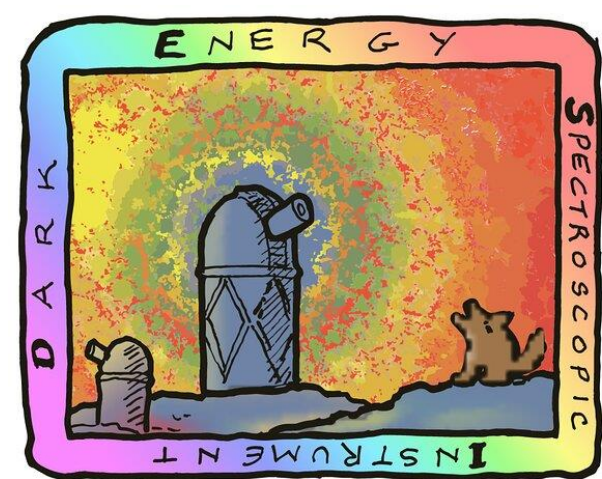




# DESI Transients Classification with Neural Networks

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DARK ENERGY  
SPECTROSCOPIC  
INSTRUMENT

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## Abstract

Astronomical transients are events that vary in brightness over a finite length of time. Classifying them is crucial to our understanding of various sources of radiation busts throughout the universe. The Dark Energy Spectroscopic Instrument Transient Identification Pipeline (DESI<sup>Tr</sup>IP) uses a convolutional neural network (CNN) to classify transients based on their spectra. With this approach, we investigated the nature of 127 spectra collected by the Dark Energy Spectroscopic Instrument (DESI). We found that DESI<sup>Tr</sup>IP classified 36 of them with a confidence score greater than 90%. Of those 36 transients, DESI<sup>Tr</sup>IP identified 34 as core collapse supernovae and 2 as kilonovae.

## Data

We began with a selection of transient candidates from the Dark Energy Camera (DECam) Survey of Intermediate Redshift Transients (DESIRT). This survey is a time domain program carried out in parallel with the Dark Energy Spectroscopic Instrument (DESI) to detect and observe transients and their host galaxies. We leveraged data from both surveys to build a catalog containing both spectroscopic data and transient activity data for each candidate.

To match the selections from DESIRT with spectroscopic data from DESI, we matched the right ascension (RA) and declination (DEC) of each DESIRT transient candidate to the nearest DESI fiber within a 1.6 arcsecond radius (the coverage of each fiber). Figure 1 shows a plot generated for visual inspection of these location matches for a single candidate. Using this method, we were able to match 1,024 DESIRT candidates to DESI spectra.

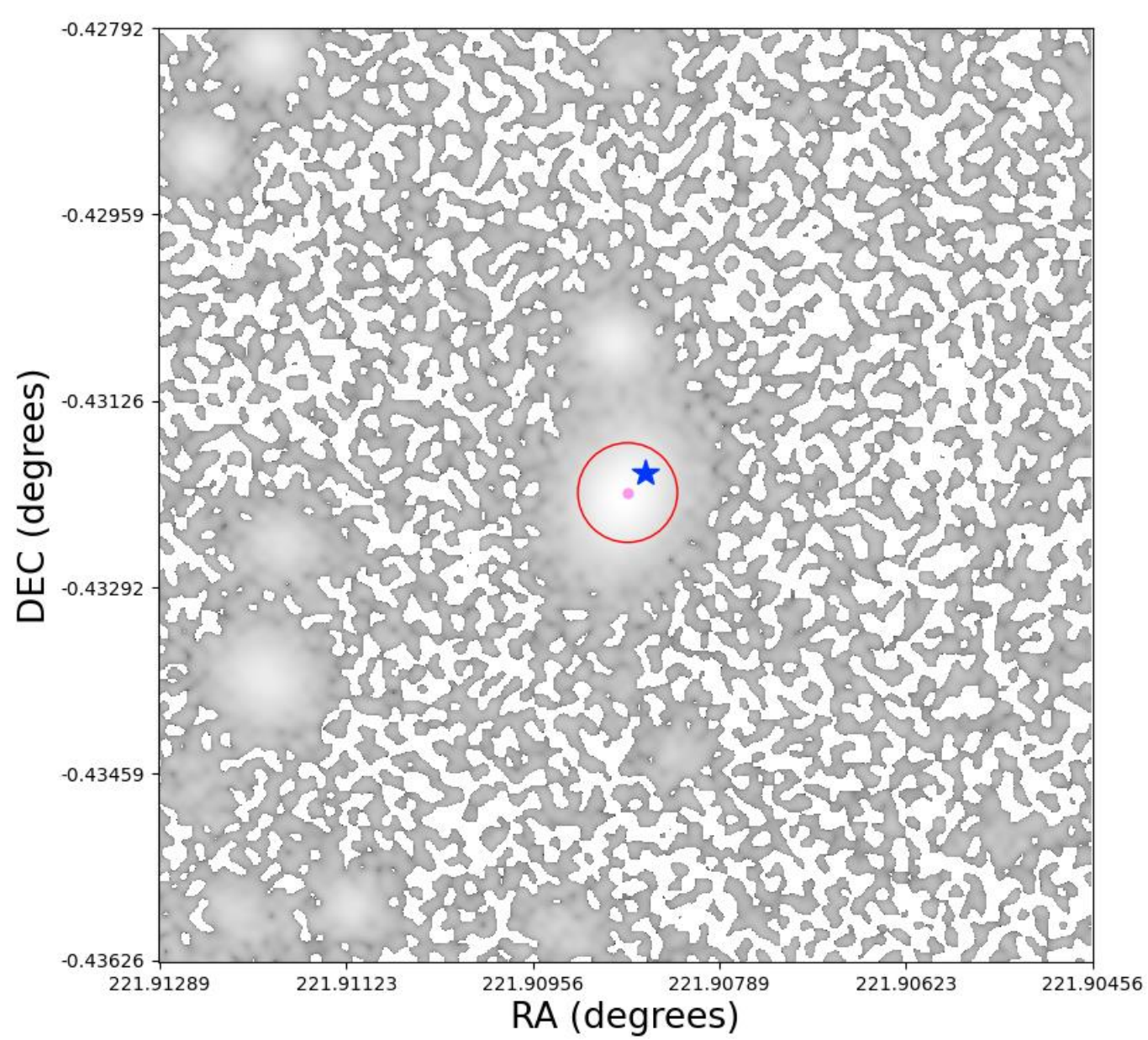


Figure 1: Plot of locations of the DESI Fiber (red circle), transient (blue star), and host galaxy (pink dot)

This plot was generated for the transient C202104061447381m002555.

Next, we selected only the candidates with spectra collected when the transient was active. Transient activity is determined by the times where the object's changes in brightness start and finish. We visualize this activity using a light curve like the one shown in Figure 2. This narrowed down our list to 127 candidates which we then passed to DESI<sup>Tr</sup>IP for classification.

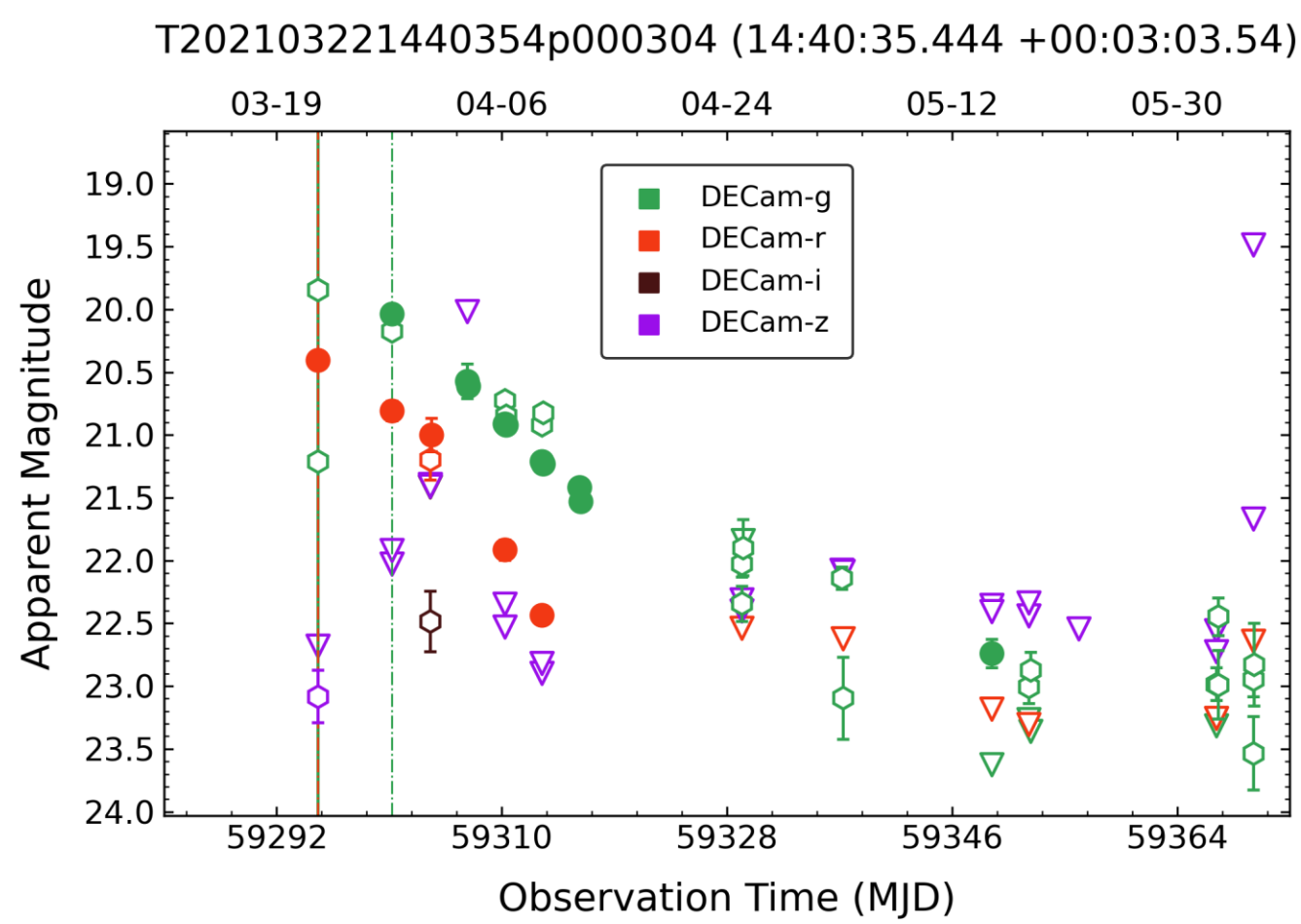


Figure 2: Light Curve Plot

This figure plots the brightness (in apparent magnitude) against the observing day (in MJD) for transient T202103221440354p000304.

## Methods

DESI<sup>Tr</sup>IP is a model trained on simulated spectra based on data collected by DESI. During each classification process, DESI<sup>Tr</sup>IP generates a Grad-CAM heat map (aka a “class activation heat map”) highlighting the most important features used in classification. This is achieved by computing the gradient of the prediction in the output layer with respect to the activations of the last convolutional layer. See Figure 3 for a simplified diagram of how layers are mapped to each other within DESI<sup>Tr</sup>IP. Though they aren't shown below, DESI<sup>Tr</sup>IP also features several sequences of convolution, normalization, and activation layers between “normalization” and pooling” as well as a “dropout” layer before the final output layer to mitigate overfitting.

### DESI Transient Identification Pipeline (DESI<sup>Tr</sup>IP)

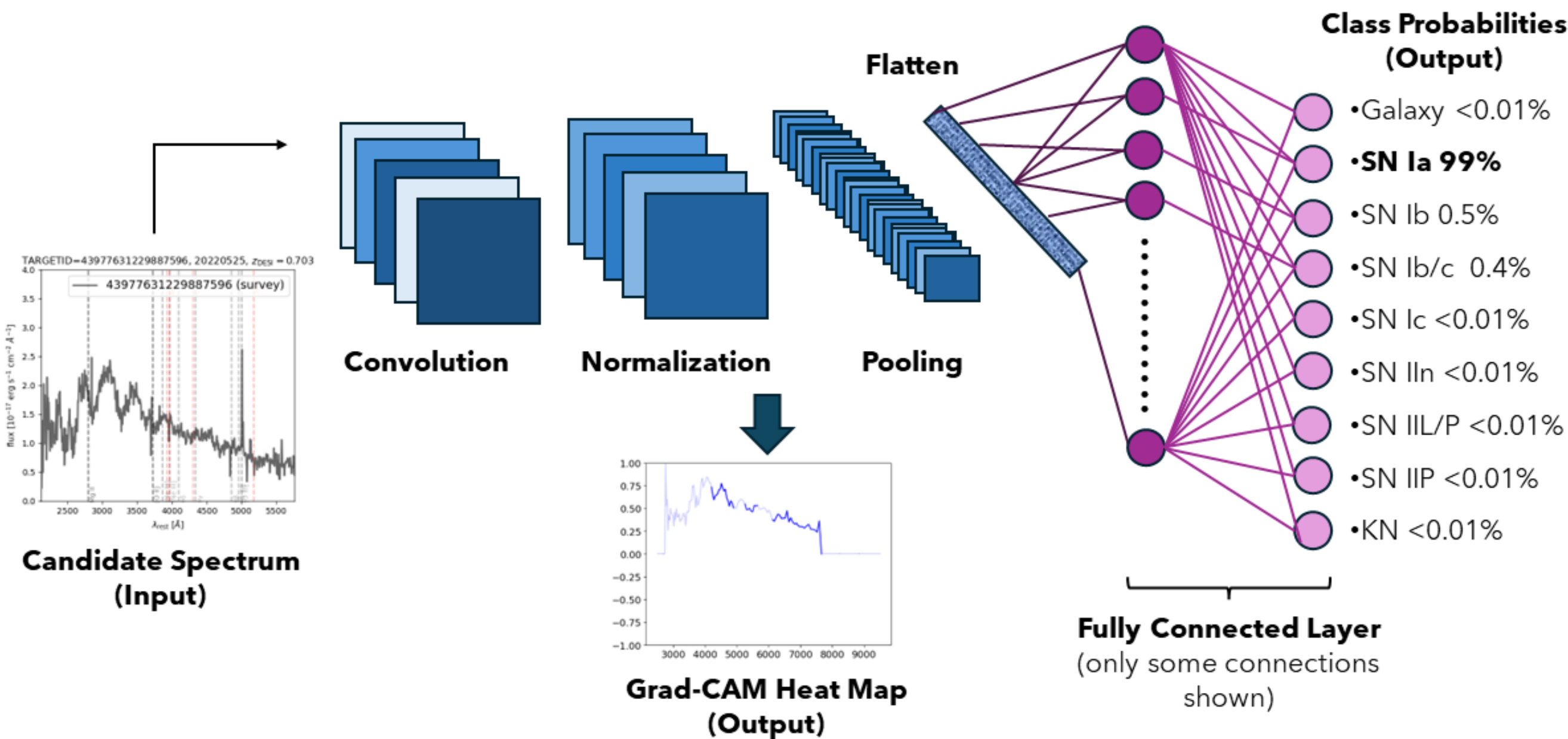


Figure 3: DESI<sup>Tr</sup>IP Flowchart

This example shows the classification of a spectrum that was assigned a 99% confidence score as a Type Ia supernova. The class activation heat map highlights the most influential features in bold.

## Results

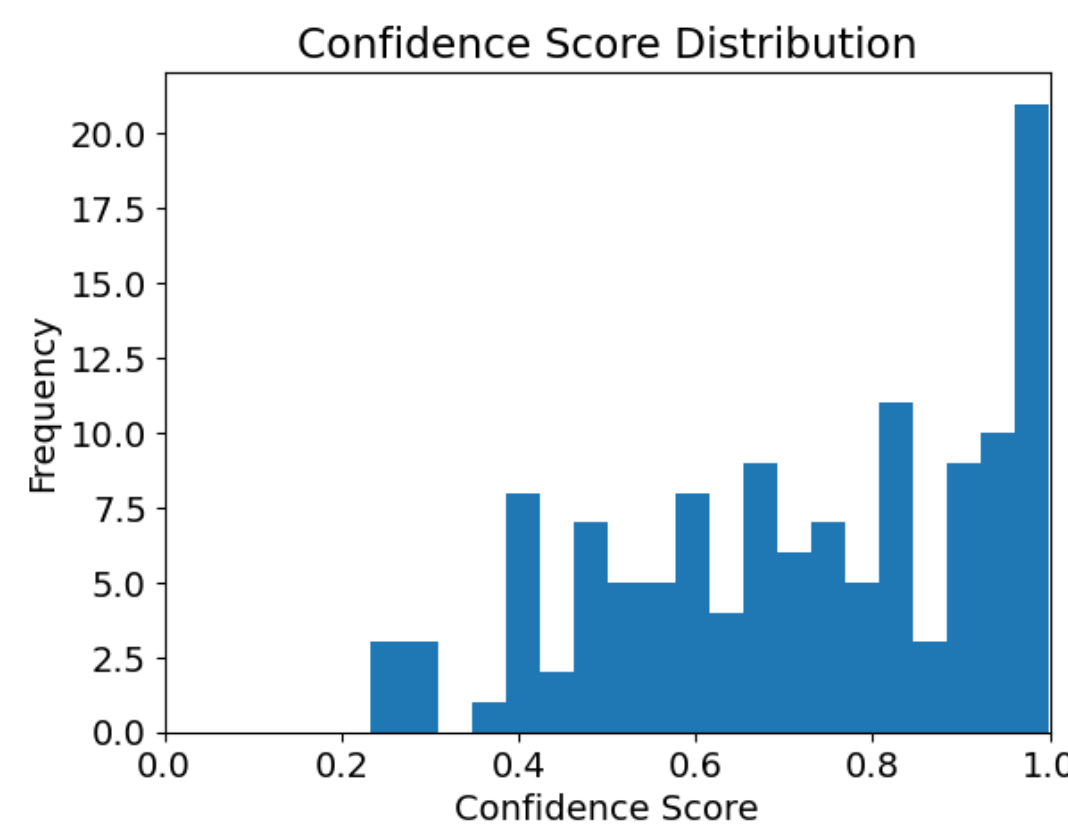
The types of objects DESI<sup>Tr</sup>IP can recognize are galaxies, SN Ia, SN Ib, SN Ib/c, SN Ic, SN IIn, SN IIL/P, SN IIP, and KN (kilonovae). Our selection of 127 candidates classified by DESI<sup>Tr</sup>IP comprises both nuclear (A and C type) and off-nuclear (T type) transients.

From our original selection of 127 transients, DESI<sup>Tr</sup>IP classified 36 of them with a confidence level greater than 90%. Out of these classifications there were 27 Type IIP supernovae, 1 Type IIn supernova, 6 Type Ic supernovae, and 2 kilonovae. Core collapse supernovae (Type II and Ic) made up over 94% of these high confidence classifications. See the figures below for more details.

Object_ID	DESI <sup>Tr</sup> IP_Label	Confidence_Score
T202103221440354p000304	SN Ic	0.999374
T202103221440354p000304	SN Ic	0.999374
C202104061447381m002555	SN Ic	0.999239
C202309152312561m013432	SN IIP	0.999199
C202204211257235p063531	SN IIP	0.998902
A202103221423503p001446	SN IIP	0.997907
A202103221423503p001446	SN IIP	0.997907
A202103221423503p001446	SN IIP	0.997907

Figure 4: Table displaying statistics for spectra with the top 8 highest confidence scores.

Figure 5: Histogram showing the distribution of confidence scores among the original selection of 127 transients. For each transient, only the highest confidence score (corresponding to the final label) is plotted.



## Conclusion

We find that classifying transients based on spectral features shows promising results in revealing the types of objects within a set of spectra. However, this approach requires having a set of spectra with distinct features (emission/absorption lines, continua, etc.) and known redshifts. By using redshifts measured from the DESI spectra of the host galaxies of transients, DESI<sup>Tr</sup>IP produced high confidence scores for a significant portion of our dataset collected within transient activity.

To further validate the results of DESI<sup>Tr</sup>IP, visual inspection should be conducted to ensure that the classifications are reasonable. We should compare each classification with other data such as light curves when evaluating their accuracies. As we obtain more information about the strengths and weaknesses of DESI<sup>Tr</sup>IP, we can revise the model's architecture to produce even more accurate results in the future.

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