AI-Augmented Methods for Interpretable and Efficient Modeling in Modern Astronomy

25-26J-108

Project Proposal Report

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CONTRASTIVE LEARNING FOR CLASSIFICATION OF RARE ASTRONOMICAL TRANSIENTS IN MULTI-BAND SKY SURVEYS

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DECLARATION

DECLARATION

I declare that this is our own work, and this proposal does not incorporate without acknowledgement any material previously submitted for a degree or diploma in any other university or Institute of higher learning and to the best of my knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text.

Name	Student ID	Signature
Senevirathne B.A.N.K.	IT22133922	Vipu

The supervisor/s should certify the proposal report with the following declaration.

The above candidates are carrying out research for the undergraduate Dissertation under my supervision.

.... 31/08/2025......

Signature of the Supervisor: Date:

DEDICATION

This study is dedicated in earnest to our supervisor, **Mr. Samadhi Rathnayake**, and our co-supervisor, **Dr. Kapila Dissanayake**, whose expertise, support, and wisdom have played a key role in the development of this study. We also offer our sincerest gratitude to our friends and family, whose unstinting support, determination, and motivation have been a constant source of strength throughout this endeavor

ACKNOWLEDGEMENT

I would like to offer my heartfelt thanks to our supervisor, Mr. Samadhi Rathnayake, and our co-supervisor, Dr. Kapila Dissanayake, for offering their valuable guidance, dedicated time, and continuous motivation throughout the course of this work. Their experience and support were invaluable to the successful completion of this project.

ABSTRACT

Astronomical transients such as supernovae, kilonovae, and tidal disruption events are of scientific interest but are rare events. Although they are scarce in labelled data, their lack in annotated data exposes supervised deep learning techniques to overfitting and bad generalisation. This paper proposes a self-supervised contrastive learning approach to acquire strong, generalisable representations out of multi-band light curve observations gathered from extensive surveys of the sky. By leveraging time-series astronomy data augmentation methods (i.e., temporal jitter, magnitude scaling, noise injection), the model learns representations of intrinsic temporal patterns without mass labels. These are subsequently fine-tuned with few-shot labeled examples for precise classification of anomalous transients. The study will compare against conventional supervised baselines using accuracy, precision, recall, F1-score, and embedding separability measured via dimensionality reduction visualizations. They are expected to have superior classification performance under the imbalance conditions, superior representation quality, and the potential for unsupervised new event detection.

Keywords: contrastive learning, self-supervised learning, astronomical transients, few-shot learning, light curves.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

Abbreviation	**Description**
AI	Artificial Intelligence
CNN	Convolutional Neural Network
GRU	Gated Recurrent Unit
ML	Machine Learning
NT-Xent	Normalized Temperature-scaled Cross Entropy Loss
RNN	Recurrent Neural Network
SHAP	SHapley Additive exPlanations
LIME	Local Interpretable Model-agnostic Explanations
t-SNE	t-distributed Stochastic Neighbor Embedding
UMAP	Uniform Manifold Approximation and Projection
ZTF	Zwicky Transient Facility

1 INTRODUCTION

Astronomical transients are among the most dramatic and scientifically precious phenomena found in the universe. These events—ranging from supernovae and kilonovae to tidal disruption events and cataclysmic variables—represent short but extremely energetic events that may give us important insight into a range of astrophysical processes. The investigation of such transients plays a very important role in our knowledge of stellar life cycles, the chemical enrichment of the cosmos, and the evolution of the large-scale structure of galaxies. In particular, certain transients, e.g., kilonovae, are also important electromagnetic counterparts to gravitational wave events and are a unique chance to explore the crossroads between high-energy astrophysics and multi-messenger astronomy.

In the past decade, advances in wide-field time-domain surveys have revolutionized detection and monitoring of these fleeting events. Surveys such as the Zwicky Transient Facility (ZTF) now cover large parts of the night sky every night, gathering vast amounts of time-series photometry in multiple wavelength bands (e.g., g, r, and i bands). This has led to the production of never-before-seen large datasets consisting of thousands of previously unseen transients per night. Every transient is represented by its light curve—a change of brightness with time in various filters—bundling a mine of information about the physical origin and history of the transient.

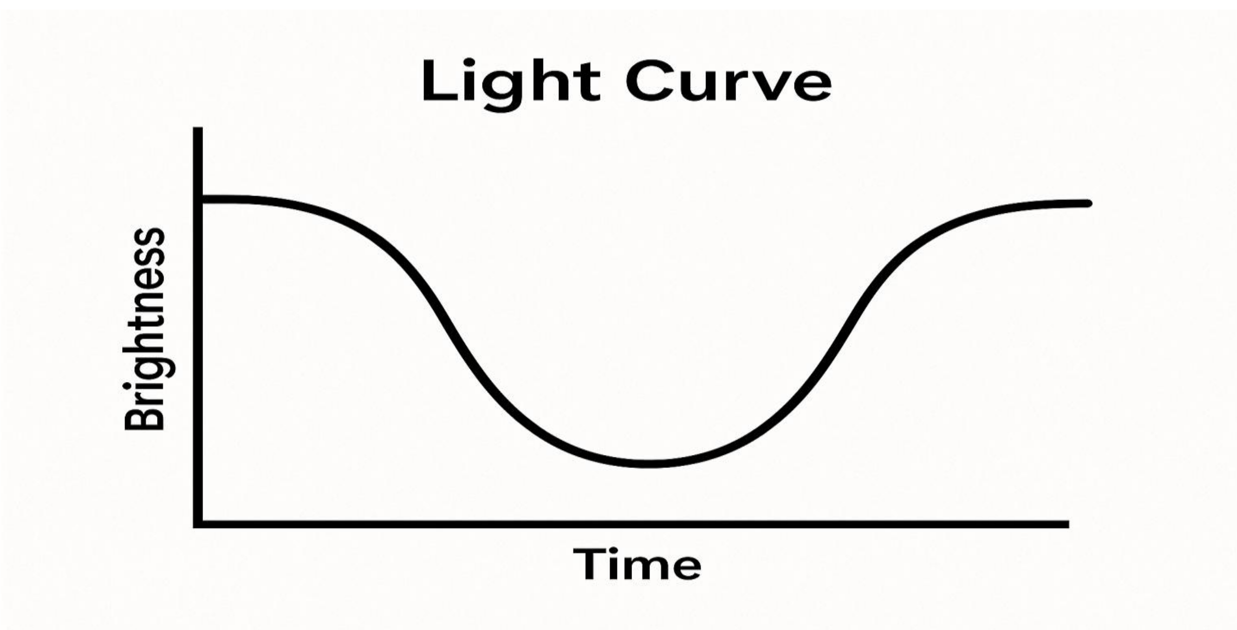


Figure 1.1

Despite this abundance of observational data, the exact classification of rare astronomical transients remains a considerable challenge. There are two inherent issues hindering progress in this area. Firstly, the sheer lack of labelled examples for the rarest transient classes, such as kilonovae, severely limits the applicability of traditional supervised learning approaches, which heavily depend on massive annotated datasets to perform efficient training. Second, the severe class imbalance inherent in astronomical transient datasets—where common classes such as Type Ia supernovae vastly outnumber rare ones—biases models toward majority classes, leading to low recall and reduced detection rates for rare events. These issues are compounded by the complexity of light curves, which can vary in cadence, sampling irregularities, and noise levels due to observing constraints.

Conventional supervised deep learning approaches, while robust in other applications, struggle under these circumstances. They require large sets of labelled training data to learn discriminative features, and their performance collapses dramatically when dealing with sparse and class-imbalanced datasets. Breaking these limitations calls for a paradigm shift towards learning methods that can take advantage of the riches of unlabelled data available in astronomical surveys.

Figure 1.2

The paper presents a self-supervised contrastive learning framework judiciously designed for the prediction of rare astrotransients from multi-band light curves. Massive collections of unlabelled light curves are used to pre-train a representation model capable of learning to identify the intrinsic temporal and spectral patterns of transient activity. By training through the use of domain-specific data augmentation techniques—temporal jittering, magnitude scaling, noise injection, and partial sequence cropping—the model gains the capacity to generate robust embeddings for different augmented views of a single light curve and to stay separated across embeddings of different events. Then, trained in this self-supervised manner, the model can be fine-tuned with a small number of labelled samples to achieve robust classification performance.

Through reducing reliance on labeled data, improving representation quality, and mitigating effects of class imbalance, the proposed framework aims to offer a real-time and practical solution for transient classification in modern astronomical surveys. Beyond classification accuracy, this approach may also facilitate discovery of heretofore unknown or low-abundance event classes, enhancing astrophysical knowledge as well as data-driven astronomy in general.

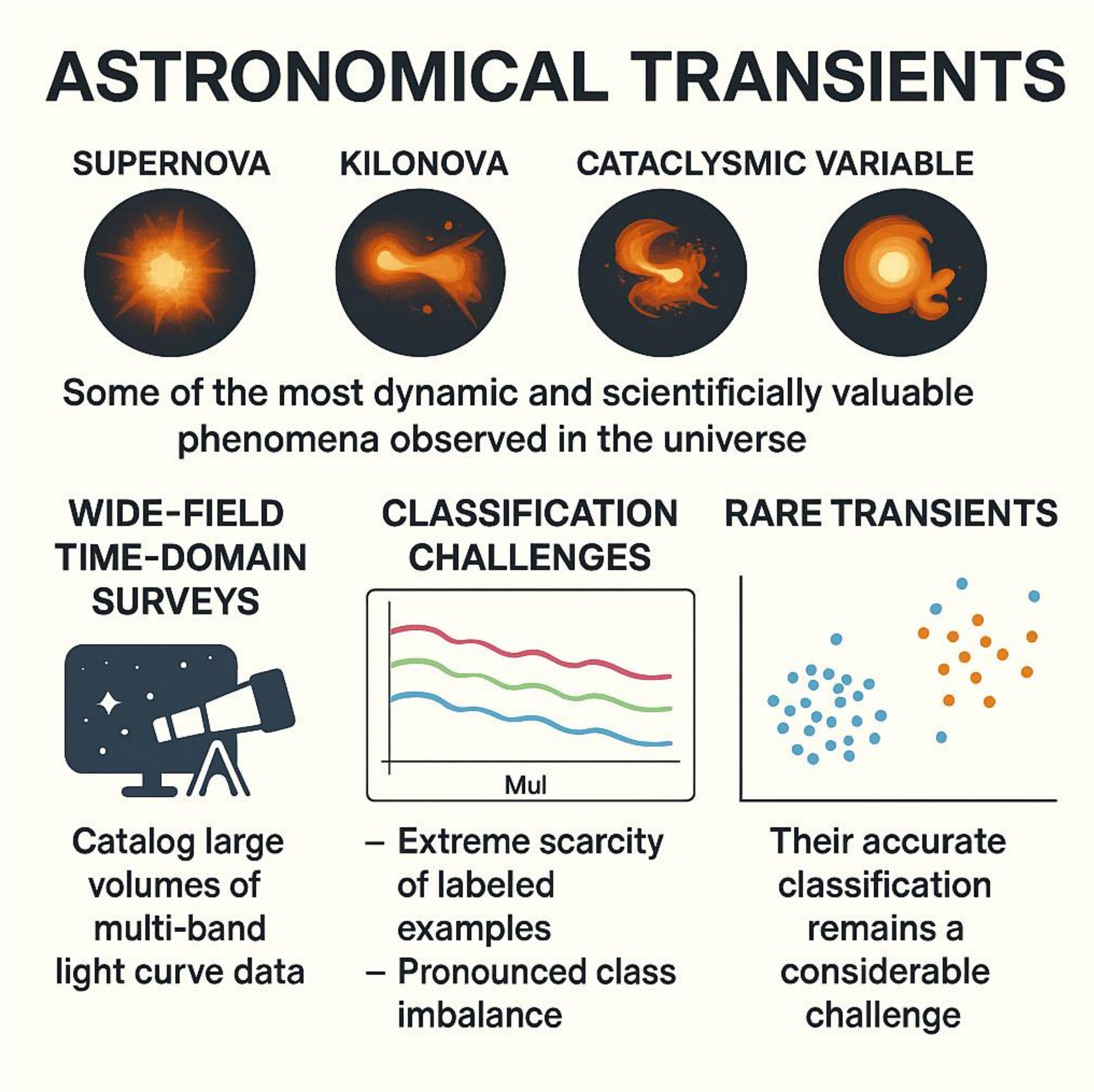

ASTRONOMICAL TRANSIENTS
SUPERNOVA
KILONOVA
CATACLYSMIC VARIABLE
Some of the most dynamic and scientificially valuable phenomena observed in the universe
WIDE-FIELD TIME-DOMAIN SURVEYS
CLASSIFICATION CHALLENGES
RARE TRANSIENTS
Mul
Catalog large volumes of multi-band light curve data
– Extreme scarcity of labeled examples
– Pronounced class imbalance
Their accurate classification remains a considerable challenge

Figure 1.3

2 BACKGROUND &LITERATURE SURVEY

2.1 Astronomical Transients and Light Curve Analysis

Astronomical transients are short-lived, energetic events that provide infrequent opportunities to study intense astrophysical processes. Certain transients, such as Type supernovae, are standard candles against which to gauge cosmic distance and thus are essential to measure the history of cosmic expansion. Others, such as kilonovae, are the electromagnetic counterparts of neutron star mergers and provide essential information on heavy element nucleosynthesis in addition to gravitational wave sources. They are best characterized by light curves—time sequences of brightness observations made via multiple photometric filters, for example, g, r, and i bands. Multi-band photometry not only enables one to diagnose the type of transient, but also reveal its physical parameters: temperature evolution, ejecta composition, and expansion velocity. Although the detection of stellar transients from light curves is problematic due to sparsity of data, varying sampling rates, and observational noise, these are artifacts that are consequences of telescope scheduling constraints, the weather, and limitations of the instrumentation that all lead to noisy or incomplete data sets.

2.2 Machine Learning in Astronomy

Machine learning (ML) has, in recent years, become a successful technique for the automation of transient classification in large-scale astronomical surveys. Supervised ML algorithms, ranging from basic random forests and gradient boosting classifiers to convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have been proved effective in distinguishing typical types of transients using well-curated data. For example, models that are trained on light curve observations from surveys such as the Zwicky Transient Facility (ZTF) and Pan-STARRS have achieved competitive performance in distinguishing supernovae from other variable sources. Yet, this is highly dependent on the availability of huge labelled data sets, which is unrealistic for sparse event types such as kilonovae or tidal disruption events. Along with this, astrophysical datasets are generally severely class-imbalanced in which the majority classes dominate the training and biased predictions are obtained along with low recall over rare but scientifically valuable events. Purely supervised techniques do not generalise well under real-world scenarios where labelled data is scarce and class-imbalanced.

2.3 Self-Supervised and Contrastive Learning

Self-supervised learning (SSL) has emerged as a promising paradigm to bypass the limitation of supervised learning, particularly in domains where data with annotations are scarce. In the SSL algorithms, methods such as contrastive learning-based methods including SimCLR and Bootstrap Your Own Latent (BYOL) have achieved state-of-the-art results on computer vision and time-series analysis. The core idea of contrastive learning is to learn an embedding space where views of the same sample are mapped near each other and embeddings of distinct samples are pushed apart. This training process enables models to acquire intrinsic structures and relationships between the data in an unlabaled manner. Transferring this to time-series data, such as astronomical light curves, contrastive learning can leverage domain-specific augmentations such as temporal jittering, magnitude scaling, and noise injection to learn invariant and robust representations. The resulting embeddings can subsequently be fine-tuned from a limited amount of labelled samples to significantly improve classification performance in few-shot learning regimes. Beyond astronomy, contrastive learning has been used with great success in bioinformatics, speech recognition, and climatology, demonstrating its utility in diverse scientific disciplines.

2.4 Related Work in Astronomy

Several pieces of work have employed machine learning for transient classification, which has predominantly focused on supervised learning approaches. Standard techniques typically use CNNs, RNNs, or feature-engineered classifiers trained on light curves or image cutouts to classify events. Even though the models perform well on well-sampled, balanced samples, their performance is poor in instances having rare event types and noisy, incomplete observations. In more recent research, researchers have also begun to explore representation learning methods in astrophysics, for example, the use of autoencoders and unsupervised clustering to acquire representative features from astronomical observations. A small but growing body of research has explored self-supervised approaches for astronomical applications, like the use of contrastive objectives for galaxy images or variable star light curves. However, these studies haven't been comprehensively leveraging domain-specific improvements or extending contrastive learning models to the particular requirements of transient light curves. The project taps into this new direction by developing a self-supervised pipeline of contrastive learning that is optimized for multi-band light curves to enhance performance in rare transient classification under realistic survey conditions.

Table 1

Method	Domain	Dataset	Limitations
CNN Classifiers	Astronomy	ZTF Light Curves	Needs large labels
RNN Models	Astronomy	Pan-STARRS	Struggles with imbalance
Autoencoders	Astronomy	Archival Surveys	Weak for rare events
Transformers	Astronomy	Simulated Light Curves	Requires long sequences
Contrastive SSL	Generic/Astronomy	Multi-band Light Curves	Still underexplored

3 RESEARCH GAP

Existing techniques for transient classification in astronomy have some inherent shortcomings that hamper their efficiency, particularly while classifying rare and scientifically valuable events. First, the majority of them rely on big labeled datasets and need high performance, which is not feasible for rare types of transients such as kilonovae and tidal disruption events, where there are possibly fewer than a dozen such events in survey archives. Second, existing models rarely leverage domain-specific augmentation strategies specific to astronomical light curves, which limits their potential for learning robust representations that are immune to observational issues such as irregular sampling, variable cadence, and photometric noise. Third, extreme class imbalance—where common transients such as Type Ia supernovae dominate less common counterparts—is typically biased towards unfair model predictions, which provides low recall and reduced rates of detection for the less common classes. Finally, where the success of self-supervised learning in other areas of science has been demonstrated, its potential is yet to be explored for astronomical time-series data, which opens a door in approaches that can benefit from the vast unlabelled light curves produced by contemporary surveys.

This effort meets these limitations head on by introducing a self-supervised contrastive learning pipeline that is specially optimised for multi-band light curve data. The proposed framework leverages domain-informed augmentation strategies and representation learning to discover strong and generalisable representations from unlabelled observations. By subsequently fine-tuning those representations over little, imbalanced labelled examples, the approach aims to significantly improve classification accuracy and recall for infrequent transients, with little dependence on large-scale annotation effort.

Table 2

Research	Domain	Contrastive /Self Supervised Learning	Domain Specific Augmentations	Few-Shot Learning	Multi – Band Light Curves	Handle Class Imbalance
A - Fully Supervised CNN for Transients	Astronomy	✗	✗	✗	✓	✗
B – Semi-Supervised with Autoencoders	Astronomy	Partial	✗	✗	✓	Partial
B – Semi-Supervised with Autoencoders	Astronomy	Partial	✗	✗	✓	Partial
C – Transformer for Light Curve Classification	Astronomy	✗	✓	✓	✓	Partial
D – Self-Supervised in Time-Series (Generic Domain)	Generic Time-Series	✓	✗	Partial	✗	✗
E – Vision SimCLR in Astronomy Images	Astronomy Images	✓	✗	✗	✗	✗
Proposed Work	Astronomy	✓	✓	✓	✓	✓

4 RESEARCH PROBLEM

4.1 Context of the Problem

Astronomy on the timescale has been transformed by new surveys of the sky such as the Zwicky Transient Facility (ZTF) and the future Vera C. Rubin Observatory (LSST). These surveys observe the sky repeatedly, collecting terabytes of data per night in numerous photometric bands. They are charged with discovering astronomical transients — objects which abruptly appear as flashes, change on short timescales, and often vanish within weeks or days. They consist of supernovae, signifying the death of stars; kilonovae, signaling neutron star mergers and electromagnetic counterparts to gravitational waves; tidal disruption events (TDEs), where stars are being torn apart by black holes; and cataclysmic variables, due to interactions between binary star systems. All transients hold crucial astrophysical information but are infrequent and difficult to follow up in a systematic manner.

Challenges:

4.1.1 Lack of Labels

Supervised learning methods rely on thousands of labeled examples per class to work well regularly. However, in astronomy, unusual events occur with very few confirmed detections. Kilonovae, for instance — as precious as they are to nucleosynthesis and gravity wave astrophysics — have fewer than a dozen well-documented examples in the literature. This paucity of labels is a training bottleneck for deep learning algorithms, which perform best in information-rich environments.

4.1.2 Severe Class Imblance

The occurrence of transient classes in survey data is drastically skewed. Universal events such as Type Ia supernovae occur in gigantic numbers every year, while rarer classes such as TDEs and kilonovae are vastly underrepresented. Typical supervised models then become biased in favor of populous classes, often achieving high overall accuracy but being incapable of recalling rare, scientifically valuable events. This imbalance negates the very purpose of transient surveys, i.e., to detect the least frequent and most exotic events.

4.1.3 Noisy and Irregular Data

Astronomical light curves — time-series brightness measurements via filters — are by no means unblemished datasets. They are beset by:

- Irregular sampling due to weather, telescope scheduling, and visibility constraints.
- Incomplete coverage where observations omit significant phases of an event's evolution.

- Noise and instrumentation errors due to instruments, atmospheric conditions, or background light.

These are problems that render it difficult for standard machine learning models to learn robust patterns. Unlike well-behaved time-series in other application areas (e.g., finance or IoT), astronomical light curves are more likely to look sparse, irregular, and noisy, which makes feature extraction and classification more challenging.

5 OBJECTIVE

5.1 Main Objective

In order to design, develop, and evaluate a self-supervised contrastive learning system that is able to extract strong and generalisable feature representations from multi-band astronomical light curve data to effectively classify scarce transient events such as supernovae, kilonovae, and tidal disruption events. The system must be in a position to operate well under limited labelled sample conditions, thereby reducing the necessity for extensive manual annotation to improve detection quality for poorly represented transient classes.

5.2 Specific Objectives

5.2.1 Develop a contrastive learning framework for multi-band transient light curve feature extraction.

This objective is focused on building the core self-supervised learning pipeline with the potential to acquire meaningful embeddings from massive unlabelled light curve data. The process entails:

• tuning a comprehensive literature review of contrastive and self-supervised learning techniques in astronomy and cross-disciplinary time-series domains, selecting suitable architectures and training paradigms.

• Gather and preprocess multi-band light curve datasets of relevant sky surveys (e.g., ZTF) with appropriate calibration, filtering, and handling of irregular sampling and noise.

• Implement and run domain-specific data augmentation schemes suitable for transient light curves, such as temporal jittering, magnitude scaling, injection of noise, cropping of partial sequences, and filter-dependent transformations.

• Train the contrastive learning model (e.g., SimCLR or BYOL-based) to learn the latent embeddings that capture the intrinsic temporal and spectral attributes of transients in multiple photometric bands.

5.2.2 Fine-tune the pre-trained encoder with few-shot labelled data for rare transient classification.

Once the contrastive model is trained, the learned representations will be used for downstream classification tasks with minimal labelled data. The steps are:

• Acquire a few-shot labelled dataset with typical examples of significant transient categories, emphasizing rare events such as kilonovae and cataclysmic variables.

• Appending a classification head (e.g., softmax layer or shallow neural network) on top of the frozen or partially trainable pre-trained encoder.

• Fine-tune the joint model with the few-shot labelled examples to align the learned embeddings to classification.

• Test the performance of the model's classification against appropriate metrics like accuracy, precision, recall, and F1-score, such that the observed results are significant in an imbalanced class scenario.

• Observe performance trends in particular for the rare classes, determining betterments compared to conventional supervised models.

5.2.3 Compare the new contrastive learning method with baseline supervised methods.

In order to validate the effectiveness of the suggested approach, its performance will be evaluated against that of traditional supervised learning techniques learned directly from labeled data. The procedure is:

• Train baseline supervised models (e.g., CNN, RNN, or LightGBM-based classifiers) exclusively on labelled data without pre-training.

• Plot contrastive and baseline model learned embeddings via dimensionality reduction methods like t-SNE and UMAP for qualitative assessment of representation separability.

• Comparative performance measures for models like accuracy, confusion matrix, per-class recall, and capacity to generalise to unseen transient types.

• Indicate computational efficiency and training stability, with the advantage of contrastive pre-training under limited labels.

6 METHODOLOGY

6.1 System Architecture

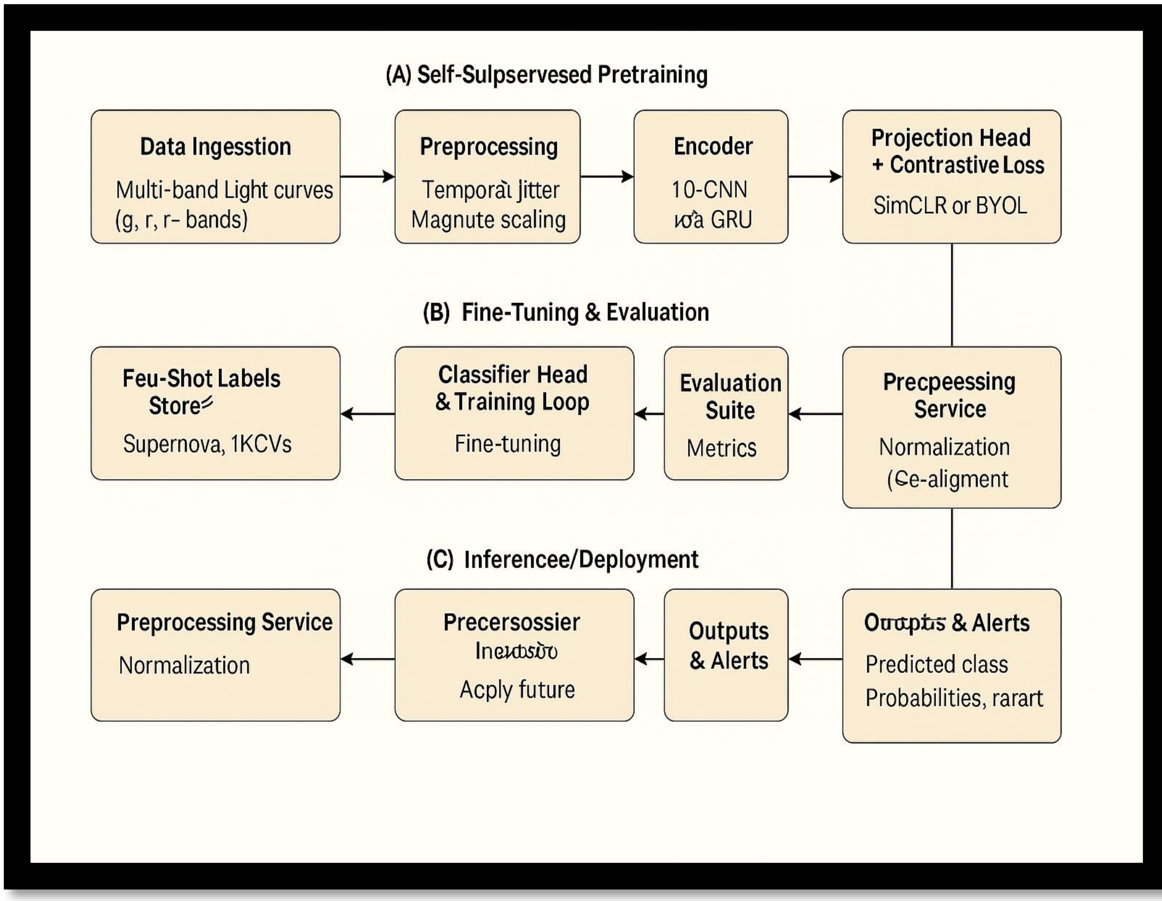


Figure 6.1

The proposed methodology comprises five sequential stages designed to systematically address the research objectives and overcome the limitations of existing transient classification approaches.

- **Step 1 – Data Collection and Preprocessing:**

Multi-band light curve data in the g, r, and i filters will be obtained from the publicly available Zwicky Transient Facility (ZTF) dataset. The raw data will be cleaned to address missing or inconsistent values, normalised in terms of magnitude, and temporally aligned to ensure uniform sampling across all filters. These preprocessing steps are essential to maintain data integrity and enhance the quality of subsequent feature extraction.

- **Step 2 – Data Augmentation for Contrastive Learning:**

Domain-specific augmentation techniques will be applied to generate diverse positive and negative sample pairs for self-supervised representation learning. These augmentations include temporal jittering to simulate observational cadence variations, magnitude scaling to replicate different brightness levels, Gaussian noise injection to mimic photometric uncertainties, and time-segment cropping to emulate incomplete observations.

- **Step 3 – Contrastive Pretraining:**

A feature encoder—implemented as either a hybrid 1D CNN with GRU layers or a Transformer-based architecture—will be trained using a contrastive learning framework such as SimCLR or BYOL. The NT-Xent loss function will be employed to maximise similarity between augmented views of the same light curve (positive pairs) while ensuring dissimilarity between different light curves (negative pairs). Batch-wise sampling will be used to maintain a balanced and efficient training process**.**

- **Step 4 – Fine-Tuning:**

The pre-trained encoder will be integrated with a classification head comprising dense layers and a softmax output layer. Fine-tuning will be conducted on a small set of labelled examples representing rare transient classes, with the option to either freeze the encoder to preserve learned representations or allow partial updates to adapt to the classification task.

- **Step 5 – Evaluation:**

Model performance will be quantitatively assessed using standard metrics such as accuracy, precision, recall, and F1-score. Additionally, embedding quality will be visualised using dimensionality reduction techniques such as t-SNE or UMAP to provide qualitative insights into representation separability. A baseline supervised CNN, trained exclusively on labelled data, will be implemented for comparative analysis to validate the effectiveness and efficiency of the proposed contrastive learning approach.

6.2 Technology Specifications

Programming Language

- Python 3 (Jupyter Notebook environment)

Deep Learning Framework

- PyTorch (torch, torch.nn, torch.optim, torch.nn.functional)

Machine Learning & Utilities

- scikit-learn (preprocessing, model_selection, metrics, manifold.TSNE, cluster)
- UMAP (umap-learn) for embedding visualisation
- SciPy (scipy.ndimage) for signal/image ops
- tqdm for training/evaluation progress bars

Data Handling & Manipulation

- NumPy (numpy)
- Pandas (pandas)

Visualisation

- Matplotlib (matplotlib.pyplot)
- Seaborn (seaborn)
- Plotly (plotly.express, plotly.graph_objects, plotly.subplots) for interactive plots

Data Access / APIs

- requests (HTTP client)
- ALeRCE API for ZTF (https://api.alerce.online/ztf/v1) used to fetch ZTF real data

General Utilities

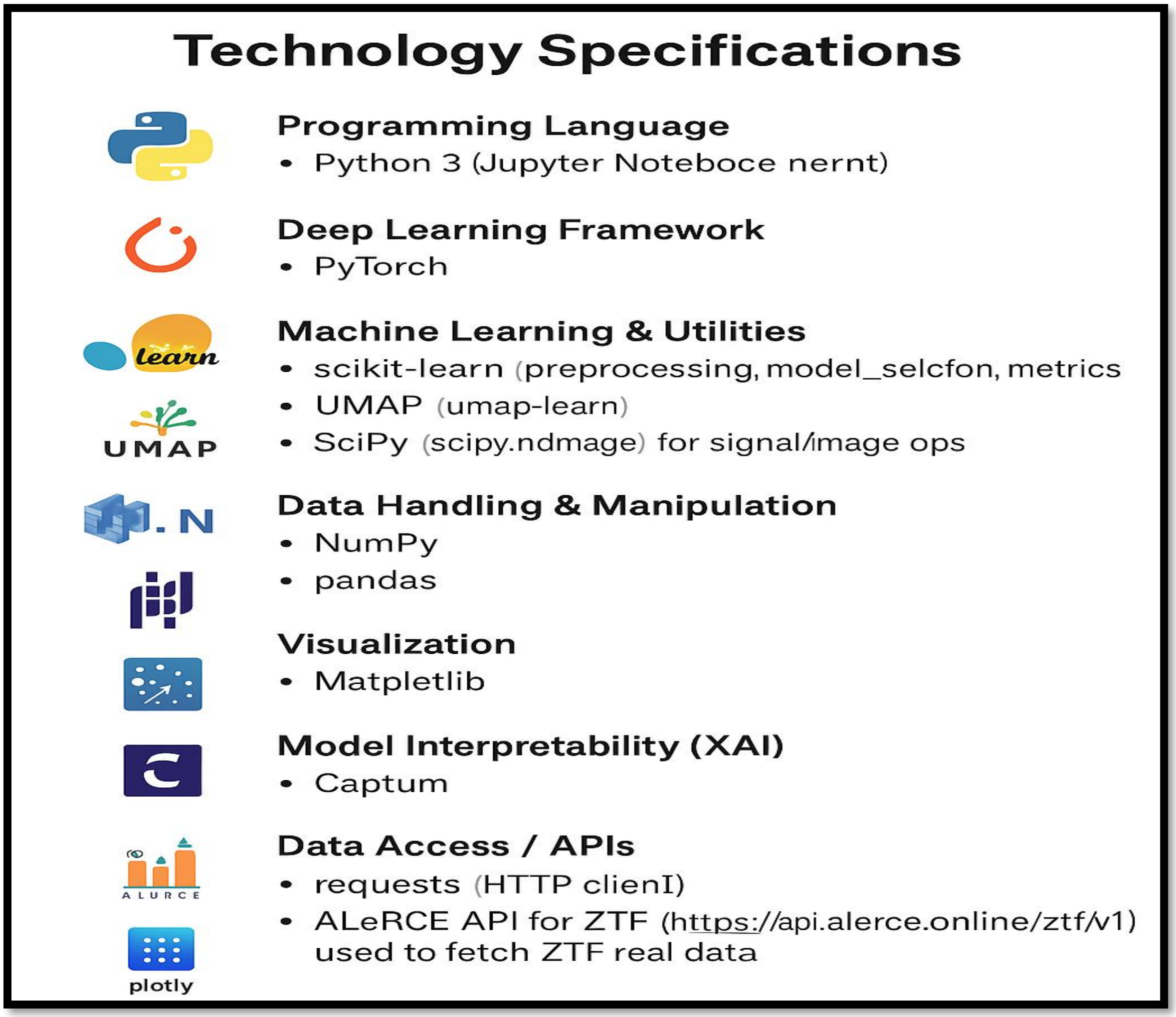
- json, pickle, os, time, datetime, random, warnings, collections

Development Environment

- Jupyter Notebook (kernelspec: Python 3)

Table 3

Tool/Library	Purpose	Version
Python 3	Programming	3.10
PyTorch	Deep Learning Framework	2.2
scikit-learn	Preprocessing & ML utilities	1.4
UMAP	Embedding Visualization	0.5
Matplotlib/Seaborn	Plotting & Analysis	3.8 / 0.11
ALeRCE API	Fetch Real ZTF Data	Latest


Technology Specifications
Programming Language
• Python 3 (Jupyter Noteboce nernt)
Deep Learning Framework
• PyTorch
Machine Learning & Utilities
• scikit-learn (preprocessing, model_selcfon, metrics
• UMAP (umap-learn)
• SciPy (scipy.ndmage) for signal/image ops
Data Handling & Manipulation
• NumPy
• pandas
Visualization
• Matpletlib
Model Interpretability (XAI)
• Captum
Data Access / APIs
• requests (HTTP clienI)
• ALeRCE API for ZTF (https://api.alerce.online/ztf/v1) used to fetch ZTF real data
learn
UMAP
. N
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plotly

Figure 6.2

7 PROJECT REQUIREMENTS

7.1 Functional Requirements

- Load and process multi-band light curves.
- Apply contrastive augmentations.
- Train self-supervised model.
- Fine-tune classifier.
- Evaluate and compare with baselines.

7.2 Non-Functional Requirements

- Reproducibility.
- GPU-accelerated training.
- Scalability to large datasets.

Table 4

Requirement	Justification	Priority
Load and process light curves	Essential preprocessing	High
Apply augmentations	Improve representation learning	High
Train SSL model	Core research framework	High
Fine-tune classifier	Enable rare event detection	High
GPU-accelerated training	Efficiency and scalability	Medium

8 WORK BREAKDOWN STRUCTURE

Work distribution table outlines the distribution of work between team members for different phases of the project. It ensures that each aspect — literature review, preparation of the dataset, designing methodology, training the model, evaluation, documentation, and presentation — is assigned to specific individuals based on their expertise. This systematic distribution promotes responsibility, fair work distribution, and smooth coordination, while also ensuring that all aspects of the research are addressed completely within the time frame allocated.

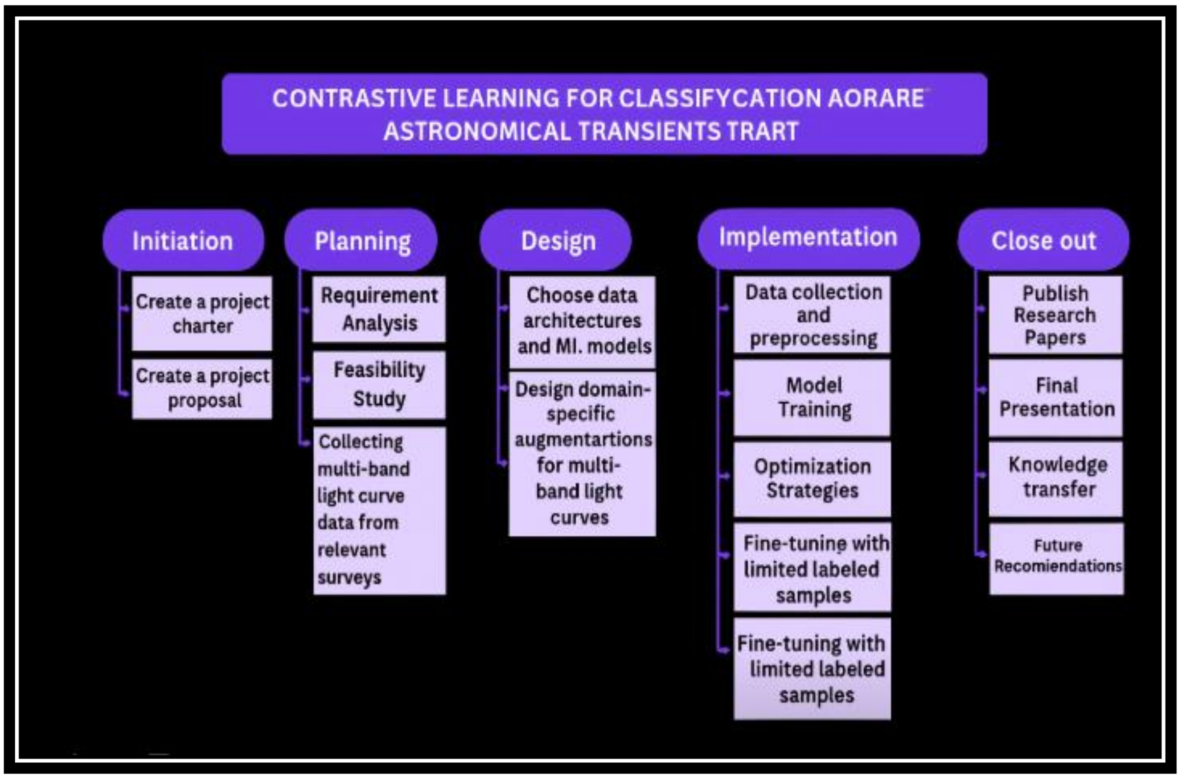

Figure 8.1

9 GANTT CHART

The Gantt chart illustrates the research project timeline from start to completion. It outlines the sequential and overlapping activities like literature review, data collection, model design, implementation, evaluation, documentation, and final presentation. Each activity is stretched across particular months to ensure sequential progress, proper time management, and compliance with project milestones. The chart also shows dependencies between phases, enabling deliverables to be tracked easily across the research period

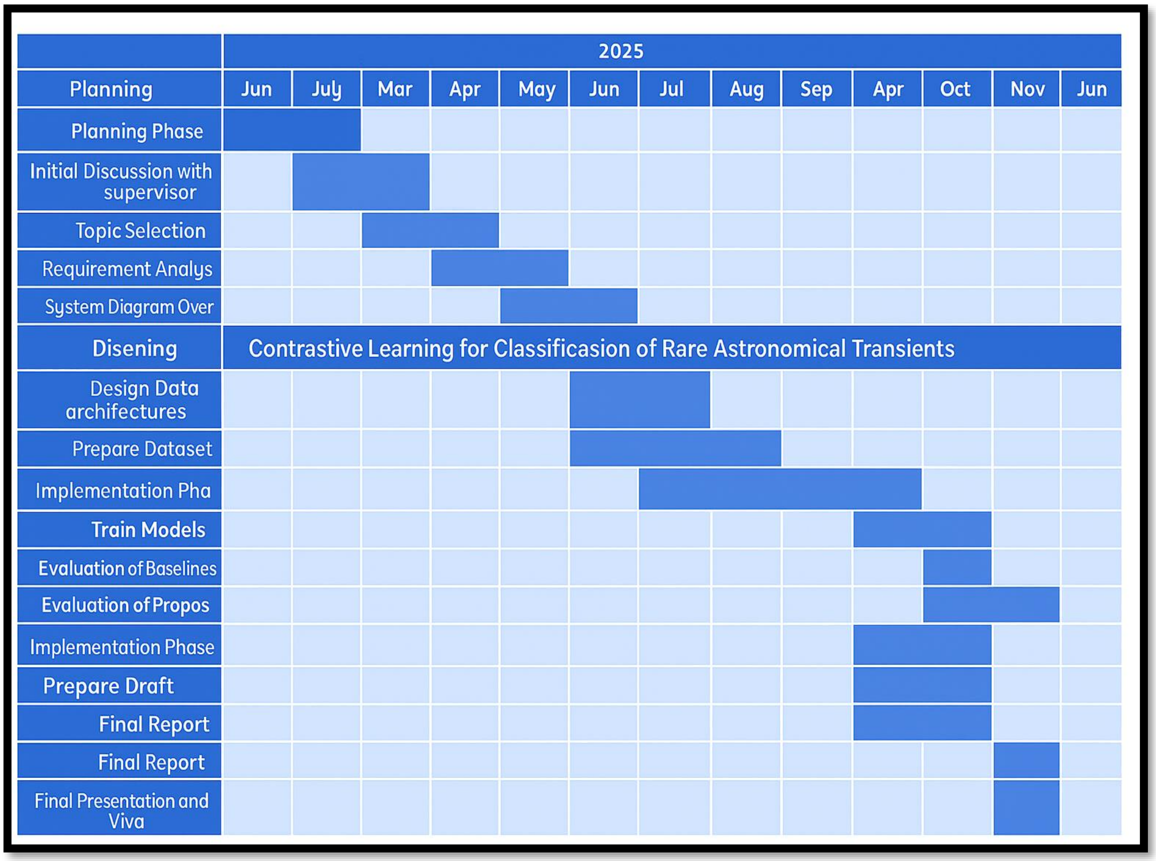

Figure 9.1

10 COMMERCIALIZATION AND CONTRIBUTION TO THE DOMAIN

The proposed contrastive learning architecture for rare astrophysical transients classification is extremely valuable scientifically and commercially. Space research organizations, such as NASA, ESA, and leading time-domain survey collaborations (e.g., Zwicky Transient Facility, Vera C. Rubin Observatory), can utilize this approach to enhance the precision of identifying rare transients without large amounts of labelled data. This has the potential to accelerate discovery in transient astronomy, particularly for phenomena such as kilonovae, tidal disruptions, and other rare explosions.

The architecture enables astronomers to process vast quantities of multi-band light curve data in real-time, learning robust and generalisable representations from unlabeled observations. This reduces dependence on costly manual labelling and improves sensitivity to rare phenomena, thus improving the capability to spot scientifically interesting events that would otherwise be overlooked due to imbalance in data.

Aside from direct astronomical research, this technology can be used in satellite surveillance, deep-space exploration, and space situational awareness systems, where the detection of uncommon or rare signatures is of paramount concern. The research groups can use learned representations to improve goal-driven follow-up observation planning, optimizing telescope time in cases with the most scientific significance.

By improving the efficiency and reliability of rare transient classification, the proposed system contributes more to astrophysical process understanding, stellar life cycles, and conditions for extreme cosmic events. Furthermore, the flexibility of the method to other time-series applications (e.g., Earth observation, climate monitoring, and biomedical signal processing) offers cross-disciplinary commercialization avenues in remote sensing, defence, and health diagnosis markets.

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