Towards a Unified Machine Learning Model for Time-Domain Alert Classification Across Roman Surveys

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Abstract

Maximizing the scientific return from Roman's time-domain surveys requires rapid, reliable alert classification across domains with very different source density, exposure depth, cadence, and filter coverage. Training separate classifiers for every survey and filter combination is impractical, motivating a shared machine-learning approach that can generalize between HLTDS-like extragalactic fields and dense GBTDS fields. We build a Real/Bogus artifact-filtering model, RuBR-AT, and adapt the same multimodal design toward real-source transient/variable classification. The models take in image cutouts, PSF-fit measurements, survey/filter context, pre-alert light curves, and continuous-time embeddings, providing a path toward automated discovery within the Roman Alerts Promptly from Image Differencing (RAPID) pipeline.

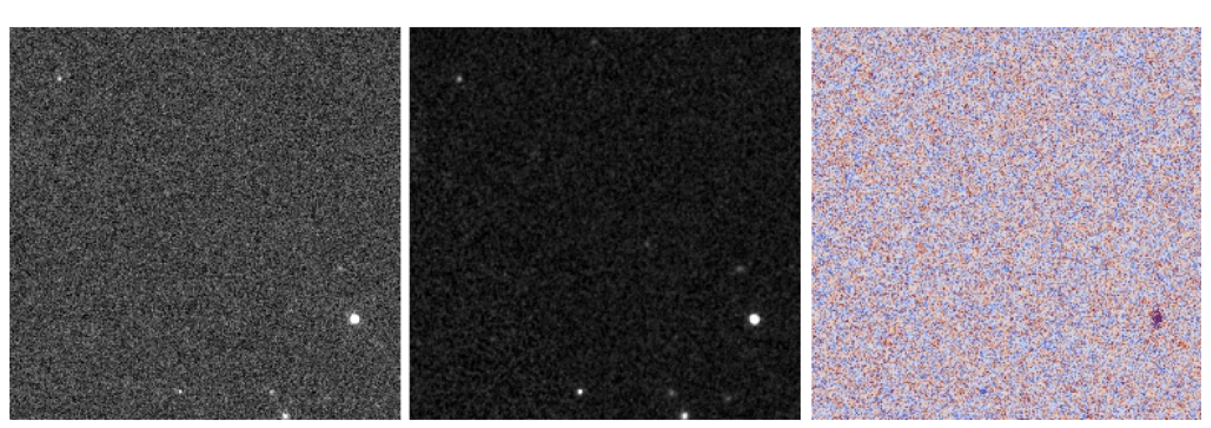
Introduction

Roman's time-domain surveys require fast automated alert classification across environments with very different source densities, depths, cadences, and filter coverage. This work develops a shared model family for two stages of the alert stream: first rejecting image-subtraction artifacts with RuBR-AT, then classifying real astrophysical candidates as transient or variable sources.

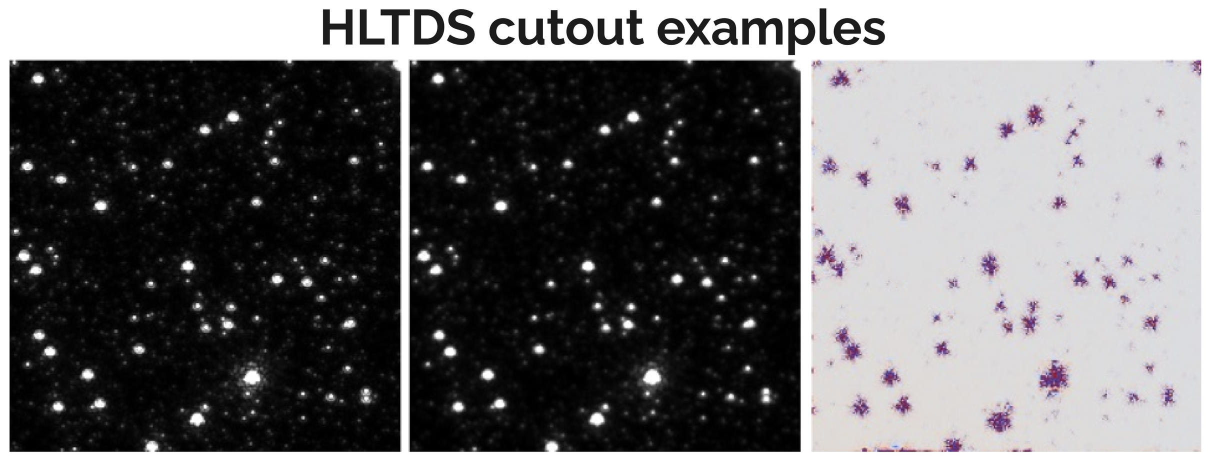
The central design goal is survey transfer: image cutouts, PSF-fit measurements, survey/filter context, and pre-alert light curves are encoded into a common representation before task-specific classification heads.

Background

Survey	Simulation source	Domain represented
HLTDS	OpenUniverse2024	Deep high-latitude fields with extragalactic transients and injected variables
GBTDS	RimTimSims	Crowded Galactic Bulge fields with dense stellar backgrounds and variables



HLTDS cutout examples



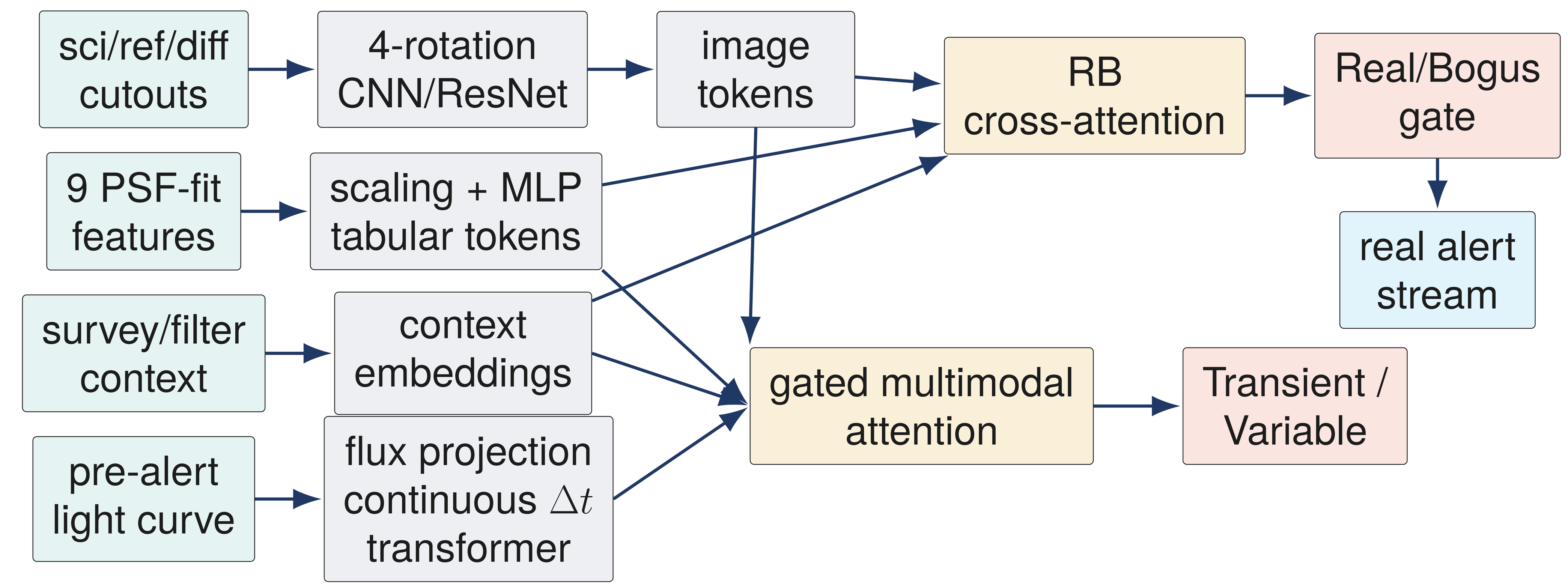
GBTDS cutout examples

science, reference, and SFFT difference images

Survey-aware context embeddings let one representation cover both sparse high-latitude images and crowded bulge fields.

Roman Alert Classification Architecture

Shared candidate representation with task-specific heads: Real/Bogus filters artifacts, then real candidates feed the transient/variable head.



The shared representation supports both high-latitude fields and dense galactic bulge fields.

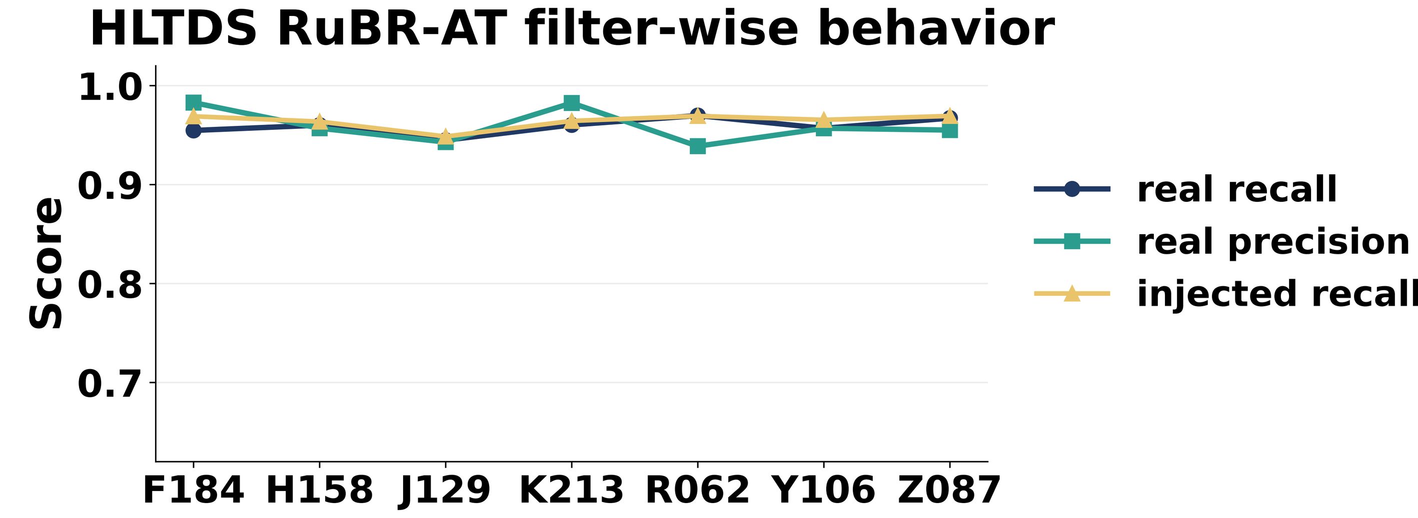
Real/Bogus Artifact Filtering

First-stage gate: RuBR-AT combines rotation-averaged cutouts, PSF features, and survey/filter context to clean the candidate stream before astrophysical classification.

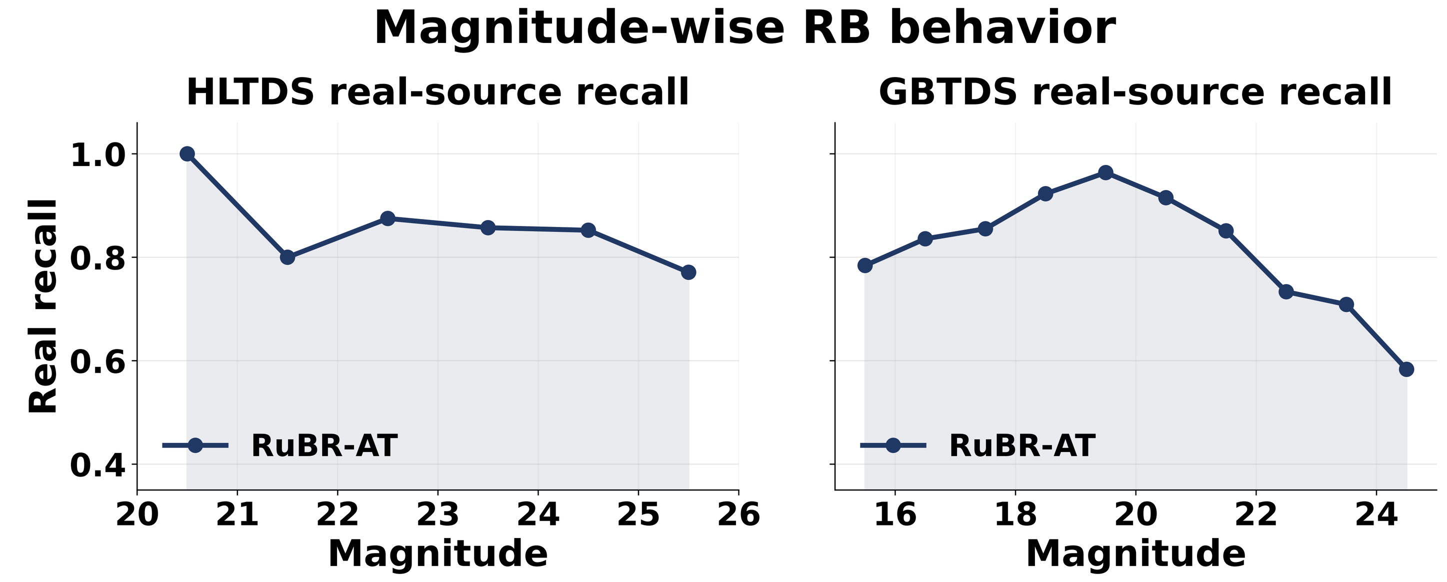
Real/Bogus held-out classification

Survey	Model	Real F1	Real prec.	Real rec.
HLTDS	**RuBR-AT**	**0.95**	**0.97**	**0.93**
HLTDS	RuBR	0.83	0.87	0.79
GBTDS	**RuBR-AT**	**0.89**	**0.96**	0.84
GBTDS	RuBR	0.72	0.61	**0.89**

HLTDS RuBR-AT filter-wise behavior



Magnitude-wise RB behavior



At bright magnitudes, GBTDS recall drops because high source density makes sources harder to separate cleanly.

Transient/Variable Classification

Transient/variable stage: for both HLTDS and GBTDS, cutouts, PSF measurements, survey/filter context, and pre-alert light curves are fused to classify real candidates as transient or variable.

GBTDS object-level transient/variable results

Input features	Macro-F1	Variable recall	Transient recall
Image + PSF meas. + LC	**0.95**	**0.97**	0.94
Light curve only	0.92	0.93	**0.95**
Image + PSF meas. only	0.90	0.95	0.85

HLTDS row-level transient/variable results

Input features	Row macro-F1	Transient recall	Variable recall
Image + PSF meas. + LC	**0.78**	**0.78**	0.79
Light curve only	0.73	0.65	0.81
Image + PSF meas. only	0.72	0.63	**0.82**

Future Work

- Extend the transient/variable head to astrophysical subclassification, including supernovae, microlensing-like events, and variable-star classes.
- Evaluate the model on GBTDS simulations with additional filters once that data becomes available.
- Improve the HLTDS transient/variable objective so OU24 transients, injected transients, and injected variables do not force conflicting binary labels.
- Add calibrated confidence estimates so ambiguous real alerts can be flagged for follow-up instead of being forced into a hard real/bogus decision.
- Use counterfactual cutouts and light curves to test which image, PSF, and temporal evidence drives each model decision.

References: NASA Roman overview; OpenUniverse2024 Collaboration 2025; Muthukrishna et al. 2019; Wilson, RimTimSim; Gandhi et al. 2026