD observation (207); Neural networks (1933); Cosmic rays (329); Classification (1907)

1. Introduction

Cosmic rays (CRs) are a key source of artifacts in data from astronomical observations using charge-coupled devices (CCDs). These charged particles excite electrons in the detector, creating artifacts that can be mistaken for astronomical sources. Space-based instruments like the Hubble Space Telescope (HST), which are not protected by Earth’s atmosphere, are heavily affected by CR, with an average flux density of 0.96 CR s\(^{-1}\) cm\(^{-2}\) (Miles et al. 2021). Ground-based instruments are also affected but at a rate about five orders of magnitude lower, typically of \(\sim 0.00001\) CR s\(^{-1}\) cm\(^{-2}\) in thin CCDs, as observed in Las Cumbres Observatory (LCO) global telescope network imaging data. CCD thickness is another factor that affects an imager’s sensitivity to CRs.

Detecting CRs is straightforward when multiple exposures of the same field are available (see example in Figure 1). By comparing the deviation of a pixel from the mean or median value in a stack of aligned images, CRs (and other artifacts) can be effectively identified (Windhorst et al. 1994; Zhang 1995; Freudling 1995; Fruchter & Hook 2002; Desai et al. 2016). However, multiple exposures may not be available, especially for spectroscopic observations. Variations in image quality (e.g., seeing) can also complicate this procedure, so robust detection of CR pixels on individual images is still necessary.

CRs do not travel through the telescope’s optical path nor do they follow the point-spread function (PSF): they are not blurred by the atmosphere and are therefore sharper than a real PSF. Furthermore, they can come in any incidence angle to have less symmetrical morphologies than real astronomical sources. Several algorithms leverage this feature, like adapted PSF convolution (Rhoads 2000), histogram analysis (Pych 2004), fuzzy logic-based algorithms (Shamir 2005), and Laplacian edge detection (van Dokkum 2001). These methods and the IRAF task like \texttt{xzap} by M. Dickinson often require adjusting one or more hyperparameters experimentally to obtain the best result per image. Machine-learning algorithms like k-nearest neighbors, multilayer perceptrons (Murtagh & Adorf 1991), and decision-tree classifiers (Salzberg et al. 1995) showed promising results on small HST data sets, but lacked generality when compared to image-filtering techniques like \texttt{LA Cosmic} (van Dokkum 2001).

Machine-learning methods have been widely adopted in astronomical research recently (see Baron 2019 for a review). Zhang & Bloom (2020) used a convolutional neural network (CNN) to identify CR-contaminated pixels in HST ACS/WFC images, in a method called deepCR. In contrast to using the Laplacian kernel (Chen et al. 1987) for edge detection as is in \texttt{LA Cosmic}, CNNs learn the intrinsic characteristics of the CR artifacts, enabling them to detect CRs of arbitrary shapes and sizes.

The deepCR model outperforms the state-of-the-art method \texttt{LA Cosmic} without manual parameter tuning, demonstrating the promise of deep learning for CR detection. However, its
neural network architecture is an adaptation from U-Net (Ronneberger et al. 2015) which was originally designed for biomedical images, limiting its ability to train a generic model for astronomical observations from different instruments, specifically ground-based data with variable conditions from multiple instruments. Furthermore, the low CR rates in ground-based data: a \( \sim 1:10,000 \) ratio between CR and non-CR pixels leads to an extreme class-imbalance issue (Buda et al. 2018) that provides too few CR pixels for spatial convolution, rendering the training on LCO data more difficult compared to HST data.

To address these issues, we present Cosmic-CoNN, a deep-learning framework designed to train generic CR-detection models for ground-based instruments by explicitly addressing the class-imbalance issue and optimizing the neural network for the astronomical images’ unique spatial and numerical features. Cosmic-CoNN also generalizes to other types of data like biomedical images, limiting its ability to train a generic model for astronomical observations from different instruments and the CRs need to be labeled accurately and consistently across different instruments. With this in mind, we build a custom Python CR-labeling pipeline to generate a large CR ground-truth data set, leveraging some unique characteristics of the LCO global telescope network.

Our CR-labeling pipeline stacks consecutive images of the same field to identify CRs. To limit artifacts due to variations in CCD response, we only selected sequences that have at least three repeated observations with identical exposure time and filter. The LCO CR data set consists of over 4500 scientific images from LCO’s 23 globally distributed telescopes. About half of the images are 4K \( \times \) 4K pixel resolution and the rest are 3K \( \times \) 2K or 2K \( \times \) 2K. To the best of our knowledge, this is the largest CR data set that identifies CRs in science images across various ground-based instruments. Each sample in our data set is a multi-extension FITS file including three images, the corresponding CR masks, and ignores masks. We encoded hot pixels, pixels with no data, and astronomical sources in the ignore masks to reject false-positive CR pixels. The implementation of our ground-truth CR-labeling pipeline is presented in Appendix A. The LCO CR data set is available for download at https://zenodo.org/record/5034763.

The data set covers a variety of CCD imagers with different pixel scales, fields of view, and filters used in LCO’s global telescopes network (Table 1). From a deep-learning perspective, diverse data greatly benefits model generality. But having ground-truth CRs labeled consistently on different instruments is not a trivial task. The BANZAI data reduction pipeline (McCully et al. 2018) performed instrumental signature removal (bad-pixel masking, bias and dark removal, and flat-field correction), making LCO data suitable for building such a
data set. Instrument artifacts exist as two identical CCDs could have different response curves after years of bombardment by photons and CRs. Standardized data reduction is key to allowing our CR-labeling pipeline to consistently and accurately label CRs across various instruments.

We chose images from across three telescope classes and across the year as shown in Figure 2. Images from different times of the year sampled a variety of source densities for different sets of scientific goals. The varying source density proved to be of great importance to robust CR detection (Farage & Pimbblet 2005). In the task of CR detection, diversified real objects provide rich features for the negative class, which greatly improves model robustness.

We further constrained a sequence of exposures to come from the same scheduling unit: the frames are typically separated by just a few minutes. Repeated exposures in a short period of time help mitigate the PSF variation induced by atmospheric attenuation but PSF wings still cause noticeable false-positive labels adjacent sources. We reject CRs that are overlapping with astronomical sources so that variations in the PSF do not create artifacts in the training samples.

Of all CR pixels, 1.21% were rejected in an effort to tackle the PSF-variation-induced artifacts. This trade-off ensures the remaining 98.79% CR pixels are labeled at higher confidence. Therefore, models trained with this data set focus on distinguishing CRs from real sources, and it is anticipated that CRs overlapped with sources will not be detected. Training on raw images with arbitrary PSFs also guarantees consistent performance at inference time. In future versions, we will model the PSF explicitly to make sure that we do not bias our training sample.

Our data set is not affected by transient sources that evolve at a timescale of hours or longer because of the very tight space between exposures. At this timescale, near-Earth objects (NEOs), satellites, and airplanes could still cause false-positive labels in the stack-based CR masks. Large satellite or airplane trails are rejected by our CR-labeling pipeline automatically. A very small fraction of false-positive labels from NEOs and satellites exist but we have manually verified every single mask to ensure their impact is negligible.

### 3. Deep-learning Framework

Cosmic-CoNN’s neural network architecture is inspired by the recent success of deepCR (Zhang & Bloom 2020), a U-Net (Ronneberger et al. 2015) based deep-learning framework that identifies CR-contaminated pixels in imaging data. In contrast to the unique Laplacian kernel used in LA Cosmic (van Dokkum 2001), a deep CNN model optimizes millions of kernel parameters during training and outputs a pixel-level probability map directly. The U-shaped architecture (Figure 3) convolves the image at multiple scales, creating a larger receptive field in deeper layers of its hierarchical architecture to capture not only CRs’ morphological features (edges, corners, or sharpness) but also the contextual features from peripheral pixels, allowing it to predict CRs of arbitrary shapes and sizes.

deepCR demonstrates the promise of using a CNN-based model for CR detection on HST ACS/WFC observations. However, training on ground-based images exposes a number of network architecture and data-sampling limitations it inherited from U-Net (Ronneberger et al. 2015). First, it is worth noting that U-Net was initially proposed to solve biomedical image segmentation problems. The higher dynamic range and extreme spatial variations found in astronomical images need to be addressed explicitly in order to optimize the neural network for these special features in astronomical data. In addition, the high CR rates in HST ACS/WFC data do not reflect the extreme class-imbalance issue observed in LCO imaging data. The low CR rates make it difficult for deepCR to train and converge on the ground-based LCO imaging data.

In deepCR, Zhang & Bloom (2020) adopted a two-phase training design to address some of these issues. Assuming correct data statistics are learned in the initial phase, the model freezes feature-normalization parameters in the second phase in order to converge. This design works when the inference data shares the same statistics with training data, i.e., an instrument-specific model could be learned. But it works against our goal of a generic CR-detection model that works for a wide variety of ground-based instruments with varying data statistics.

Cosmic-CoNN adopted the U-shaped architecture and proposed (Section 3.1) a novel loss function that specifically addresses the class-imbalance issue, and (Section 3.2) adopted data sampling, augmentation, and feature-normalization approaches that are more suitable for ground-based data that work jointly to improve model generality and training efficiency.

#### 3.1. Median-weighted Loss Function

The CR-detection task is in essence a pixel-wise binary classification problem. Our goal is to learn a function \( f \), which takes an image \( I \) as input and outputs \( P \), the probability map of each pixel being affected by CR: \( P = f(I), P_i \in [0, 1] \), where \( ij \) is the pixel coordinate. The user could then apply an appropriate threshold on \( P \) to acquire the binary CR mask.

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**Table 1**

LCO Science Imagers Covered in the CR Data Set

| Imager       | Class | Pixel Scale (") | Binning | Format (pixels) | Pixel Size (microns) | FOV (") | Filters |
|--------------|-------|-----------------|---------|-----------------|----------------------|----------|---------|
| SBIG 6303    | 0.4 m | 0.571           | 1 x 1   | 3K x 2K         | 9                    | 29 x 29  | 9       |
| Sinistro     | 1 m   | 0.389           | 1 x 1   | 4K x 4K         | 15                   | 26 x 26  | 21      |
| Spectral     | 2 m   | 0.304           | 2 x 2   | 4K x 4K         | 15                   | 10 x 10  | 18      |

**Figure 2.** LCO CR data set sample distribution by month and telescope class, from 2018 November to 2019 December. Diverse source densities sampled around the year help improve model robustness.
Binary cross entropy (BCE) is commonly used to optimize classification models, which can also be used to calculate the loss between the prediction $P$ and the ground-truth CR mask $Y$:

$$BCE(P, Y) = -(Y_y \log(P_y) + (1 - Y_y) \log(1 - P_y)),$$

where the ground-truth mask $Y$ is defined as $Y_y = 1$ for CR pixels and $Y_y = 0$ for non-CR pixels. The first term $Y_y \log(P_y)$ measures the loss for CR pixels and the second term for non-CR pixels. The optimization objective is to minimize their sum to account for both CR and non-CR classes.

The low CR rates in LCO data cause the non-CR loss to dominate the total loss. Training on LCO imaging data, the observed losses from the two terms in Equation (1) have a ratio of $\sim 1:6300$ (averaged over 10 random experiments), with the second term (non-CR loss) dominating the optimization objective. This verifies the class-balance issue.

Furthermore, background pixels are the culprit for an extra layer of imbalance within the non-CR class. From dark background to bright sources, the non-CR class often covers the image’s entire dynamic range (see example in Figure 4(a), (b)). Although both are labeled as 0 in $Y$ (Figure 4(c)), the lopsided numerical difference between background and sources in fact creates two subclasses within the non-CR class to introduce inconsistency, making the training path even more convoluted.

The class imbalance and the numerical imbalance within the non-CR class are clear indications that we should directly focus on learning to distinguish between CRs and sources. It inspired us to create an adaptive per-pixel weighting factor that prioritizes CR and source pixels by downweighting the less useful yet dominant loss from background pixels.

Since we already acquired a sequence of consecutive exposures building the LCO CR data set, we could use the CR-free median frame (Figure 4(b)) as a unique ground truth to separate sources from the background. The brightness variation between different sources makes it hard to use the median frame as a weight mask directly, so we perform a series of transformations (sky subtraction, clipping between one and five robust standard deviations, $5 \times 5$ kernel with $\sigma = 2$ Gaussian smoothing, unit normalization, and finally clamping with a lower-bound parameter $\alpha$ to separate sources from the background to acquire the median-weighted mask ($M$) shown in Figure 4(d). We apply $M$ to the non-CR loss term in BCE to get the novel median-weighted loss function ($L_M$):

$$L_M(P, Y, M) = -(Y_y \log(P_y) + M_{ij}(1 - Y_y) \log(1 - P_y)),$$

where $M_{ij} \in [\alpha, 1]$. Pixel by pixel, $M$ adaptively down weights the loss from the background by scaling with the lower bound $\alpha$, mitigating the extreme imbalance between the two loss

\[\text{Figure 3.} \text{Cosmic-CoNN’s neural network architecture is based on U-Net. The symmetric design concatenates high-resolution features from the downsampling path to the upsampling path via skip connections (blue arrows), allowing the network to propagate contextual information to higher-resolution layers, thereby producing pixel-level classification predictions on CRs of arbitrary shapes and sizes.}\]

\[\text{Figure 4.} \text{3D visualization of the median-weighted mask. (a) An image stamp that includes sources, CR-affected pixels, and background. (b) The ground-truth CR mask shows the imbalance between CR and non-CR pixels. (c) 3D visualization of the CR-free median image shows the non-CR pixels can be further split into two subclasses: sources and background, while the background pixels may be dominant in quantity. We transform (b) to acquire (d), the median-weighted mask ($M$) by normalizing the brightness variation between sources. $M$ in Equation (2) adaptively downweights background pixel loss in the proposed median-weighted loss function. In this figure, $M_{ij} \in [0.2, 1.0]$.}\]
terms and redefines the optimization objective to directly learning to distinguish between sources and CRs.

With $M$ applied to the second term in BCE, it immediately reduces the observed CR to non-CR class losses to $\sim 1:300$ in Equation (2), compared to the $\sim 1:6300$ using Equation (1) (in identical conditions). Although this ratio can be further reduced with a more aggressive weight mask, the median-weighted mask preserves all real sources without introducing inconsistency. After training with 500 images, the observed loss of the two terms further reduce to $\sim 1:6$ using $L_M$, compared to $\sim 1:110$ using BCE loss. In Figure 5, we show that the deepCR model optimizes sooner and to a better minimum with $L_M$ while holding other variables constant. The median-weighted loss function ($L_M$) makes use of the median frame’s unique CR-free property as a robust weighting factor to effectively suppresses the dominating loss from background pixels, at the same time prioritizes learning to distinguish between CRs and sources by maintaining their weighting factor at 1.0. As training progresses, the lower bound $\alpha$ linearly increases the weight for background pixels from 0.0 to 1.0 so the model could learn a clear boundary for CRs. We could also cap $\alpha$ at less than 1 to learn a model that produces CR prediction with soft edges, leaving more control to the user-defined threshold when a binary CR mask is needed. We choose to increase $\alpha$ to 1 so that $L_M$ converges to the BCE loss, working with the standard Sigmoid function (Little 1974; Little & Shaw 1978) at the last layer of our network to produce a theoretical best classification boundary of around 0.5. We also experimented using a loss function based on the Sørensen–Dice coefficient that is robust for imbalanced data (Sørensen 1948) but the model learned a strong bias to avoid CRs near real objects, making the more interpretable BCE-based loss a better choice for optimization.

3.2. Data Sampling and Normalization

Large-scale deep-learning models are often optimized using stochastic gradient descent (Kiefer & Wolfowitz 1952), motivated by stochastic methods’ efficiency benefits, at the same time constrained by the ever-growing data set size and limited GPU memory (usually on the order of 10 GB) for parallel computation. Model parameters are iteratively optimized over a small batch of data, colloquially known as a mini-batch, randomly sampled from the full data set. If iterating over all $N$ samples in a data set is considered an epoch, then training a model with $n$ samples in a mini-batch means the model updates about $\frac{N}{n}$ times in an epoch (Bottou et al. 2016).

By slicing HST ACS/WFC images into $256^2$ pixel stamps, deepCR (Zhang & Bloom 2020) samples a mini-batch from a data set of fixed stamps. However, this approach is unsuitable for ground-based astronomical images featuring much lower CR rates: a small $256^2$ stamp might not include a single CR, making many of the samples less useful for training.

Recall that each sample in the LCO CR data set is a multi-extension FITS including three images between $2K \times 2K$ and $4K \times 4K$ pixels. This design empowers a more flexible data-sampling strategy than having the data set stored in a fixed size. The Cosmic-CoNN framework could crop a stamp of any size, up to the entire image from each FITS, ensuring a reasonable number of CRs in every mini-batch. The sparsity of source and CR in ground-based astronomical data motivated us to increase the sampling stamp size to $1024^2$ pixels. A larger area is more likely to include all three types of features: sources, CRs, and background in a single stamp and also provides more spatial and contextual information for the convolution operations in CNN models.

One consequence of the increased stamp size is the decreased number of samples in a mini-batch, given the same amount of GPU memory. Increasing the stamp width and height by $m$ times will reduce the batch size $n$ to $\left\lfloor \frac{n}{m^2} \right\rfloor$, e.g., the memory that fits a mini-batch of $16 \times 256^2$ pixel images can only fit a single $1024^2$ pixel image. The accuracy of batch normalization (BN) (Ioffe & Szegedy 2015), an important feature-normalization method widely used in deep CNN architectures, including in deepCR, decreases rapidly when the batch size becomes too small, so adopting the proposed larger stamp size alone might even hurt model accuracy, as shown in Figure 5. We adopt GN (Wu & He 2018), whose

![Figure 5](image-url)

Figure 5. Using deepCR as a baseline, we demonstrate our proposed improvements’ effects on the model performance as a function of training progress. All variant models are initialized with the same random seed, trained on an identical set of LCO data, and evaluated with identical validation images using the same model-input dimension. Performance is measured by the Sørensen–Dice coefficient (Sørensen 1948) (henceforth, the Dice score) to gauge the similarity between the model’s prediction and the ground-truth CR mask. Here, we plot (1—Dice score) in logarithmic scale, lower is better. Models without using group-normalization (GN) were trained in two phases, thus the delayed optimizations that start after 500 epochs. The median-weighted loss helped deepCR achieve better performance, while the larger $1024^2$ pixels stamps proved to be vital for models using GN. The proposed median-weighted loss function, increased stamp size, and GN work jointly to allow Cosmic-CoNN to converge rapidly and to a better minimum. Quantitative results are presented in Table 4 in an ablation study (Appendix B).
computation is independent of batch size to address the accuracy loss in BN. Unlike BN, which normalizes over all feature channels across all samples in a mini-batch, GN divides feature channels into groups and computes the normalization statistics for each sample. We used GN as a remedy for the decreased batch size but found it to play a major role in improving training efficiency on astronomical imaging data.

The high dynamic range, high variance, low source density, and low CR rates in ground-based astronomical images make it difficult to learn accurate per-sample normalization statistics from small stamps: one sample could include a bright source but another could be entirely dark. By pairing GN with the proposed stamp size of 1024² pixels, the learned per-sample normalization is more accurate because of the extra spatial and contextual information from the wider field of view.

As a common practice in deep-learning research, we conduct an ablation study to demonstrate the individual and combined effects of median-weighted loss, 1024² pixel sampling size, and GN. The results are presented in Figure 5 and Appendix B. Controlled experiments show applying GN alone improves training efficiency but not model performance. By pairing GN with the increased 1024² stamps, it dramatically improves performance and model generality, while the proposed new loss function provides Cosmic-CoNN a better convergence path to further improve the model’s performance and generality on both LCO and Gemini instruments (see Table 4).

Finally, in addition to randomly cropping image stamps form a large image, we perform weak data augmentation like random rotations as well as horizontal and vertical mirroring, allowing the model to learn invariance to pose variation in astronomical observations (González et al. 2018). Strong augmentations like elastic deformations adopted by Ronneberger et al. (2015) have proved to be effective in improving performance on a small data set but we avoided such deformation as it could change real CRs’ sharp profiles. Given the large number of diverse samples in the LCO CR data set, we found weak augmentations sufficient. With pose augmentation, we also saw more stabilized training and improved performance on HST ACS/WFC data, showing that weak augmentation is effective in increasing model robustness.

4. Results

We trained and evaluated the Cosmic-CoNN framework on various types of instruments and data to access its generalization capabilities. Most importantly, we evaluated the LCO-trained model on new imaging data from Gemini Observatory’s GMOS-N/S telescopes (Gillett et al. 1996) to understand how well the model generalizes to other unseen ground-based instruments. The results are presented in the following structure:

1. Ground-based imaging data
   (a) Training and evaluation on LCO data (Section 4.1)
   (b) Evaluating LCO-trained models on Gemini GMOS-N/S data (Section 4.2)
2. Space-based imaging data (Section 4.3)
3. Ground-based spectroscopic data (Section 4.4)

We first use receiver operating characteristic (ROC) curves as an evaluation metric to compare different detectors’ performance at varying thresholds. A ROC curve depicts relative trade-offs between benefits (true-positive rate (TPR)) and costs (false-positive rate (FPR)) (Fawcett 2006). In the context of CR detection:

\[
TPR = \frac{\text{CR pixels correctly found}}{\text{all CR pixels}}, \quad (3)
\]

\[
FPR = \frac{\text{non - CR pixels mistaken as CR}}{\text{all non - CR pixels}}. \quad (4)
\]

Simply put, a higher TPR is desirable at a fixed FPR. While ROC provides a model-wide evaluation at all possible thresholds, standard ROC can be misleading for data sets that feature different CR rates (e.g., space- versus ground-based data). Thus it is not suitable to directly compare a model’s TPR given the same FPR between different instruments.

The precision-recall curve, on the other hand, is a more robust metric for imbalanced data sets (Saito & Rehmsmeier 2015). While recall is equivalent to TPR, in the context of CR detection, precision is defined as

\[
\text{precision} = \frac{\text{CR pixels correctly found}}{\text{all CR pixels predicted by model}}. \quad (5)
\]

Unlike FPR, precision is determined by the proportion of correct CR predictions given by the model, which is less sensitive to the ratio between CR and non-CR pixels in an image, i.e., it is also less sensitive to the varying CR rates between different data sets. Given a fixed proportion of real CRs correctly discovered (e.g., 95% recall), the better model should make less mistakes, thus a higher precision. It also helps us to understand how well a model performs on two different data sets given the same recall, or vice versa.

The precision-recall curve can also be used as an indicator of prediction confidence. We used this property to provide supplementary evidence that helped Hiramatsu et al. (2021) determine a candidate progenitor to be a new type of stellar explosion—an electron-capture supernova. We rule out the presence of CR hits at or around the progenitor site to determine the peak pixel is an actual stellar PSF with >3σ confidence by plotting deepCR’s (Zhang & Bloom 2020) predicted score on the corresponding precision-recall curve.

4.1. Training and Evaluation of LCO Data

For ground-based imaging data, we randomly sampled and withheld ~10% of images from the LCO CR data set as the test data set. We first analyzed the test set using the filtering-based CR detector Astro-SCRAPPY (McCully et al. 2018) for reference. We used objlim=2.0 for LOC 1.0 and 2.0 m telescopes’ data and objlim=0.5 for 0.4 m for optimal performance in different telescope classes. sigfrac=0.1 is held constant for all telescope classes and we produce the ROC curves by varying the sigclip between [1, 20]. Both the Cosmic-CoNN and deepCR (Zhang & Bloom 2020) models are trained with identical data and settings. They are evaluated by varying the threshold r. Details of the training environment and experiment settings are presented in Appendix C.

The Cosmic-CoNN model achieves 99.91% TPR at a fixed FPR of 0.01%, outperforming other methods, as illustrated in Figures 6(a) and (b). The precision-recall curves in Figure 6(c) show for both deep-learning models to discover 95% of the real CR pixels (95% recall), the predictions given by Cosmic-CoNN are over 4% more accurate than deepCR’s (93.70%
versus 89.46% in precision). If we continue to lower the threshold to allow 99% of the CR pixels to be found, Cosmic-CoNN’s lead increases to ~11%. Quantitative results are presented in Table 2.

### 4.2. Evaluating LCO-trained Models on Gemini GMOS-N/S Data

The goal of this work is to produce a generic ground-based CR detection model. In order to understand how well the...
models trained on LCO CR data set perform on unseen instruments, we produced a test data set consisting of 98 images from the Gemini Observatory’s GMOS-N/S telescopes (Gillett et al. 1996). The ground-truth CR masks are reduced by the DRAGONS software (Labrie et al. 2019) with hsigma = 5.0 to match the setting we used to produce the LCO training data.

As shown in Figure 7 and Table 2, at 95% recall the deepCR-trained model has −13.19% and −7.59% loss in precision on Gemini’s 1 × 1 and 2 × 2 binning images, respectively, compared to its performance on LCO images, while the Cosmic-CoNN model has consistent precisions of −1.67% and +2.99%. It shows that the Cosmic-CoNN framework is superior in producing more generic models for unseen instruments not included in the training data.

Examples of detection discrepancies are shown in Figure 8. The Cosmic-CoNN model is better at detecting complete CRs of arbitrary shapes, especially the worm-shaped CRs that frequently appear in the GMOS-N/S images.

The Cosmic-CoNN model’s consistent performance on other CCD imagers also shows the large, diverse LCO CR data set produces rich CR feature coverage that could be effectively generalized to other ground-based instruments. Figure 9 (top row) shows the robust detection result of a heavily CR-contaminated image from Gemini GMOS-N.

Bhavanam et al. (2022) recently tested Cosmic-CoNN on DECam data (Flaugher et al. 2015) and showed it generalizes well to yet another unseen instrument—our Cosmic-CoNN model trained on the LCO CR data set achieved a precision of 96.60% at 95.0% recall, a similar performance as in Gemini’s 2 × 2 binning images (Table 2). Their improvement of adding attention gate modules (Oktay et al. 2018) only brought marginal performance gain: 0.12% higher in TPR at 0.01% FPR and 0.07% higher in precision at 95.0% recall than training with the original Cosmic-CoNN framework. We argue potentially better performance from Cosmic-CoNN as Bhavanam et al. (2022) incorrectly trained on 2562 pixel patches, which is against our training strategy discussed in Section 3.2.

4.3. Space-based Imaging Data

We also trained Cosmic-CoNN on Zhang & Bloom (2020)’s HST ACS/WFC F606W data set consisting of an extragalactic field, globular cluster, and resolved galaxy observations to demonstrate the framework’s broad applicability. The Cosmic-CoNN-trained model has better performance in all three types of observations compared to the deepCR model (version 0.1.5), as shown in Table 3. When testing model robustness on augmented images with random mirroring and rotation (González et al. 2018), we found more robust performance from Cosmic-CoNN with little or no performance loss, especially in resolved galaxy data (italics in parentheses in Table 3).

Unlike the LCO CR data set which releases full-size images in FITS format, the F606W data set sliced and stored images as 2562 pixel stamps in Numpy arrays, so we were not able to test the effect of increased sampling stamp size on these data. Kwon et al. (2021) recently trained an all-filter HST ACS/WFC deepCR model on an extended data set covering the entire spectral range of the ACS optical channel. Cosmic-CoNN supports loading deepCR models to use with our toolkit, instructions are available at https://github.com/cy-xu/cosmic-conn.

4.4. Ground-based Spectroscopic Data

Finally, we expand the Cosmic-CoNN framework to detect CRs in single-exposure spectroscopic images, a task that has remained challenging for conventional methods. Bai et al. (2017) was able to detect as many as 80% of the CRs in single-exposure, multi-fiber spectral images. Based on the two-dimensional profile fitting of the spectral aperture, their method takes about 20 minutes to process a 4K × 4K pixel image. Cosmic-CoNN detects nearly all CRs in about 25 s on CPU and less than 5 s with GPU acceleration.

To prepare the data for deep-learning training, we modified our custom CR-labeling pipeline (Appendix A) and produced a data set of over 1500 images using repeated observations from the four instruments of LCO’s Network of Robotic Echelle Spectrographs (NRES) located around the world. We randomly sampled and reserved 20% of the data as the test set and used the rest for training and validation.

Cosmic-CoNN reaches 97.40% TPR at 0.01% FPR with a precision of 94.4% at 95% recall. Considering the high CR rates in spectroscopic images because of the 15 minutes or
longer exposure time, the NRES model in fact demonstrates exceptional performance. A detection result example is shown in Figure 9 (bottom row). We consider these results preliminary because the focus of this paper is on a generic ground-based imaging model and we will conduct a thorough comparison with other methods in a future work. Nevertheless, the versatility of Cosmic-CoNN framework potentially paves a way for solving the CR-detection problem in the accuracy-demanding spectroscopic data.

5. Toolkit

We built a suite of tools to democratize deep-learning models in order to make automatic, robust, and rapid CR detection widely accessible to astronomers. The toolkit includes console commands for batch processing FITS files, a web-based app providing CR mask preview and editing capabilities, and Python APIs to integrate Cosmic-CoNN models into other data workflows.

The Python toolkit package is released on PyPI. We host the open-source Cosmic-CoNN framework on GitHub https://github.com/cy-xu/cosmic-conn with complete documentation including the toolkit manual, developer instructions on using the LCO CR data set, and training new models. We also released the LCO CR data set and the code used to generate the results to facilitate reproducibility.

Table 3
Reproduced DeepCR’s Results on HST ACS/WFC Images to Compare with Cosmic-CoNN

| Data   | Method | 0.01% FPR (TPR loss w/ mirror+rotation) | 0.05% FPR |
|--------|--------|----------------------------------------|-----------|
| EF     | deepCR | 79.5 (−0.2)                             | 88.6 (−0.2) |
|        | Cosmic-CoNN | 80.2 (−0.1)                | 89.0 (−0.1) |
| GC     | deepCR | 85.4 (−0.6)                             | 93.4 (−0.3) |
|        | Cosmic-CoNN | 86.0 (0.0)               | 93.8 (0.0) |
| RG     | deepCR | 62.1 (−6.8)                             | 75.2 (−6.1) |
|        | Cosmic-CoNN | 63.6 (0.0)              | 76.3 (0.0) |

Note. To test model robustness, we randomly rotated and mirrored the images and indicated each method’s performance loss in italic parentheses. All values are FPR (%) in fixed TPR. EF: extragalactic field, GC: globular cluster, RG: resolved galaxy.

Figure 9. A pair of CR-detection examples that shows both the Cosmic-CoNN model’s generality and the framework’s broad applicability. (Top) Cosmic-CoNN’s generic ground-imaging model was trained entirely on LCO data yet all visible CRs in a new Gemini GMOS-N 1 × 1 binning image stamp are correctly detected regardless of their shapes or sizes. (Bottom) The Cosmic-CoNN framework also trains well on spectroscopic images and detects CRs over the spectrum robustly on an LCO NRES image. The horizontal bands in the left image are the spectroscopic orders, which are left out of the CR mask.
more accurate prediction than conventional methods in comparable time on the CPU. Processing a $2K \times 2K$ pixels image takes $\sim7.5$ s on an AMD Ryzen 9 5900HS laptop processor. With GPU acceleration, it takes only $\sim0.8$ s on a high-end Nvidia Tesla V100 GPU, and $\sim1.2$ s on an entry-level Nvidia GTX 1650 laptop GPU.

The $\$\texttt{cosmic-conn \ -a}$ command starts an interactive CR detector in the browser, as shown in Figure 10. We adopt the interface layout and controls from the SAOImageDS9 (Joye & Mandel 2003). In addition, we provide an array of CR thumbnails for quick navigation and the ability to edit CR masks in real time. The JavaScript-backed web app provides the necessary tools for users to fine-tune the appropriate post-processing parameters for different instruments. The preview window supports various scaling methods like the zscale for better visualization.

Cosmic-CoNN is designed to be integrated in custom data pipelines. Let $\text{image}$ be a two-dimensional float32 array:

```python
from cosmic_conn import init_model
# initialize the generic ground-imaging model
# CR_model = init_model(“ground_imaging”) 
# the model outputs a CR probability map
# CR_prob = CR_model.detect_cimage(image)
# acquire a Boolean mask with a 0.5 threshold
# CR_mask = CR_prob > 0.5
```

Our Python APIs allow other facilities to integrate rapid CR detection into their data reduction pipeline. The framework checks if the host machine supports GPU acceleration and prioritizes computation on GPU. Then it optimizes the detection strategy (full image or slice and stitch using smaller stamps) based on available memory without human intervention.

We are planning to deploy the web app on the cloud to provide GPU-accelerated CR detection as a free service. This will allow users to upload their failure cases to us to expand the training set and improve the model. In the current release, the web app is a local instance that does not collect or upload any user information.

6. Conclusion

In this work, we presented an end-to-end solution to help tackle the CR-detection problem in astronomical images. The large, diverse LCO CR data set produces rich feature coverage, allowing deep-learning models to achieve state-of-the-art CR detection on single-exposure images from LCO. The Cosmic-CoNN deep-learning framework trained generic CR-detection models that maintain consistent performance on unseen instruments. An extensive evaluation showed the framework’s broad applicability in ground- and space-based imaging data, as well as spectroscopic data. Finally, we released a toolkit to make deep-learning CR detection easily accessible to astronomers.

Using the generic Cosmic-CoNN model as a pretrained initialization, other facilities could fine-tune a model optimized for their own CCD imager with a lot less data. The LCO CR data set also lays the foundation for a potential universal solution. By expanding our data set with more instruments from other facilities, we are confident to see a universal CR-detection model that achieves better performance on unseen ground-based instruments without further training.

The Cosmic-CoNN framework and the toolkit will be a valuable resource for the community to develop future deep-learning methods for source extraction, satellite detection, NEOs detection, and more. These topics are not the focus of this paper but our improvements to the neural network made Cosmic-CoNN a suitable deep-learning architecture for these tasks, as we have seen in some preliminary experiments.

With the current Cosmic-CoNN model rejecting CRs that could be falsely recognized as astronomical sources, we could better profile the PSFs in order to address the $\sim1.21\%$ excluded CR pixels in the next release of our data set. We expect to see further improvement in the Cosmic-CoNN model.

As large surveys like the Vera Rubin Observatory’s Legacy Survey of Space and Time (LSST; Ivezić et al. 2019) go online, we will see an explosion of new data that requires automatic, robust, and rapid CR detection. With GPU acceleration, deep-learning methods like Cosmic-CoNN will likely be the solution for future data reduction pipelines that is needed to process the over 100 TB of data produced each night from LSST and many follow-up facilities.

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Facilities: LCOGT, HST(ACS/WFC), Gemini: Gillett, Gemini: South.

Software: Astropy (Astropy Collaboration et al. 2013, 2018), Astro-SCRAPPY (McCully et al. 2018), Cosmic-CoNn (Xu et al. 2021; Xu et al. 2022), DRAGONS (Labrie et al. 2019), reproject (Robitaille et al. 2020), Matplotlib (Hunter 2007), NumPy (Harris et al. 2020), scikit-image (van der Walt et al. 2014), SExtractor (Bertin & Arnouts 1996), PyTorch (Paszke et al. 2019).

Appendix A
CR-labeling Pipeline

The ground-truth CR-labeling pipeline starts with searching for successive exposures of the same field. We acquire the publicly available scientific observations from LCO’s Science Archive5 and filter the number of visits users requested (more than three but no more than 12). It is unlikely a CR will hit the same pixel location twice, so every three consecutive exposures are saved as a sequence into a multi-extension FITS file for alignment and CR labeling, while maintaining all the header information for future community research. For higher signal-to-noise ratio and higher CR rates, we only used images with an exposure time of 100 s or longer. We further constrained the consecutive images to be taken within the same schedule molecule, the minimal LCO scheduler unit. Images from the same molecule ensure intervals between exposures are minutes or less, which minimizes the variations in seeing conditions and PSF. We reject a sequence whose background varies over σ > 5 between frames, as they are not stable enough to robustly identify CRs.

We then reproject to align each frame in the sequence with astropy/reproject (Robitaille et al. 2019) using nearest-neighbor interpolation to ensure CRs are not distorted during resampling. Figure 1 shows an image stamp from an aligned sequence. LCO’s BANZAI (McCully et al. 2018) data reduction pipeline has bias and dark frame subtracted to remove instrument signature, allowing us to use one CR-labeling pipeline across all LCO instruments. Let I be an image in the sequence then I’s noise uncertainty σI is simplified to

\[ \sigma_I = \sqrt{|I| + N_R^2 + N_S}, \]  

where \( N_R \) is the CCD read noise, \( N_S \) is the sky background noise, which corrects for the background variation between exposures. We then approximate the median frame uncertainty \( \Sigma \) by performing median filtering at each pixel location across the uncertainties from the three frames \( I_1, I_2, \) and \( I_3 \) in order to reject the variance from the CR pixels:

\[ \Sigma = \text{median}(\sigma_{I_1}, \sigma_{I_2}, \sigma_{I_3}) / \sqrt{3}. \]  

We update each frame \( I \) with sky subtraction \( I := I - \text{median} (I) \) before calculating the median frame \( M_I \). We then define a deviation score that calculates how much each frame deviates from the median frame represented in Gaussian distribution:

\[ \text{deviation score} = \frac{|I - M_I|}{\sqrt{(\sigma_I)^2 + \Sigma^2}}. \]  

Pixel locations with a deviation score >5.0 are identified as bright CR pixels and labeled in a preliminary outlier mask. A morphological dilation of five pixels is applied to the outlier mask, and we use a lower threshold of >2.5 to include the dimmer peripheral pixels around the CRs.

A key step to acquiring the final CR mask is to remove false-positive outliers caused by PSF wings and isolated hot pixels. We perform source extraction with SEP (Barbary 2016) on the CR-free median frame to acquire a robust source catalog. We then perform windowed background estimation to include the astrophysical source pixels in an ignore mask to reject false-positive outliers from PSF wings (Howell 2006).

BANZAI provided a mask for permanent dead CCD pixels but we also noticed a very small fraction of remaining standalone hot pixels that are more likely to be Poisson noise or persistent pixels due to oversaturation in previous exposures. Thus, our last step is to reject isolated (single) hot pixel events to acquire the final CR mask. Different types of artifacts and rejected pixels, including 100 pixels ignored around CCD boundaries are coded and included in the ignore mask. Instruction on using the data pipeline, the LCO CR data set, and the ignore mask coding rules can be found in the documentation https://github.com/cy-xu/cosmic-conn.

Appendix B
Ablation Study

An ablation study helps us understand how a building block or a design choice affects a machine-learning system’s overall performance. It applies or removes a single component in a controlled experiment while holding other parameters constant. We evaluate the proposed improvements discussed in Section 3 through variant models corresponding to Figure 5 and present the quantitative results in Table 4.

The complete ablation study (combining quantitative results from Table 4 with training visualizations in Figure 5) shows applying the proposed median-weighted loss function to the baseline method improves model performance on LCO data from 89.19% to 92.98%, at the same time improves training efficiency from 2980 to 2080 epochs, which validates that the new loss function does indeed provide a better model convergence path discussed in Section 3.1.

While the median-weighted loss alone does not produce a more generic model, all variant models trained with the larger 1024 2 pixel sampling stamps demonstrated better model generality on the unseen Gemini data, especially the 1024 2 pixel + GN combination that we discussed in Section 3.2. GN alone does not improve performance but mainly contributes to

5 https://archive.lco.global/
training efficiency, which is better visualized in Figure 5 when compared with models that adopt the two-phase training.

The proposed median-weighted loss further provided the (1024^2 pixel + GN) variant model a better convergence path to produce the Cosmic-CoNN model that excels in both training efficiency (from 2980 to 380 epochs) and performance on not only LCO instruments, which were used for training (from 89.19% to 93.40%) but also Gemini instruments that were not included in training data (from 79.59% to 86.80% on 1 × 1 binning and from 84.88% to 94.37% on 2 × 2 binning) among all variant models.

The ablation study shows each of our proposed improvements affects certain aspects of the machine-learning system and their joint effect contributes to the generic and best-performing Cosmic-CoNN model suitable for the CR-detection task in ground-based astronomical data with variable conditions from multiple instruments.

**Appendix C**

**Training Details**

We implement the Cosmic-CoNN framework in PyTorch 1.6.0 (Paszke et al. 2019) with the Adam optimizer (Kingma & Ba 2014). Models for the same type of observation are trained with identical data, random seed, and hardware. We use the Nvidia Tesla v100 32GB GPU for training. The large GPU memory allows us to maximize the batch size n in each iteration. All training settings are identical unless it is clearly specified for a variant model. Scripts to reproduce our experiments are included in the source code.

For LCO imaging data, we randomly sampled and withheld 20% of the training set for validation. An initial learning rate of 0.001 was used for all models. During training, we monitor the validation loss for each model and manually decay the learning rate by 0.1 when the loss plateaus. In the ablation study, we reduce the learning rate to 0.0001 at epoch 3000 for all models. Models using group normalization adopt a fixed group = 8 for all feature layers. For the median-weighted loss we linearly scale the lower bound α from 0 to 1 over 100 epochs. We re-implemented deepCR with an identical network and adopted the two-phase training that Zhang & Bloom (2020) used to train deepCR models. The Cosmic-CoNN BN variant model also adopted the two-phase training. In order to make fair comparisons, all Cosmic-CoNN and deepCR models were carefully tuned, and the best models were used for evaluation.

The Cosmic-CoNN model and variant models with 1024^2 pixels sampling stamp size used a batch size of n = 10 in the ablation study. deepCR and its variant models adopt 256^2 pixels stamp size with n = 160 to ensure the model sees the same amount of pixels in a mini-batch. For a data set of N samples, models trained with batch size n = 10 updates \( \frac{N}{10} \) times in an epoch but models trained with n = 160 only update \( \frac{N}{160} \) times, which leads to unfair comparisons on training efficiency. We addressed this issue by sampling a subset of \( \frac{N}{10} \) samples as an epoch for models with batch size n = 10.

For HST ACS/WFC imaging data, the Cosmic-CoNN model is trained on identical data as deepCR (Zhang & Bloom 2020) but with a new PyTorch data loader that added random rotation and mirroring while sampling images. The larger GPU memory allowed us to use 256^2 pixels sampling stamp size with n = 160.

For LCO NRES spectroscopic data, the neural network is identical to the Cosmic-CoNN ground-imaging model. We used a stamp size of 1024^2 pixels with n = 8, an initial learning rate 0.0001, and manually monitor and decay the learning rate.

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**Table 4**

Cosmic-CoNN Ablation Study on LCO and Gemini Imaging Data

| Method                              | Dice score >0.85 | LCO Precision | Gemini 1 × 1 Precision | Gemini 2 × 2 Precision |
|-------------------------------------|------------------|---------------|------------------------|------------------------|
| deepCR (baseline)                   | 2980             | 89.19%        | 79.59%                 | 84.88%                 |
| deepCR + median-weighted loss       | 2080             | 92.98%        | 78.76%                 | 83.08%                 |
| deepCR + 1024^2 pixel               | n/a              | 89.35%        | 82.57%                 | 86.55%                 |
| deepCR + GN                         | 1420             | 90.82%        | 77.07%                 | 89.30%                 |
| deepCR + 1024^2 pixel + GN          | 1040             | 93.17%        | 84.54%                 | 92.09%                 |
| Cosmic-CoNN (MW loss + 1024^2 pixel + GN) | 380              | 93.40%        | 86.80%                 | 94.37%                 |

Note. All variant models are evaluated with identical validation images and the same input stamp size. We gauge training efficiency by the number of epochs a model takes to reach a Dice score >0.85 (Settens 1948) during training, corresponding to convergence curves in Figure 5. We discussed in Section 4 that precision is less sensitive to the varying CR rates between different data sets than TPR at fixed FPR, thus we measure a model’s precision at 95% recall on LCO and Gemini data to evaluate how well it generalizes to unseen data, corresponding to a model’s performance at epoch 4000 shown in Figure 5, higher is better.
