DeepRubin-Explorer: Real-time Transient Classification via Temporal Convolutional Networks for the LSST Era

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Abstract

As we enter the era of the Vera C. Rubin Observatory's Legacy Survey of Space and Time (LSST), the astronomical community faces the unprecedented challenge of classifying approximately 10 million alerts per night. While current brokers provide classifications based on established models, there is a critical need for independent, high-speed, and deep-learning-based architectures capable of early-stage classification. This work presents a complete pipeline, from data ingestion via the ALeRCE broker to classification using a Temporal Convolutional Network (TCN) with dilated convolutions. We evaluate the model's performance on four classes of transients (QSO, CEP, SNIa, and SNII), utilizing Gaussian Processes for light curve interpolation and noise handling. Preliminary results show high precision in identifying stochastic and periodic sources, while revealing significant challenges in supernova sub-type discrimination due to morphological similarities in the first 100 days. This pipeline serves as a modular testbed for exploring end-to-end deep learning strategies that bypass manual feature engineering, offering a scalable alternative for real-time alert streams.

1 Introduction

The Vera C. Rubin Observatory is fundamentally transforming our exploration of the universe. By shifting from detecting 2,000 supernovae per year to an estimated 10,000 per night, the sheer volume of data necessitates a close collaboration between astronomers and data scientists.

Processing this astronomical data stream requires robust machine learning models capable of real-time classification. The primary challenge lies in providing early alerts; we need to identify specific objects or anomalies as they occur to allow for rapid follow-up observations. This work focuses on developing specialized models that prioritize low latency and high response speed compared to general-purpose brokers like ALeRCE.

In this first experiment, we implement a **Temporal Convolutional Network (TCN)**. Unlike standard architectures, TCNs are specifically designed for time-series data, utilizing **exponentially dilated convolutions** to capture long-term trends within fixed 100-day windows. This approach allows us to model brightness variations as continuous signals, potentially identifying the early stages of a supernova explosion. While this work is a "work in progress," it serves as a modular testbed for exploring more efficient and specialized deep learning strategies in the LSST era.

2 Exploratory Data Analysis

Before training, we analyzed the dataset characteristics to identify potential classification challenges.

2.1 Class Distribution

Our dataset, retrieved via the ALeRCE API, exhibits a significant class imbalance, which is representative of real-world survey conditions (see Figure 1).
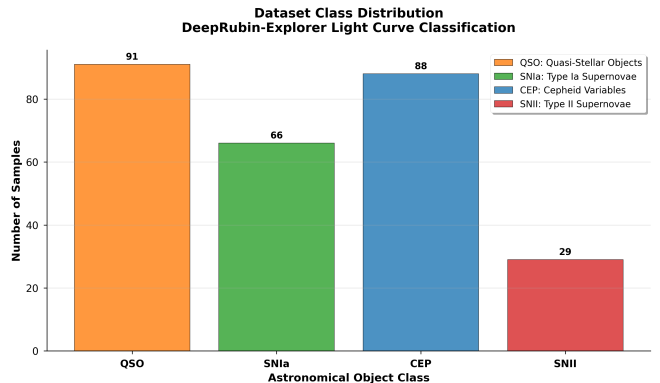

Figure 1: Distribution of astronomical samples across the four selected classes.

2.2 Data Selection and Class Imbalance

The dataset was constructed by querying the ALeRCE API for objects with a classification probability $P > 0.70$. The resulting imbalance (91 QSOs vs. 29 SNII) reflects two main factors: (1) the intrinsic volumetric rate and luminosity functions of these sources in the ZTF survey, and (2) the selection bias of the broker's base classifier, which achieves higher confidence levels for stochastic and thermonuclear transients compared to core-collapse supernovae. Instead of forcing a synthetic balance, we maintained this distribution to evaluate the TCN's performance under realistic, "long-tail" survey conditions.

2.3 Photometric Signatures

The morphology of the light curves (Figure 2) shows that while Quasi-Stellar Objects (QSO) and Cepheids (CEP) exhibit distinct temporal signatures, Supernovae sub-types (SNIa and SNII) show high overlap in their early decay phases.
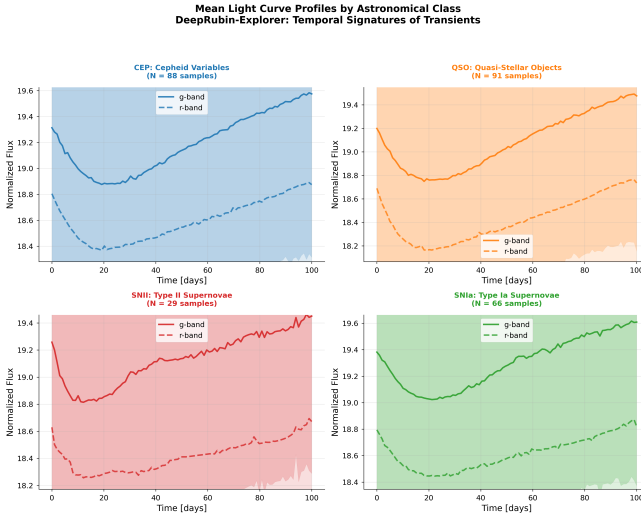

Figure 2: Mean light curve profiles for g and r bands with 1σ standard deviation shading.

3 Methodology

3.1 Data Preprocessing and Gaussian Processes

Astronomical time series from ZTF are inherently irregularly sampled due to weather conditions and survey cadence. To transform these sparse observations into a continuous representation suitable for the TCN, we employed **Gaussian Process Regression (GPR)**.

We chose a Matern 3/2 kernel to model the light curves, as it provides a physically plausible balance between smoothness and the ability to capture rapid transient changes. For each object, the GPR interpolates the

flux in the g and r bands over a fixed grid of 100 days. A key advantage of this approach is the estimation of **epistemic uncertainty**; as shown in our preliminary visualizations, the model's predictive variance increases in regions with sparse observations. This uncertainty is propagated as an additional feature or used to weight the importance of specific temporal windows.

3.2 TCN Architecture

The core of our classification pipeline is a **Temporal Convolutional Network (TCN)**. This architecture was selected over Recurrent Neural Networks (RNNs) due to its superior ability to handle long-range dependencies without vanishing gradient issues.

The model utilizes **dilated causal convolutions**, where the dilation factor d increases exponentially with depth ($d = 2^k$). This allows the network's receptive field to cover the entire 100-day observation window using only a few layers. To ensure stability during training, we incorporated residual blocks and weight normalization. The final layer employs a Global Average Pooling operation followed by a Softmax activation to output probabilities for the four classes: QSO, CEP, SNIa, and SNII.

3.3 Training and Experiment Tracking

The model was trained using the **Adam optimizer** with a fixed learning rate of 10^{-3} (or 10^{-4} depending on the run), selected to ensure stable convergence of the cross-entropy loss function. Training was performed over 50 epochs with a batch size of 32.

To ensure the **reproducibility** and **auditability** of our experiments, we integrated **MLflow** into the training pipeline. This allowed for systematic tracking of hyperparameters, loss curves, and validation metrics in real-time. By logging each iteration, we can compare different architectural tweaks and ensure that the results presented in this report are fully traceable, a critical requirement for scalable pipelines in the Rubin Observatory era.

4 Results

The first results of our model are a mix of success and things to improve. You can see the details in the Confusion Matrix (Figure 3).

4.1 What worked and what didn't

The model was **perfect for QSOs**, with 100% accuracy (21 of 21). This means the TCN is very good at identifying the "noisy" brightness of Quasars.

On the other hand, the **SNII class** was very difficult. We only had 4 samples in the test set, which is
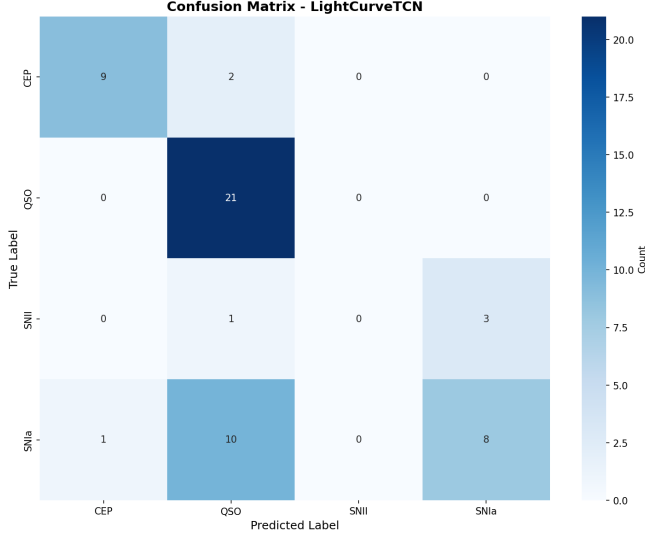
Figure 3: Distribution of astronomical samples across the four selected classes.

not enough for the model to learn. Also, 10 **SNIa** samples were confused with QSOs. This happens because, in a 100-day window, a Supernova can look similar to a Quasar if we don't have enough data points.

5 Conclusions

This is the first version of the DeepRubin-Explorer. The metrics are not perfect yet, but they are **promising**. We proved that a TCN can classify astronomical alerts in real-time without manual work.

For the next version, we need to:

- **Data Enrichment:** Getting more samples for the SNII class to fix the imbalance.

- **Dynamic Windows:** We will explore different time windows. Instead of a fixed 100-day window, using "dynamic windows" could help us identify Supernovae faster and not confuse them with long-term objects like QSOs.

- **New Architectures:** Testing if adding "Attention" mechanisms helps the TCN focus on the most important parts of the light curve.

I'm happy with this start, and I think there is a lot of room to explore and make the model better.