Variable Star Classification

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What can the platform help us do?

A guided experience of variable-star classification using astronomical observations

01

Choose a start

Recommended workflow or data overview

02

Understand the data

Light curves and Gaia observations

03

Use or train a classifier

Apply existing models or train new ones

04

Review results

Classification performance and sample predictions

OneAstronomy extracts feature vectors for classification and evaluation

Three ways to use the same observations

The same stars, three observation inputs

01

Light curves

How a star’s brightness changes over time

02

Gaia observations

Colour, brightness and distance information

03

Joint input

Light curves and Gaia information together

Compare the three inputs to examine how complementary observations affect classification

Start from recommended choices

01 Start the recommended workflow

02 Understand the data and files first

After each stage, the platform explains the outputs and offers the next choices

What You Can Do Here

This case lets you compare **three ways** of classifying periodic variable stars across **12 classes** (Cepheids, DSCT, EA, EB, EW, GCAS, HADS, ROT, RRab, RRcd, UV, YSO):

Input	Description
LC-only	Light curve features from TESS observations
Gaia-only	Gaia colour, brightness, and distance information
LC+Gaia	Native joint representation from both

Data Available

- `Data/12classes_sample8.h5` — An 8-object interactive sample for feature extraction
- `ResearchSpace/embeddings/12classes/` — Pre-extracted embeddings for train/validation/test splits (9 NPZ files total)
- `ResearchSpace/task_heads/12classes/` — Three pre-trained classifier heads (`lc_head.pt` , `gaia_head.pt` , `lc_gaia_head.pt`)

The Workflow (4 Stages)

1. **Data audit** — Inspect splits, class distribution, identity alignment, and valid counts
2. **Feature extraction** — Extract LC-only, Gaia-only, and native LC+Gaia representations from the 8-object sample
3. **Load or train task heads** — Use pre-trained heads or retrain with the fixed demo protocol
4. **Frozen test and interpretation** — Evaluate all three on test data and compare metrics

How would you like to begin?

Option 1: Start the recommended workflow — I'll proceed through all 4 stages, beginning with a data audit.

Option 2: Understand the data and files first — I'll do a deeper dive into the data structure, schemas, and what each file contains before starting the workflow.

Case overview and available workflow choices

Understand the data and extract features

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OneAstronomy

Our self-developed astronomical multimodal scientific foundation model encodes the three inputs as feature vectors for classification

Confirm the stars, observations and class labels. An eight-star sample supports the extraction experience

Stage 1 — Data Audit Complete

Embedding Files Structure

All 9 files present and accounted for:

- **Train**: 340 samples × 768 features
- **Validation**: 65 samples × 768 features
- **Test**: 60 samples × 768 features

Class Distribution (12 classes)

Class	Train
Cepheids	23
DSCT	50
EA	50

Stage 2 — Eight-Object Representation Extraction Complete

Upload Summary

Destination: `https://oneastronomy.zero2x.org/api/v2/skills/search-astro-objects/upload-extract-4modalities`

All three extractions succeeded with consistent results:

Modality	Features Shape	Valid Counts
LC	(8, 768)	[409, 514, 514, 308, 409, 479, 461, 514]
Gaia	(8, 768)	[114, 114, 114, 114, 114, 114, 114, 114]
LC+Gaia	(8, 768)	[523, 628, 628, 422, 523, 593, 575, 628]

Key Findings

Identity Alignment: TIC IDs and labels match perfectly across all three modalities.

Native Joint Representation: The LC+Gaia valid counts exactly equal the sum of LC and Gaia valid counts (e.g., 409 + 114 = 523), confirming that the joint represent

Metadata:

- LC: `tess_lightcurve`
- Gaia: `gaia_metadata`
- LC+Gaia: Both modalities, native joint output

Route 1: direct inference

Apply existing classification models matched to the three feature types

Load model parameters Run inference Calculate evaluation metrics

Stage 3 — Task Heads Loaded and Verified

All three pre-trained task heads have been successfully loaded, verified, and passed a finite validation forward pass.

Architecture Verification

Property	LC Head	Gaia Head	LC+Gaia Head
Architecture	768 → 128 → 12	768 → 128 → 12	768 → 128 → 12
Activation	GELU	GELU	GELU
Dropout	0.1	0.1	0.1
Parameters	99,980	99,980	99,980
Class Names	12 classes (0–11)	12 classes (0–11)	12 classes (0–11)
Scaler	modality_train_only	modality_train_only	modality_train_only

Protocol Match

All heads follow the fixed demo protocol:

- MLP: `768 → 128 → 12` with GELU and `dropout=0.1`
- AdamW: `lr=0.001`, `weight_decay=0.001`
- `batch_size=64`, `max_epochs=50`, `patience=8`
- `seed=20261016`

Validation Forward Pass Results

Modality	Validation Accuracy
LC	72.31%
Gaia	47.69%
LC+Gaia	75.38%

All logits are finite, probabilities sum to 1, and predictions are well-formed.

Route 2: train classifiers on the platform

Train a classification model for each of the three feature types

Training set

Learn model parameters

Validation set

Select the training state

Test set

Final evaluation only

Retraining complete. Here's a summary of the three independently trained heads:

Modality	Validation Accuracy	Weighted F1	Macro F1
LC	67.69%	0.6648	0.4809
Gaia	47.69%	0.4347	0.2651
LC+Gaia	**75.38%**	**0.7335**	**0.5882**

Key Observations

1. **LC outperforms Gaia alone** — light-curve dynamics provide richer discriminative signal for periodic variable classification than Gaia photometric/astrometric features in isolation.
2. **LC+Gaia achieves the highest scores** across all four metrics, confirming multimodal gain. The joint representation exceeds both single-modality baselines.
3. **Macro F1 and Balanced Accuracy are lower** than accuracy/weighted F1 for all modalities, reflecting the class imbalance in this dataset — rare classes drag down unweighted metrics.
4. **Early stopping engaged quickly** — LC at epoch 12, Gaia at epoch 18, LC+Gaia at epoch 12. This suggests the models converge rapidly on this small subset; the validation split is modest (65 samples), so patience=8 is appropriat

Training summary and model verification

Classification results and evaluation

Overall performance, results for each variable-star class and individual predictions

Interpret results alongside class sample sizes and compare inputs within this task

Stage 4 — Frozen Test and Interpretation Complete

Overall Metrics (n=60)

Modality	Accuracy	Weighted F1
LC	0.6833	0.6582
Gaia	0.4167	0.3831
LC+Gaia	**0.7167**	**0.7014**

Per-Class Accuracy

Class	LC	Gaia
Cepheids	0.6667	0.3333
DSCT	0.8000	0.6000
EA	0.9000	0.1000
EB	0.6000	0.6000
EW	0.8571	0.8571
GCAS	0.5000	0.5000
HADS	0.0000	0.0000

Key Observations

LC+Gaia shows multimodal gain across all four overall metrics, exceeding both single-modality values in each case.

LC alone outperforms Gaia alone on all metrics, suggesting light-curve features carry more discriminative power for this 12-class problem.

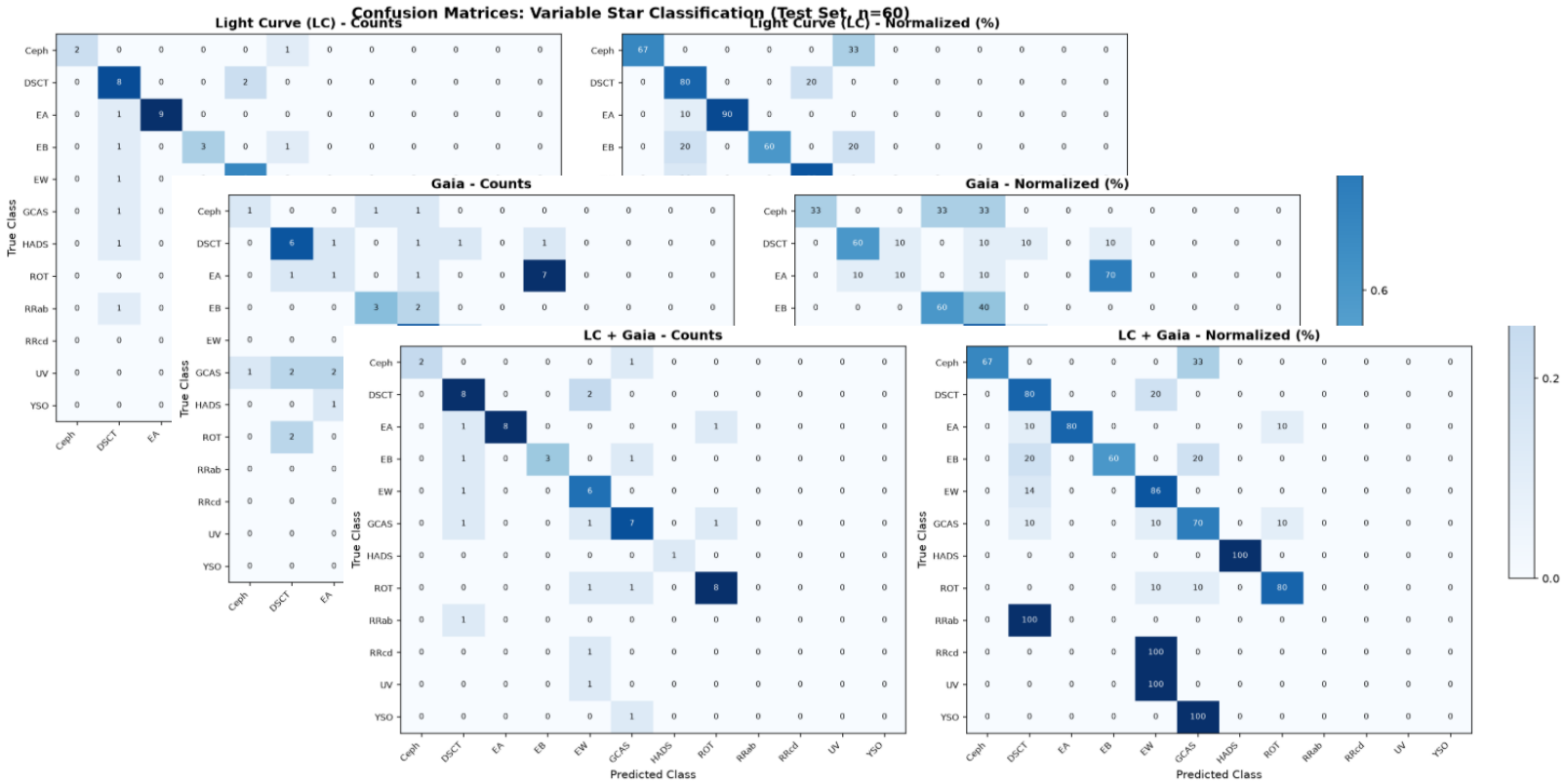
Classes with very low support (HADS, RRab, RRcd, UV, YSO — each 1 sample) are poorly predicted by LC and Gaia individually. LC+Gaia improves HADS to 100% accuracy.

Well-represented classes (DSCT, EA, EW, ROT with 7–10 samples) are generally well-classified by LC and LC+Gaia.

Gaia alone struggles with most classes, only matching LC on EB and EW.

Continue the analysis

Follow the recommended workflow or use suggested Prompts in the guide for focused analysis



Main Confusions in Plain Language

Light Curve (LC) — 68.3% Accuracy

True Class	Most Common Misclassification
GCAS → ROT	3 out of 10 GCAS stars misclassified as ROT
Cepheids → GCAS	1 out of 3 Cepheids
HADS, RRab, RRcd, UV, YSO	All misclassified

Pattern: LC performs well on well-represented classes (DSCT, EA, EW, ROT) b

Gaia — 41.7% Accuracy

True Class	Most Common Misclassification	What Happen
EA → ROT	7 out of 10 EA stars	EA (detached space

Inspect confusion patterns, two-dimensional feature views or predictions for a selected class

The complete classification workflow

01

Recommended steps

Organize observations and outputs at each stage

02

Inference or training

Connect OneAstronomy features to classification models

03

Result evaluation

Summarize overall, class-level and sample-level results

Results apply to the current data and settings
Prediction changes alone do not establish physical causes