There’s no difference: Convolutional Neural Networks for transient detection without template subtraction

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ABSTRACT

We present a Convolutional Neural Network (CNN) model for the separation of astrophysical transients from image artifacts, a task known as “real-bogus” classification, that does not rely on Difference Image Analysis (DIA) which is a computationally expensive process involving image matching on small spatial scales in large volumes of data. We explore the use of CNNs to (1) automate the “real-bogus” classification, (2) reduce the computational costs of transient discovery. We compare the efficiency of two CNNs with similar architectures, one that uses “image triplets” (templates, search, and the corresponding difference image) and one that adopts a similar architecture but takes as input the template and search only. Without substantially changing the model architecture or retuning the hyperparameters to the new input, we observe only a small decrease in model efficiency (97% to 92% accuracy). We further investigate how the model that does not receive the difference image learns the required information from the template and search by exploring the saliency maps. Our work demonstrates that (1) CNNs are excellent models for “real-bogus” classification that rely exclusively on the imaging data and require no feature engineering task; (2) high-accuracy models can be built without the need to construct difference images. Since once trained, neural networks can generate predictions at minimal computational costs, we argue that future implementations of this methodology could dramatically reduce the computational costs in the detection of genuine transients in synoptic surveys like Rubin Observatory’s Legacy Survey of Space and Time by bypassing the DIA step entirely.

1 INTRODUCTION

Modern observational astronomy has shown us that the Universe is not static and immutable: to the contrary, it is a lively and dynamic system. We now know and understand a variety of different phenomena that can give rise to variations in the brightness and color of astrophysical objects, including explosive stellar death (supernovae, kilonovae, Gamma Ray Bursts, etc), less dramatic and powerful stellar variability (flares, pulsations), and variability arising from geometric effects (such as planetary transients and microlensing). The time scales for these phenomena range from seconds to years. When the variations are terminal –like supernovae– or stochastic –like stellar flares– they are referred to as “transients”. Detecting optical astrophysical transients characteristically requires sequences of images across a significant temporal baseline. Surveys like the Dark Energy Survey (The Dark Energy Survey Collaboration 2005, DES) or the future Rubin Observatory Legacy Survey of Space and Time (Ivezić et al. 2019a, LSST) search for spatially localized changes in brightness in patches of sky previously observed.

Due to the rarity of astrophysical transients, a long baseline in conjunction with the observation of a large area of the sky is typically required to detect a statistically significant sample of transients like supernovae and individual examples of rare events, such as kilonovae. The process itself is arduous and requires considerable human intervention at multiple stages. The first step is typically the creation of high quality templates of each region of the sky that is to be searched; the templates are then subtracted from nightly images, a process known in astrophysics as Difference Image Analysis (DIA) that was initially pioneered by Tomaney & Crotts (1996) and then formalized by Alard & Lupton (1998) and there is a rich history of subsequent improvements in the efficiency and accuracy of DIA models. Templates (tmpl) are typically constructed as stacks of high quality (favorable observing conditions) sky images. These high quality images must then be aligned with the “today” image, typically called the “search image” (srch), and degraded to match its Point Spread Function (PSF, which we note may vary across a single large field of view image) and scaled to match its brightness. The
product generated by the subtraction of the template from the search image is the so-called “difference image” (diff; see for example a description of the DIA processing pipeline for DES in Kessler et al. 2015. Transients can then be detected as clusters of adjacent pixels deviating significantly from the sky noise. However, even the best existing DIA algorithms produce difference images with large pixel value deviation from an ideal 0-average that would be expected if no changes occurred in a patch of sky. Transients, variable stars, and moving objects will result in detections, but also a typically large number of artifacts will be detected by these thresholding schemes. 

Machine learning models offer an excellent opportunity to improve the efficiency of transient detection at this stage, automating the classification between “real” astrophysical transients and “ bogus” artifacts: these models are often referred to as “Real-Bogus” (hereafter, RB). Generally, the applications of machine learning to this problem are based on the extraction of features from the (difference) images that are then fed to models like Random Forests, k-Nearest Neighbors, or Support Vector Machines (Goldstein et al. 2015; Sánchez et al. 2019; Mong et al. 2020). These models have achieved high accuracy and enabled the discovery of transients at scale in larger synoptic surveys, for example in the Palomar Transient Factory (PTF Bloom et al. 2012) and Zwicky Transient Facility (ZTF Mahabal et al. 2019).

The process of engineering features for machine learning models allows the experts to embed domain knowledge in models. In the case of RB classification, the features engineered to be used by models such as the ones described above usually rely on visual inspection of a subset of the data. However, these features may overlook abstract associations between image properties that can be effective for classification, and in fact, may be biased towards human perception and theoretical expectations. An alternative approach involves the use of models that can learn features directly from the data, such as Convolutional Neural Networks (LeCun et al. 1989, CNNs). Here, it is possible to train a model using the images themselves, skipping the step of feature-design entirely.

RB CNN-based models appeared in the literature as early as 2017 (Gieske et al. 2017), and they are typically based on the analysis of the difference images arising from the DIA. While neural networks may be computationally demanding in the training phase, the “feed-forward” classification that arises from a pre-trained model is typically rapid and computationally light,\(^1\) leaving DIA as the computational bottle-neck in the process of astrophysical transients’ detection. Yet in principle, the entirety of the information content embedded in the diff-tmpl-srch image triplet is also contained in the tmpl-srch image pair. In this paper, we explore the use of CNNs as RB models concentrating on the potential for building high-accuracy models that do not require the construction of difference images.

This paper represents a first step in the process of conceptualizing a DIA-free model for astrophysical transients. Here we demonstrate the potential for a model that discriminates between astrophysical transients and artifacts, while still relying on DIA for detection. In future work we intend to develop models that will not rely on DIA for detection, and, finally, that will detect and characterize transients (measure magnitude) from the tmpl-srch image pair only.

This paper is organized as follows: in section 1, the introduction, we briefly describe DIA process, examples of architectures, and input images for CNNs models on the literature and describe the importance of our work. In section 2 we discuss the history, approaches, and details of DIA in the literature. In section 3 we present the DES data that we will use to build our RB classification models and the pre-processing steps. In section 4 we presented some general aspects of CNN and illustrate the CNN architectures used, in subsection 4.3 we present, share and discuss in some insights into the model obtained enabled by saliency maps, as well as the method used to interpret the data decisions through saliency maps. In section 3 we show the results of building a model that does not use the difference image as input, named noDIA-based model and compare its performance to one that does, named DIA-based model; we outline future work in section 6 and we conclude with a discussion of the broader implications for this result in light of upcoming surveys.

This study is reproducible and all the code that supports the analysis presented here is available on a dedicated GitHub repository.\(^2\)

2 STATE OF THE ART AND TRADITIONAL SOLUTIONS TO DETECTION OF TRANSIENTS

2.1 Difference Imaging

Difference images produced subtracting a template generated coadding multiple images (e.g. Kessler et al. 2015) from a sky image are currently the basis for most astrophysical transient search algorithms. The difference image allows brightness changes to be detected even if embedded in Galaxy light, for example, in the case of extra-galactic explosive transients. Great efforts have been made to improve the quality and effectiveness of the difference images. Although the name may suggest the process simply entails subtracting images from each other, the procedure is in fact riddled with complications because of the following reasons. First, the images used to build the template and the search images are taken principally within different atmospheric conditions (Zackay & Ofek 2017) generating variations in the quality of the images. The construction of a proper template is also a delicate task; typically templates are built by stacking tens of images taken under favourable sky conditions at different times. This improves the image quality but also mitigates issues related to variability in the astrophysical objects captured in the image (Hambleton et al. 2020): one wants to capture each variable source at its representative brightness. Typically then, the template image is of higher quality than the search image, and it is degraded to match the search image PSF and scaled to match its brightness. Yet, the scaling and PSF may vary locally in the image plane, especially for images from large field of view synoptic surveys such as the 2.2 sq. degrees DES or ~ 10 sq. degrees Rubin images. Finally it is important that the images are perfectly aligned, both in the creation of the template and in the subtraction process to create the difference image. This implies accounting for rotation as well as potentially different warping effects on the images and template. Once the PSF match and the alignment is done, it is possible to subtract the degraded template from the search images to obtain the difference image. To degrade the image quality of the template to match the search image, a convolution kernel that must be applied to the template needs to be determined (Alard & Lupton 1998),

\[
\text{tmpl}(x, y) \otimes \text{Kernel}(u, v) = \text{srch}(x, y),
\]

1 although the model may require a large amount of memory to cache.

2 https://github.com/taceroc/DIA_noDIA.
Figure 1. Example of four DIA-sets from the first season of the Dark Energy Survey (DES): from left to right the images correspond to the template (tmpl), search (srch), and difference (diff) image; the diff is generated as the subtraction of tmpl and srch. Each pair of tmpl and srch images is mapped to the same color range. We refer to these 3-images sets as “image triplets” or DIA-sets. A and B show artifacts, human-labeled as “bogus” (label = 1). C and D show transients labeled as “real” (label = 0). Above each triplet is the unique ID of the transient (see Goldstein et al. 2015).

where tmpl is the high-quality image, the template image, srch is the one night image or search image and ⊙ is the convolutional operation. The arguments x and y represent the coordinates of matrix that compose the images; u and v the coordinates of the kernel matrix.

To solve the computationally expensive problem of matching PSFs, the kernel can be decomposed in terms of simple functions, for instance Gaussian functions, and the method of least squares can be used to determine the best values for the kernel. The fitted solution of one search image can be determined in a short computational time. However, the computational cost scales with the image size and resolution. Surveys and telescopes constructed with the goal of discovering new transients are generally designed to collect tremendous amount of data to maximize event rate (detection of astrophysical transients). For the DES, the computational cost per 2.2 sq. degree image ~ 15.5 CPU hours (with roughly 2/3 of that time spent on PSF matching). The upcoming Rubin LSST will collect more than 500 images every night each with 3.2 Gigapixels. This process thus is bound to turn out to be very expensive. In this paper, we trained our models on postage stamps where transients were detected or simulated (see section 3), thus a direct comparison of the computational cost is not trivial. A detailed discussion of the computational cost of our models is included in subsection 5.2 and the CPU Node hours required to train and generate predictions from our models are reported in Table 1. We note here that, with a Deep Neural Network approach to this problem, the computational cost is high in training, but the predictions are essentially instantaneous.

A bad subtraction can occur either because of poor PSF matching, poor alignment, or poor correction of image warping. In all of these cases, the subtraction would lead to artifacts or “bogus” alerts, like the one show in the difference image in Figure 1A and B. In particular: in Figure 1A, the difference image shows a so-called “dipole”, where one side of a suspected transient is dark and the other side bright: this typically arises in case of mis-alignments, but it might also be caused by moving objects in the field, or differential chromatic refraction (Carrasco-Davis et al. 2021). Conversely, Figure 1B shows a “bogus” alert caused by an image artifact: a column of bad pixels in the search image. At this location there is no astrophysical object in the image thumbnail: no host galaxy or star that could give rise to variations.

Panels Figure 1C and Figure 1D show genuine transients in our DES training data: in both of these two examples, there is a clear transient in the diff images (high pixel values at the center of the image).

2.2 Autoscan and other feature-based Real Bogus models

We developed our models on data collected in the first year of DES. Thus, a direct precursor of our work is Goldstein et al. (2015), in which the authors created an automated RB based on a Random Forest (RF) supervised learning model (Ho 1995) to detect transients,
Figure 2. Histogram of pixel values for the data shown in Figure 1 (before scaling and normalization). While all difference images (right) show bell-shaped distribution, the template and search image in both “bogus” and “real” sets have different behaviours. For example, B and D have similar pixel values distribution, however, B is “bogus” and D is “real”. The vertical lines show the $\mu \pm 3\sigma$ interval for the srch and tmpl images. The diff images (last right column) are standardized individually to a mean of 0 and a standard deviation of 1. The srch and tmpl are instead scaled, setting the pixel contained inside the $3\sigma$ interval (vertical lines on the histograms) to the range 0-1. This allows to retain negative values or as well values above 1 while keeping the core of the distributions to within a homogeneous range.

and particularly supernovae, in the DES data, hereafter referred to as autoscan. For these kinds of models, the process of selecting and engineering features is pivotal. Autoscan is based on 38 features derived from the diff, srch and tmpl images. The selection and computation of these features was done attempting to represent quantitatively what humans would leverage in visual inspections. For instance, $r_{aper_psf}$ distinguishes a bad subtraction of srch and tmpl that would lead to a diff qualitative similar to Figure 1A; the feature $diffsum$ measures the significance of the detection by summing the pixel values in the center of the diff image; the feature colmeds, indicating the CCD used for the detection, is designed to identify artifacts specific of a CCD, like bad rows/columns of pixels.

In other RB models, like in Sánchez et al. (2019), the feature selection is performed purely statistically: features were initially selected based on variance thresholds. In the same work, different techniques are explored to reduce the number of features, and thus the complexity of the classification problem. For example, a RF model was trained using all features. Then, feature values were randomly modified and the performance on the “new” data set was analyzed. Decreased accuracy associated to a change of a feature measured the importance of the feature that was modified. In this way the authors reduced the dimensionality of the problem by removing possible redundant or irrelevant information. Examples of models based on features closer to the data include Mong et al. (2020), where the features are simply the flux values of the pixels around the center of the image.

2.3 AI approach

CNNs have demonstrated enormous potential in image analysis including object detection, recognition, and classification across domains (Deng et al. 2009). Examples of astrophysics applications of CNNs include Dieleman et al. (2015) for galaxy morphology prediction, Kim & Brunner (2016) for star-galaxy classification, Gabbard et al. (2018) for signal/background separation for Gravitational Waves (GW) searches, where the GW time series are purposefully encoded as images to be analyzed by a CNN, and many more.

CNNs are particularly well-suited to learning discriminating features from image input data. CNNs can work on high dimen-

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Figure 3. Horizontally stacked data for the examples shown in Figure 1. On the left, the composite images used as input to the DIA-based CNN model: the composite follows the order, from left to right: diff, srch, tmpl. On the right, the composite images used for the noDIA model, composed of srch and tmpl. Each images element was scaled or normalized following the description given in section 3 and Figure 2 before combining them into a single image. Above each composite are the unique transient “ID”, the original label, and prediction made by our model. The four transients were classify correctly by both DIA-based and noDIA models. Purple shades indicate negative and green positive pixel values.

sional spaces (here the dimensionality of the input is as large as the number of pixels in the image) due to the generalizability of the convolution operation to \( n \) dimensions while preserving relative position information. Vectors of raw pixel values can theoretically be used to train traditionally feature-based models, such as RFs, but pixel-to-pixel position data in higher dimensions is unequivocally lost. Previous studies already compared feature-based supervised models, like RF, and supervised CNNs for RB, demonstrating that CNN generally leads to increased accuracy. In Gieseke et al. (2017) an accuracy of \( \sim 0.984 \) is achieved with a RF model in the RB task, and it increases to \( \sim 0.990 \) when applying a CNNs to the same data. In Cabrera-Vives et al. (2016) an accuracy of \( \sim 0.9889 \) is achieved with a RF that increases to \( \sim 0.9932 \) with a CNN. In Cabrera-Vives et al. (2017), an RF gave 0.9896 and a CNN 0.9945. In Liu et al. (2019) the accuracy improves from \( \sim 0.9623 \) with a RF to \( \sim 0.9948 \) with a CNN.

Beyond RB, a model for image-based transient classification through CNNs has been prototyped by the Automatic Learning for the Rapid Classification of Events team (ALeRCE Carrasco-Davis et al. 2021). The model classifies between AGNs (Active Galactic Nuclei), SNe (SuperNovae), variable stars, asteroids, and artifacts in The Zwicky Transient Factory (Bellm et al. 2018, ZTF) survey data with a reported accuracy exceeding 95% for all types, except SNe (87%). This CNN model was trained using a combination of the srch, tmpl, and diff.

The problem we propose to address here is exclusively the RB classification, but we explore the potential of leveraging AI to bypass the DIA step. Existing CNN RB models differ not only in their architecture (for example, a single or multiple sequences of convolutional, pooling, dropout, and dense layers) but also in the choice of input. For instance, Gieseke et al. (2017) used the tmpl, srch, and diff images in combination for training their CNN; Cabrera-Vives et al. (2016) augmented this image set with an image generated as the diff divided by an estimate of the local noise; Cabrera-Vives et al. (2017) trained an ensemble of CNNs on different rotations of this four-fold image set. Conversely, Liu et al. (2019) used the diff as the sole input. Although, all these attempts have shown good results with accuracy higher than 90%, these models all rely on DIA to construct the diff. Taking into account that diff are built from the tmpl and srch, and in principle, should carry no additional information content than the search-template pair alone, a logical step to follow would be to only consider the two latter images.

A first attempt in this direction is presented in Wardega et al. (2020). Wardega et al. (2020) trained a model that could distinguish between optical transient and artifacts using a search image from Dr. Cristina V. Torres Memorial Astronomical Observatory (CTMO, a facility of the University of Texas Rio Grande Valley\(^3\)) and a template image from the Sloan Digital Sky Survey (Gunn et al. 2017).
They trained two Artificial Neural Network models, a CNN and a Dense Layer Network on simulated data and tested the models using data from CTMO and SDSS. The data used for training and testing had specific characteristics: transients were a combination of a source in the CTMO images (or \texttt{src}) and background in the SDSS image (or \texttt{tmpl}); artifacts were a combination of a source in both the CTMO and SDSS images.

Within this dataset, both models yield high accuracy (\(>95\%\)) and establish a precedent for the possibility of avoiding the construction of the \texttt{diff} to reliably detect optical transients. However, studies based on more diverse and realistic data, e.g., sources near galaxies, or embedded in clusters, are needed to demonstrate the feasibility of this approach. The data used in this paper fulfills this condition and is described in section 3.

### 3 DATA

This study is designed as a detailed comparison of CNN-based models, with and without \texttt{diff} in input, with the results from one RB model, \texttt{autoscan} (Goldstein et al. 2015). The choice of \texttt{autoscan} as our point of reference is motivated by its application to the discovery of transients in a state of the art facility, the Dark Energy Survey (The Dark Energy Survey Collaboration 2005), which can be considered a precursor of upcoming surveys like the Rubin Legacy Survey of Space and Time (Ivezic et al. 2019b). The latter, expected to start in 2024, will deliver \(\sim 20\) Tb of high resolution sky image data each night, covering a footprint of \(\sim 20,000\) sq. deg. every 3 nights, with expected millions of transients per night, demanding rapid methodological and technical advances in accuracy and efficacy of transient detection models.

The data used in this work consists of postage stamps of images collected by the DES during its first observational season (Y1), August 2013 through February 2014\(^4\) (Abbott et al. 2018). The data corresponds to 898,963 DIA-sets, a template (\texttt{tmpl}) image, search (\texttt{src}) image, and their difference (\texttt{diff}). The construction of the templates images for the DES Y1 leveraged the data collected in season two (Y2) as well as the Science Verification images (observations collected prior to survey start in order to evaluate the performance of the instrument). More information on the DES DIA pipeline can be found in (Kessler et al. 2015). Of these DIA sets, 454,092 contain simulated SNe Ia, which constitute the “real” astrophysical transients set (\texttt{label} = 0) and 444,871 are the actual data from DES, i.e., the “bogus” set (\texttt{label} = 1). Each image is offered in two formats: “.gif”, and “.fits”. The former is an 8-bit compressed format (convenient for visual inspection as it can be opened with commonly available software); the latter, the “Flexible Image Transport System”, is a common data format for astronomical data sets which enables high precision with a large dynamic range. The data in “.fits” format was used in this work.\(^5\) Each image is \(51 \times 51\) pixels - corresponding to approx 0.26 arcseconds square of sky.

Some examples of the data are in Figure 1. Each transient is identified by a unique “ID”. The metadata, includes the labels associated with each image as well as the 38 features used for classification in Goldstein et al. (2015). Because we only analyze postage stamps with detections, we implicitly still rely on the DIA to enable the detection step at this stage of our work. The \texttt{tmpl} and \texttt{diff} image in our postage stamps, however, are not PSF matched.

### 3.1 Scaling and normalization

A word about data preparation and normalization is in order as astrophysical images are inherently very different from the images upon which CNNs have been built. When training CNN models for image analysis, each image is typically simply scaled to a common range \((0–1)\). However, the dynamic range of an astrophysical image is typically large and the distribution of pixel values is generally very different from Gaussian, with the majority of pixels sitting at low values (the sky) and a few pixels at or near saturation (which in some cases may carry the majority of the information content). Furthermore, in the DIA-set case, the pixel-value distribution of the \texttt{diff} differs qualitatively from the \texttt{tmpl} and \texttt{src} ones. While the \texttt{tmpl} and \texttt{src} are naturally positive valued with a long tail at the bright end (right-skewed because of the presence of bright astrophysical sources such as galaxies that host transients or stars that vary), the \texttt{diff} image is, in absence of variable or transient sources, symmetric around 0.

The \texttt{diff} images were standardized to have a mean \(\mu = 0\) and a standard deviation \(\sigma = 1\). The \texttt{src} and \texttt{tmpl} images, instead, were scaled to the \(\mu \pm 3\sigma\) interval of the original image to \(0–1\). This scheme allows us to retain resolution in the shape of the core of the distribution while also retaining extreme pixel values. Figure 2 shows the distribution of pixel values for four DIA sets, for the same data as in Figure 1, which include two “real” and two “bogus” labels. Appendix A shows the pixel distributions before and after scaling for the same data.

One further decision has to be made in combining the three images in the DIA set to feed them to the CNN. We stacked the scaled \texttt{diff}, \texttt{src} and \texttt{tmpl} horizontally. Thus the size of the data in input to our CNN is \(N_{tr} \times 51 \times 153\), where \(N_{tr}\) is the number of transients to be considered. Four examples of the data “triplets” in input to our DIA-based CNN are in the left panel of Figure 3. Following this horizontal structure, we mimic closely the way that human scanned this type of data for classification, and we will take advantage of this scheme when examining the models’ decisions in subsection 4.3, although stacking the images along a third depth axis has also been tested, with no differences in the model accuracy.

But our goal is to test the performance of models that do not use the DIA. Thus for our \texttt{noDIA} models the training and testing data set were constructed in the same way as the previous triplets, but without the \texttt{diff} image. Some examples are in the right panel of Figure 3.

### 4 METHODOLOGY

#### 4.1 Basics of Neural Networks

Neural Networks are models that learn important features and feature associations directly from data. These are typically supervised learning models used for classification or regression. They consist of a series of layers of linear combinations of the input data each with real value parameters known as weights and biases, combined with activation functions that enable learning \textit{non-linear}, potentially very complex, relationships in the data. The weights tell us the relevance of the input feature with respect to the output, and the biases are the threshold value that determine the output. Fitting these quantities to the data minimizes the loss, meaning the prediction is

\(^{4}\) The data can be found in https://portal.nersc.gov/project/dessn/autoscan/#

\(^{5}\) More information related to how to manipulate this astronomical data format is available in https://docs.astropy.org/en/stable/io/fits/
as close as possible to the original target/label (Nielson 2015). For Deep Neural Networks (DNNs), “deep” refers to the fact that there are multiple hidden layers, besides the input and output layer. With this architecture the features learned by each layer do not follow a human selection, rather, the features arise in the analysis of the data (LeCun et al. 2015). Among DNNs, CNN models have layers that represent convolutional filters. More information on DNNs and CNNs can be found in Agarap (2018); Krizhevsky et al. (2012); Dieleman et al. (2015), as well as Gieseke et al. (2017), among many others.

We used the Keras implementation of the CNN (Chollet et al. 2015).

4.2 DIA and noDIA based models architecture

The input of our Neural Networks are the horizontally stacked images of size 51 × 153 for the DIA-based model (diff, tmpl, srch), and 51 × 102 for noDIA model (srch, tmpl). For both the DIA-based model and the noDIA model 100,000 images were used, 80,000 images for training and 20,000 for validation. The images were selected randomly from the 898, 963 and while certainly training with a larger set can lead to higher accuracy, the amount of images was sufficient for this comparison of DIA-based and noDIA models while being conservative with limited computational resource. The data is composed of 50,183 images labeled as “bogus” and 49,817 labeled as “real.”

The network architectures used for this work are shown in Figure 4, left panel, for the DIA-based model, and right panel for the noDIA model. More details about the architecture can be found in Appendix B. Both architectures follow a similar structure. In designing the neural networks, we started with the DIA-based model and developed an architecture that would match the performance of Goldstein et al. (2015). With this model in hand, we created a noDIA with a similar structure in order to enable direct comparison and measure the effect of the change in the input data. We emphasize that in the development of our models we followed two general guidelines:

(i) We pushed the accuracy of the DIA-based CNN model to match the accuracy of autoscan. While a more exhaustive architectural exploration or a hyperparameter grid search may well lead to increased efficacy, matching the accuracy of autoscan (at 97%) is sufficiently for our demonstration. We further note that this historical data set cannot be further validated (by, for example, assessing

6 https://keras.io/api/layers/convolution_layers/convolution2d/.

Figure 4. Architecture of the Neural Networks used in this project to classify “real” and “bogus” transients. Left: the DIA-based model that uses image triplets as input (diff, tmpl, srch). The input layer is 51 × 153 (see left Figure 3); a convolution layer (5 × 5) learns 16 filters; max pooling (2 × 2) and dropout; convolution (5 × 5) learns 32 filters; maximum pooling (2 × 2) and dropout; convolution (5 × 5) learns 64 filters; maximum pooling (2 × 2) and dropout; flatten layer, Dense (32) and the output is a Dense (2)-class layer. Right: the noDIA model that uses the tmpl and srch images only. The input layer is 51 × 102 (see right Figure 3); a convolution layer (7 × 7) learns 1 filter; maximum pooling (2 × 2); convolution (3 × 3) learns 16 filters; maximum pooling (2 × 2) and dropout; convolution (3 × 3) learns 32 filters; maximum pooling (2 × 2) and dropout; flatten layer, Dense (32) and the output was a Dense (2)-class layer. The illustrations were made using NN-SVG tool by LeNail (2019).

the recurrence of transients at a sky position to validate the bogus nature of a non-simulated detection) and it is subject to potential label inaccuracies that may compromise the ability to achieve a better performance. The final architecture used is one that reached the same accuracy as Goldstein et al. (2015), and False Positive and False Negative Rates most similar to the ones obtain in Goldstein et al. (2015) (see Figure 5 and section 5). Once we matched the autoscan performance, we focused on the potential for removing the diff image from the input.

(ii) While the architecture of the DIA-based CNN was designed with the attempt to achieve a specific target performance, the architecture of noDIA is deliberately kept as close as possible to that of the DIA-based model. This enables a direct comparison of the effects of the removal of the diff image. In other words, the hyperparameters and architecture of noDIA, shown on the right in Figure 4 were not optimized explicitly for RB classification, rather we chose a standard architecture, only modifying the original design to adapt for the different dimensionality of the input data. One further deliberate modification is implemented in the choice of a single-filter first layer for noDIA. The CNN that is not offered the diff image needs to learn the image PSF, which is constant across the posture stamp-size image, and can be modeled with a single filter.

4.3 Saliency maps

Saliency maps quantify the importance of each pixel of an image in input to a CNN in the training process. They provide some level of interpretability through a process akin to feature importance analysis by enabling an assessment of which are the pixels the model relies on the most for the final classification. If the task were, for example, to identify cats and dogs in images, the expectation will be to find that the most important pixels are located within the the dog or cat bodies, and not in the surrounding, while if the task were to identify activities performed by cats and dogs, one may find the important pixels both within the dogs and in the surrounding, particularly in objects associated with the performed tasks. Furthermore, some portion of the subject’s body may be most distinctive (ears, nose) and we would expect more importance being given to those pixels. The “importance”: of a pixel would be simply measured by the weight the trained NN assigns to that pixel in the case of a single-layer perceptron, but in the case of Deep Neural Networks, a highly non-linear operation is performed on the input data, and the importance, or saliency, of an input feature, or pixel, is harder to assess. We follow (Simonyan et al. 2014)’s definition of saliency: denoting the class score with $S_c$, such that the NN output

\[ S_c \]
on image $I$ is represented by $S_c(I)$, the saliency map is given by:

$$S_c(I) \approx w^T I + b,$$

$$w = \frac{\partial S_c}{\partial I} I_0.$$  \hfill (2)

That is: $w^T$ is the weight and $b$ the bias of the model. $w$ is the derivative of $S_c$ with respect to $I$ calculated specifically in the local neighborhood of pixel $I_0$, and the approximation sign indicates a first order Taylor expansion has been used to approximate the solution.

Each pixel in an image in the training set is associated with the corresponding pixel in the saliency map, and the saliency score (the importance) of that pixel measures the change in model output as a function of changes in the value of that input pixel by back-propagation. The higher the value of a pixel in a saliency map, the more influence that pixel has in the final classification. In this work we also refer to these maps as maps of pixel importance.

In our case, given the side-by-side organization of the three elements of the input image set, the saliency maps can help us assess how much the DIA-based model relied on the diff to enable correct classification, and, thus, provide some intuition in the difficulty of the challenge offered to the noDIA model.

For the DIA-based model we have an expectation guided by intuition: that a greater concentration of important pixels should be found in the diff image. In section 5, we will consider the veracity of this hypothesis both qualitatively by visually inspecting the saliency maps, and by designing a saliency-based metric that enables a quantitative approach. We calculated the normalized sum of the saliency pixel values for each third of the image-triplet, corresponding to diff, srch, tmpl:

$$I_{\text{diff}} = \frac{\sum p_d s_p}{\sum p s_p},$$

$$I_{\text{srch}} = \frac{\sum p_s s_p}{\sum p s_p},$$

$$I_{\text{tmpl}} = \frac{\sum p_t s_p}{\sum p s_p};$$ \hfill (4)

where $I$ indicated the importance of a segment of the input image, $p$ is an index running over all pixels and $s_p$ indicates the value of pixel $p$ in the saliency map. The denominator normalizes each metric by the total sum of the saliency pixel values. In the numerators, $p_d$ denotes the pixels in the leftmost third of the image, corresponding to diff; $p_s$ the middle third corresponding to the srch; and $p_t$ the right most third, corresponding to the tmpl. This metric allows us to assess the relative importance of the diff (srch or tmpl) component of the image in performing RB classification. Results from these metrics are discussed in detail in subsection 5.1.

5 RESULTS

The accuracies of our models are presented in Table 1. The DIA-based model reached, by design, the accuracy of our benchmark model autoscan: 97% on True Negative (TN) rate and 95% on True Positive (TP) rate (see section 4). We remind the reader that we use the autoscan convention for the definition of TN and TP: Positive is a “real” transient ($\text{Label} = 0$), negative is a “bogus” ($\text{Label} = 1$). There is a drop of ~4% between the accuracy of the DIA-based and the noDIA models. Along with the accuracy, in Table 1 we present computational costs of training on 20,000 images measured in CPU Node hours,\(^7\) and the clock time for the prediction for one single image.

Confusion matrices for the testing set are shown for the DIA-based model in left panel of Figure 5 and for the noDIA model in the right panel of the same figure. In this figure, as in the following confusion matrices and histograms that we will present in subsection 4.3, correct predictions are indicated in shades of blue, incorrect in shades of orange, and darker shades are associated with the true labels. The percent accuracy for each class, True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN), as well as the number of images in each class are reported within the figure.

The Receiver Operating Characteristic (ROC) curve shows the relation between the True Positive Rate (TP / (TP + FN)) also know as recall, and the False Positive Rate (FP / (FP + TN)) when changing the threshold value (e.g., a threshold of 0.5 will indicated that values greater than 0.5 would be classified as “bogus”). The ROC for the testing data for the DIA-based and noDIA models are presented in Figure 6. The Area Under the Curve (AUC), which can be used as a comprehensive metric of the aggregated classification performance of a model (Hanley & McNeil 1983; Hernández-Orallo et al. 2012), is 0.992 and 0.973 for the DIA-based and noDIA models respectively, demonstrating good performance for both models.

The loss and the accuracy curves in the left panel of Figure 7 for the DIA-based model shows some evidence of overfitting (the validation curve flattens compared to the training curve) starting just a few epochs before training came to end of the 400-epochs; meanwhile, for the noDIA model in right Figure 7, after 700 epochs there was no visual evidence of overfitting indicating that the model is still learning generalized information from the data; yet the accuracy improvements from epoch 400 to 700 were small.

The nature of the noDIA model leads to hypothesize that because the input data contains less information, this model takes longer to learn features from the data to be able to classify them. The noDIA model took in fact longer (more epochs) to come to stable accuracy and loss values. The loss and accuracy curves are also noisier for the validation of the noDIA model in right Figure 7 compared to the DIA-based model. This also can be explained with the same argument: the noDIA model had a harder problem to solve and its learning is less linear. We cannot however rule out, and in fact we suspect, that the hyperparameters or the architecture selected for the noDIA CNN model could be improved — as this is a proof of concept paper and the architecture was chosen to enable

\(^7\) The computational cost was calculated by using the formula given in https://docs.nersc.gov/jobs/policy/ and the allocations information given by the system Iris https://iris.nersc.gov. Training time is reported in CPU hours. Prediction time is reported per “postage stamp” (1ms) and the classification operation is trivially parallelizable (can be run independently on each postage stamp).

| Model     | Accuracy Train | Test | Train time\(^1\) (CPU hours) | Prediction\(^1\) (Clock-time, ms) |
|-----------|----------------|------|-----------------------------|---------------------------------|
| DIA-based | 0.962          | 0.9599±0.004 | ~35                          | 1.00 ± 0.03                     |
| noDIA     | 0.915          | 0.916±0.007  | ~56                          | 0.30 ± 0.01                     |

\(1\) Table 1. Comparative table of the accuracy and computational cost for both training and testing data for the DIA-based (Figure 4, left) and noDIA (Figure 4, right) models.
Figure 5. Confusion matrix (CM) for our testing data, a set composed of 10,078 objects labeled as “real” and 9,922 as “bogus”. Squares of the matrix, from the top left in the clockwise direction, indicate: True Positive (TP, label = 0, prediction = 0), False Negative (FN, label = 0, prediction = 1), True Negatives (TN, label = 1, prediction = 1), and False Positive (FP, label = 1, prediction = 0). We note that here, somewhat unusually, 0 corresponds to “real” and “positive”, and 1 to “bogus” and “negative”, as we chose to remain consistent with the original labeling of the data presented in (Goldstein et al. 2015). Left: The CM of our DIA-based model shows that from the 10,078 transients labeled as “real”, 9564 (i.e., 95%) were correctly classified and the accuracy for the TN is even higher, at 97%. Right: The CM for the noDIA model shows that of the 10,078 transients labeled as “real”, 9163 (i.e., 91%) were predicted correctly and the TN accuracy is 92%.

Figure 6. ROC curve for the 20,000 images used for testing. Blue line for the DIA-based model, the area under the curve is 0.992. Orange line, for the noDIA model, the area under the curve is 0.973. This figure is discussed in section 5.

a direct comparison with the DIA-based model, future work will include experimenting with different architectures and an extensive grid-search to optimize hyperparameters.

5.1 A peek into the model decisions through saliency maps
In subsection 3.1, we described how the importance of individual image pixels in the RB prediction performed by our models can be measured, and the design of a saliency-based metric to assess which component of the image is most important to perform the RB classification. Here we inspect the saliency maps, both visually and quantitatively through the measured values of $I_{diff}$, $I_{srch}$, and $I_{tmpl}$.
Figure 7. Loss (top) and accuracy (bottom) for both models presented in this work. Purple lines correspond to the validation data (20% or 20,000 images) and green to the training data (80% or 80,000 images). Left: results for our DIA-based model (Figure 4). Right: results for the noDIA model (Figure 4).

Figure 8. Saliency map for the four transients in Figure 1 for the DIA-based model. On the left, in grey color, the original diff, srch, and tmpl images are plotted in their natural flux scale (before normalization). On the right, the saliency map for the combined image. The intensity of a pixel color in the white-to-green scale indicates the pixel relative importance: the maps are normalized to 1 individually, such that dark green corresponds to high saliency score, with 1 corresponding to the most important pixel in the image triplet. With the side-by-side organization of the input data, these maps enable a visual understanding of the importance of each element of the combined image in the real-bogus classification. We note how in some cases (panel A) the decision is largely based on the tmpl, rather than the diff image, and in some cases all three image elements contribute similarly to the decision (panel B). This figure is discussed in more detail in subsection 4.3.
Figure 9. As Figure 8 but for the noDIA model: saliency map for the four transients in Figure 1. This figure is discussed in more detail in subsection 4.3.

In Figure 8 and Figure 9 we show the four transients we considered as examples throughout this work, the same images used in Figure 1 and Figure 3, and the corresponding saliency maps for the DIA-based model and noDIA model respectively. Figure 10 and Figure 11 report the results of Equation 4 for the objects in our training set.

Let’s start with some considerations about the saliency maps for the four image examples for the DIA-based model (Figure 8), and specifically from panels C and D were the transients were correctly predicted as “real”. We observe that the greatest concentration of important pixels for both these images is found in the left-most third of the image: $I_{diff} \cdot 0.5$ for both. We speculate, from our experience in labeling real/bogus by visual inspection and consulting with some of the human scanners that labeled the original autoscan images, that this behaviour is similar to what a human scanner would do: if in the diff image there is a clearly real transient, the scanner would not need to study in detail the srch and tmpl images.

Figure 8A and B show correctly classified “bogus” transients. In Figure 8A, a “bogus” produced likely by a moving object displaying a classical dipole, the majority of the important pixels are located in the tmpl ($I_{tmpl} \cdot 0.54$), concentrated around the location of the central source and the location where its “ghost” image is (the coordinates corresponding to the location the bright patch of pixels in the diff, but in the tmpl portion of the composite image). In Figure 8B, there is no central source and the detection is triggered by an image artifact. The important pixels are found in all three image segments and are spread around a large area of each image: the model has inspected the image in its entirety to decide the classification. Following our consideration about the similarity between the CNN and human decision process, we speculate that here too the CNN mimics closely what a human scanner would do: because there is not a clear central source (a “real” object) in the diff, the scanner would analyze the srch and tmpl images to extract more information from the context to enable a classification. However, it should be noted that no quantitative studies of the features the human scanners use to classify transients has been done, thus this remains simply an intriguing suggestion.

For the case of the noDIA model, the expectation was less clear: both the srch and the tmpl images are necessary to “reconstruct” the information contained in the diff, and while the pixels overlapping with the central transient are obviously expected to be important, the pixels that surround it are necessary to essentially reproduce the scaling and PSF-matching operations between tmpl and srch that the DIA performs. Accordingly, the saliency maps presented in
For the incorrect “real” and correct “bogus” classifications 76% of the cases were principally based on the portion of the input image for the model. All four classes have qualitatively similar distributions in noDIA, with a significant fraction of observations in the second column from the left to the right and values are different in each plot and the that FP and FN histograms contain far fewer observations. On the $I_{\text{tmpl}}$ Left, for the DIA-based model, the TP classification shows a preference for the diff images and the distribution peaks at $I_{\text{diff}} \sim 0.5$. For TN, however, small $I_{\text{diff}}$ values are more common, with a significant fraction of observations in the $0 < I_{\text{diff}} < 0.33$ region. This behavior is complemented by a long $I_{\text{tmpl}}$ tail in the TN distribution ($0.4 < I_{\text{tmpl}} < 0.8$). The FP and FN distributions are qualitatively similar to the TP and TN, but noisier, as they contain fewer than 10% of the objects. Right: noDIA model. All four classes have qualitatively similar distributions in $I_{\text{tmpl}}$ and $I_{\text{srch}}$. Classifications rely mostly on the tmpl in all cases ($I_{\text{tmpl}} > 0.5$).
Figure 9 are more difficult to interpret: in all four cases, important pixels are found all over the composite images.

To explore how the choice of important pixels may depend on the image label and on the correct classification we report the fraction of images for which the \( \text{diff} (\text{srch}, \text{tmpl}) \) is the dominant source of important pixels within the confusion matrix in Figure 10. To do this, we use a rough but intuitive cutoff: if the normalized sum of the saliency pixels in a third of the image is larger than \( \frac{1}{3} \), then we deduce that the model principally used that component for its decision. For example, where \( I_{\text{diff}} > 0.33 \), we conclude that the model principally relied on \( \text{diff} \) to make the RB classification.

With this cut-off we can assess if there are differences in the model behavior when classifying objects as a function of their labels or their classification. In all four cases (all combinations of “real” and “bogus” label and prediction) the concentration of important pixels is largest in the portion of the image corresponding to the \( \text{diff} \) in the \( \text{DIA-based} \) model. It is however interesting to note that, in order to correctly classify the “bogus”, the \( \text{DIA-based} \) model uses the template and search image more heavily than in all other cases (\( \text{diff}, \text{srch}, \text{tmpl} = 61\%, 12\%, 27\% \) for TN, while \( I_{\text{diff}} > 85\% \) for TP, FP, and FN).

The cut-off method described above does not allow us to distinguish between cases where multiple sections of the images were used jointly, perhaps with similar importance, from cases where the model truly only relied on one section of the image. For that, we take a closer look at the distribution of saliency values. In Figure 11 we show the distribution of values of the three metrics defined in Equation 4 for each of the four cases: TP and TN, in shades of blue, FP and FN, in shades of orange, following the color-scheme adopted in Figure 5 and Figure 10. For the \( \text{DIA-based} \) model (the two leftmost columns), for the majority of the 20,000 images in the training set \( I_{\text{diff}} > 0.33 \), but there is a secondary pick in the \( I_{\text{diff}} \) distribution near \( I_{\text{diff}} < 0.1 \) populated entirely by TN cases, complementary to a long right tail in the \( I_{\text{tmpl}} \) distribution (\( I_{\text{tmpl}} > 0.4 \)). This confirms that the correct classification in the presence of real transients relies on \( \text{diff} \), but \( \text{tmpl} \) and \( \text{srch} \) become important to correctly classify bogus transients, just like we had seen in the exemplary cases in Figure 8. We note also that the general shape of each distribution (\( I_{\text{diff}}, I_{\text{srch}}, I_{\text{tmpl}} \)) is similar for the TP and TN case (blue) and for the FP and FN cases (orange).

For the \( \text{noDIA} \) model the important pixels are concentrated in the \( \text{tmpl} \) for most images (\( I_{\text{tmpl}} > 0.5 \)) for both correct and incorrect classifications. This is somewhat counter-intuitive since the \( \text{tmpl} \) does not contain the transient itself! However, one may speculate that this is because the \( \text{tmpl} \), a higher quality image, contains more accurate information about the context in which the transient arises: e.g., if it is located near a galaxy or not. This information is important to the classification. It is also interesting to note that for the transients predicted as “real” in both TP and FP, the fraction of images that leveraged primarily the \( \text{tmpl} \) is approximately 2/3, and for images predicted as “bogus”, in both TN and FN, it is approximately 3/4.

To help guide the interpretation of the saliency maps, a few more maps are plotted in Appendix C. Where we provide 6 examples per each class of the confusion matrix, for both the \( \text{DIA-based} \) and the \( \text{noDIA} \) models.

5.2 Computational cost of our models

The computational cost of our models, reported in CPU Node hours in Table 1, confirms that while training a CNN model for RB can be computationally expensive, and significantly more so if the \( \text{diff} \) is not used in input (\( \text{noDIA} \)), the model prediction is instantaneous. Using a NN-based platform, the computational costs are front-loaded. In transient detection this could mean that the observation-to-transient discovery process is instantaneous, while computation time can be spent during off-sky hours (principally to build templates). Furthermore, while the training time is longer for the \( \text{noDIA} \) model than for the model that uses the \( \text{diff} \) in input (\( \text{DIA-based} \)) the computational cost of the forward-pass (prediction) scales superlinearly with the size of the feature set (pixels), so that our \( \text{noDIA} \) model takes less than half the time than the \( \text{DIA-based} \) one to perform the RB task. With a clock time of 0.3 ms per 51x51 pixels postage stamp, predicting over the full DES focal plane would take ~ 1 minute. However, we note that at this stage of our work we still rely on the DIA in several ways: while the \( \text{tmpl} \) and \( \text{srch} \) in input to \( \text{noDIA} \) are not PSF matched, this proof of concept is performed on transients that were detected in \( \text{diff} \) images, and we leverage the alignment of \( \text{tmpl} \) and \( \text{srch} \) and centering of the postage stamp that arose from the DIA (see section 6). Conversely, predictions would only need to be done in correspondence of the sources detected in the \( \text{tmpl} \) and \( \text{srch} \) images, and not for the entire CCD plane.

6 FUTURE WORK AND LIMITATION OF THIS WORK

This work is targeted to the investigation of CNN RB model performance, with and without \( \text{diff} \) in input, on a single data set, the same dataset upon which the development of the random-forest-based autoscan was based (see section 3). This approach enables a straightforward comparison, but it comports some limitations.

The labels in our data set come from simulations of SNe (\( \text{label} = 0 \)) and visual inspection that classifies artifacts and moving objects (\( \text{label} = 1 \)). We reserve to future work the investigation of the efficacy of the model on transients of different nature, including quasars (QSOs), strong lensed systems, Tidal Disruption Events (TDEs), and supernovae of different types. These transients may have characteristically different associations with the host galaxy, including preferences for different galaxy types and locations with respect to the galaxy center, compared to the simulated SNe events in our training set.

Specifically thinking of Rubin LSST data, an additional source of variability may be introduced by Differential Chromatic Refraction effects (Abbott et al. 2018; Richards et al. 2018), or stars with significant proper motion which, due to exquisite image quality of the Rubin images, would be detectable effects.

While we demonstrated CNN model’s potential in the detection of transients without DIA, we did not address the question of completeness as a function of \( \text{srch} \) or \( \text{tmpl} \) depth or the potential for performing accurate photometry without DIA.

Improvements in the \( \text{noDIA} \) model performance could be achieved by considering alternative network architectures, more training epochs, tuned hyperparameters, etc., and we leave these tasks as future work beyond the proof-of-concept presented here.

Finally, we note that our models did in fact implicitly leverage some of the information generated by the DIA even when they did not use the \( \text{diff} \) image itself as input. First, the \( \text{tmpl} \) and \( \text{srch} \) images are de-warped. Since the transient alerts are generated from aligned DIA images, the transient source is always located at the image center in our data. We use postage stamps that were, however, not PSF matched or scaled to match the template brightness. To move beyond a proof-of-concept, in future work we will re-train and apply our models to images whose alignment does not depend on the existence of a transient.
7 CONCLUSIONS

In this work, we have demonstrated that high-accuracy models for classifying true astrophysical transients from artifacts and moving objects (a task generally known as “real-bogus”) can be built without leveraging the results of a difference image analysis (DIA) pipeline that constructs a “template-subtracted” image.

Starting from the Dark Energy Survey dataset that supported the creation of the well known real-bogus autoscan model (Goldstein et al. 2015), we first built a CNN-based model, dubbed DIA-based, that uses a sky template (tmpl), a nightly image (srch), and a template-subtracted version of the nightly image (diff) that performs real-bogus classification at the level of state-of-the art models. Our DIA-based model reaches a state-of-the art 97% accuracy in the bogus classification with an Area-Under-the-Curve of 0.992 and does not require human decision in the feature engineering or extraction phase.

We then created noDIA, a model which uses only the tmpl and srch images and can extract information that enables the identification of bogus transients with 92% accuracy even with a naïve model architecture that, to enable a direct comparison, is purposefully designed to be minimally different from our high accuracy DIA-based model.

We further investigated what information enables the real-bogus classification in both the DIA-based and noDIA models and demonstrated that a CNN trained with the DIA output primarily uses the information in the diff image to make the final classification, and that the model examines a diff-srch-tmpl image-set fundamentally differently in the cases where there is a transient, than in the cases where there is not one. The noDIA model, conversely, takes a more comprehensive look at both tmpl and srch images, but relies primarily on tmpl to enable the reconstruction of the information found in the diff.

Implementation of this methodology in future surveys could reduce the time and computational cost required for classifying transients by entirely omitting the construction of the difference images.
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TAC: Prepared the data, conducted the analysis, created and maintains the machine learning models, wrote the manuscript. FBB: Advised on data selection, curation, and preparation, selection and design, revised the manuscript. GD: Advised on data preparation and model selection and design, revised the manuscript. MS: Advised on data selection, shared knowledge about the compilation and curation of the original dataset, revised the manuscript. HQ: Advised on data preparation and model design, revised the manuscript.

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9 DATA AVAILABILITY

The data underlying this article are available in https://portal.nersc.gov/project/dessn/autoscan/#tdata, and explain in more detail in Goldstein et al. (2015).

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Figure A1. Violin plot of pixel values inside the $\mu \pm 3\sigma$ interval for srch and temp image of the data shown in Figure 1 (before normalization). These values were scaled between 0 and 1. Left and right curve correspond to srch and temp distribution of values respectively. The distribution of values correspond to the same shown in Figure 2 for srch and temp, the green and purple colors has its correspondence to Figure 2.

Figure A2. Violin plot of pixel values for srch and temp image of the data shown in Figure 1 (after normalization). Values between the vertical lines in 0 and 1 were mapped to the values in Figure A1. Negative values and above 1 correspond to the scaled values outside the $3\sigma$ clip.

APPENDIX A: SCALING ASTROPHYSICAL IMAGES FOR INPUT TO NEURAL NETWORKS

To visualize and compare the behaviour of the flux of the srch and tmpl images, the value distribution for the four transients presented in Figure 1 is shown as a violin plot in Figure A1. The first transient on the left is labeled as “bogus”, the srch distribution pixel values are in general greater, positive and non-zero center than the values for tmpl, the same behaviour is observed to the last transient on the right, but this one is labeled as “real”. This same comparison can be applied to the transients plotted on the middle of Figure A1, both show similar distributions, however one is “bogus” and the other is “real”. For the four transients presented the pixel values have long tails, outside the $\mu \pm 3\sigma$ values. The scaling of the srch and tmpl images for the four transients, according to the description given in subsection 3.1 is visualized in Figure A2.
APPENDIX B: DETAILED ARCHITECTURE OF DIA-based AND noDIA MODELS

We designed a network of 12 layers using tensorflow.keras in python, for the DIA-based case as follows:

```python
layer1 = keras.layers.Conv2D(16, kernel_size=(5, 5), padding="valid", activation="relu",
    input_shape=(51,153,1))
layer2 = keras.layers.MaxPooling2D((2, 2), strides=2)
layer3 = keras.layers.Dropout(0.4)
layer4 = keras.layers.Conv2D(32, kernel_size=(5, 5), padding="valid", activation="relu")
layer5 = keras.layers.MaxPooling2D((2, 2), strides=2)
layer6 = keras.layers.Dropout(0.4)
layer7 = keras.layers.Conv2D(64, kernel_size=(5, 5), padding="valid", activation="relu")
layer8 = keras.layers.MaxPooling2D((2, 2), strides=2)
layer9 = keras.layers.Dropout(0.4)
layer10 = keras.layers.Flatten()
layer11 = keras.layers.Dense(32, activation="relu")
layer12 = keras.layers.Dense(2, activation="softmax")
```

and a network of 11 layers using tensorflow.keras in python, for the noDIA case as follows:

```python
layer1 = keras.layers.Conv2D(1, kernel_size=(7, 7), padding="valid", activation="relu",
    input_shape=(51,102,1))
layer2 = keras.layers.MaxPooling2D((2, 2), strides=2)
layer3 = keras.layers.Conv2D(16, kernel_size=(3, 3), padding="valid", activation="relu")
layer4 = keras.layers.MaxPooling2D((2, 2), strides=2)
layer5 = keras.layers.Dropout(0.4)
layer6 = keras.layers.Conv2D(32, kernel_size=(3, 3), padding="valid", activation="relu")
layer7 = keras.layers.MaxPooling2D((2, 2), strides=2)
layer8 = keras.layers.Dropout(0.4)
layer9 = keras.layers.Flatten()
layer10 = keras.layers.Dense(32, activation="relu")
layer11 = keras.layers.Dense(2, activation="softmax")
```

To compile the models we used the optimizer SGD (stochastic gradient descent) with a learning_rate=0.01 the "sparse_categorical_crossentropy" loss function and the "accuracy" metric. Our models are available in a dedicated GitHub repository.

8 https://github.com/taceroc/DIA_noDIA.
APPENDIX C: SALIENCY MAPS FOR VARIOUS TRANSIENTS

We include a series of saliency maps in the following 8 figures. Several interesting behavioral patterns can be observed. The figures are organized by model and by classification as follows: TN —Figure C1 and Figure C2—, TP —Figure C3 and Figure C4—, FN Figure C5 and Figure C6—, and FP —Figure C7 and Figure C8.

In Figure C1 and Figure C2 we include the transient’s contours overplotted onto the saliency maps for the DIA-based and noDIA model respectively to guide the reader’s eye. Notice the offset of the DIA-based model’s focus in Figure C1A with respect to the transient: the model is principally inspecting the diff and tmpl at the location corresponding to the bright patch in the diff. In Figure C1C a correctly predicted “bogus”, characterized by a very tight dipole probably arising from a poorly centered DIA, the saliency map inspect the tmpl and even seem to reproduce traditional aperture photometry, with pixel values measured at the core of the transients, and in the sky surrounding the transients, but away from the tails of the bright pixels cluster. The behavior is principally different for the same transients when they are inspected, and also correctly predicted, by the noDIA model (Figure C2): the focus of the model is in all three cases away from the transients, and shifted to the surrounding: the model is learning the transients’ context and extracting information to enable the comparison of tmpl and diff (essentially, to enable the image differencing). This behavior is generally seen throughout all examples in the following figures. In addition, for each figure we highlight potential reasons for failed predictions, and potential inaccuracies in the labeling that may lead to an artificial lowering of our measured accuracy.
Figure C1. Transients (diff-srch-tmpl) and their respective saliency map for DIA-based model True Negative predictions (correctly identified “bogus”). Contour plot of light intensity from the original images are overplotted, delineating the bright sources. In panel A: $I_{\text{diff}} \sim 0.4$; B: $I_{\text{diff}} \sim 0.69$ and C $I_{\text{tmpl}} \sim 0.42$. In panel C, the saliency for the tmpl portion of the image looks strikingly similar to the selection of pixels that is made in aperture photometry, with pixel values considered in the core of the source, ignored in a region immediately around the source, and again considered farther out to calculate the source’s background. This figure is further discussed in Appendix C.

Figure C2. The same transients (srch-tmpl) shown in Figure C1 and their respective saliency maps for noDIA model True Negatives (correctly identified “bogus”). Important pixels are found at nearly all locations in the image, rather than in a small region around the center. The model needs to learn properties of the image at large to enable a comparison of the tmpl and diff. This figure is further discussed in Appendix C.
Figure C3. Transients (diff-srch-tmpl) and their respective saliency map for DIA-based model True Positives (correctly identified “real” astrophysical transients). The important pixels are generally found in the diff portion of the image for the DIA-based model, as discussed in section 5, but there are exceptions: here we show several cases of True Positives (real transients) classifications where the component of the image that was principally leveraged by the model was the diff (the leftmost third) but two cases where the noDIA relied principally on the srch and/or tmpl (bottom two panels).
Figure C4. Transients (src-tmpl) and their respective saliency map for the noDIA model True Positives (correctly identified “real” astrophysical transients). Important pixels are found everywhere in the image, as the CNN learns how to compare the diff and tmpl taking a synoptic look at the properties of each image component.
Figure C5. Transients (diff-src-tmpl) and their respective saliency map for DIA-based model False Negatives (real transients identified as “bogus”). We remind the reader that the labels are inherited from Goldstein et al. (2015) and cannot be verified. Some level of label inaccuracy is expected. The “real” transients in this dataset are implanted supernovae onto real DES images. However, in this collection, several transient display DIA inaccuracies (row 1, 2, 4, 6 show “dipoles”, see subsection 2.1) that likely lead to the incorrect classification. Two very low signal-to-noise detections are missed (row 3 and 5) by our model. Important pixels are more commonly found in diff portion of the image. In the src saliency maps we see again that the core of the central source is used in the classification, as well as pixels that surround the source, but these two sets of important pixels are separate by it by a gap, again reminiscent of the typical aperture photometry technique (top two panels).
Figure C6. Transients (srch-tmpl) and their respective saliency map for the noDIA model False Negatives (astrophysical sources classified as “bogus”). In all cases but row 5 it is not clear why the classification fails. In row 5, another source dominates the image scaling (and pre-processing) reducing the visibility of the transient (that is completely missed by human inspection). We remind the reader that the “real” transients in this dataset are implanted supernovae onto real DES images. Important pixels are found everywhere in the image, as the CNN learns how to compare the diff and tmpl taking a synoptic look at the properties of each image component.
Figure C7. Transients (diff-srch-tmpl) and their respective saliency map for DIA-based model False Positives (“bogus” predicted as “real”). We remind the reader again that the labels are inherited from Goldstein et al. (2015) and cannot be verified. Some level of label inaccuracy is expected. Bogus transients were labeled by human scanners among astrophysical images with detection. However, in this collection, we cannot verify the nature of the transient and we argue that in the cases presented here there is no obvious evidence of its “bogus” nature. Important pixels are most commonly found in the \textit{diff}, but in \textit{tmpl} and \textit{srch} we see again the CNN analyzes the central source and its surrounding, but avoiding the tail of the central source, in a way similar to traditional aperture photometry techniques.
Figure C8. Transients (srch-tmpl) and their respective saliency map for the noDIA model False Positives (“bogus” classified as “real”). Important pixels are found everywhere in the image, as the CNN learns how to compare the diff and tmpl taking a synoptic look at the properties of each image component.