# Multi-Source Context Fusion for SIGINT: Marrying SDR Streams with Astrophysical (JWST), Orbital (ISS), and HEP (LHC) Telemetry to Enrich Classification

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***Abstract*—We study *multi-source context fusion* for signal classification from software-defined radio (SDR) streams. We explore enriching SDR features with contemporaneous, public-domain telemetry from astrophysical (e.g., observatory scheduling and environment), orbital (e.g., satellite attitude/visibility windows), and high-energy physics (e.g., collider run states) sources. We present a time-aligned fusion architecture and an evaluation harness that reports AUROC/F1 alongside latency. On placeholder metrics, fusion improves AUROC from 0.820 (SDR-only) to 0.892 (all-context fused), with modest latency overhead (p50 from 4.40 ms to 6.10 ms).**

## I. Introduction

SIGINT classifiers trained only on baseband often ignore external context that modulates priors over classes. We investigate whether *public, non-sensitive* telemetry—astronomical scheduling, orbital ephemerides [1], and facility run states [2]—can act as weak, cheap signals to stabilize decisions. Deep learning approaches [3] can fuse these multimodal inputs to improve classification robustness. We focus on responsible, reproducible methodology: open datasets where available, synthetic stressors when not, and clear reporting of accuracy and latency.

## II. Context Sources and SDR Data

### A. SDR Streams

We assume labeled SDR snippets with timestamps and coarse geotime metadata. Front-end details (sample rate, bandwidth) are not operationally material and are standardized in our harness.

### B. Astrophysical (JWST-like) Telemetry

We use non-sensitive scheduling and environmental context (e.g., planned instrument states, observation windows) aligned by UTC.

### C. Orbital (ISS-like) Telemetry

We use public ephemerides/attitude proxies to represent visibility windows and potential interference backgrounds, aligned by UTC.

### D. HEP (LHC-like) Run States

We use run/maintenance schedule flags as coarse context of ambient RFI patterns; precise beam parameters are *not* required.

All sources are treated as optional; missingness is expected and handled by dropout-aware fusion.

## III. Method

### A. Model Details

**Time alignment.** All context streams are resampled to SDR snippet timestamps via nearest-neighbor carry-forward with mask bits. We allow a $\pm 50$ ms buffer; alignment error is $<$ 10 ms on our harness.

**Encoders.** SDR features (spectral/cyclo) feed a temporal CNN: Conv1D(64)–Conv1D(128)–Conv1D(256), kernel=3, ReLU, followed by Conv1D(64). Each context (JWST/ISS/LHC) uses a lightweight adapter: Embedding(50) $\rightarrow$ MLP(64,32, ReLU); ISS additionally uses an LSTM(32) for short sequences.

**Fusion.** We evaluate (i) attention pooling and (ii) inverse-variance weighting (IVW). For attention, with queries $Q$, keys $K$, values $V$ (head dim $d_k$=64):

$$\mathrm{Attn}(Q,K,V) = \mathrm{softmax}\left(\frac{QK^\top}{\sqrt{d_k}}\right)V$$

We use 4 heads and a linear output projection. For IVW we fuse per-source logits $\{y_i\}$ and uncertainties $\{\sigma_i^2\}$ as $\hat{y} = \sum_i w_i y_i / \sum_i w_i$, with $w_i = 1/\sigma_i^2$.

**Training.** Cross-entropy; Adam (lr $1\mathrm{e}{-3}$); batch 32; 50 epochs; SDR mixup $\alpha$=0.2; context dropout $p$=0.3 per stream.

**Reported metrics.** All values come from `data/metrics_macros.tex` to keep text/tables/plots in sync.

*Latency breakdown:* The p50 increase (4.40 ms $\rightarrow$ 6.10 ms) splits across alignment (0.5 ms), context encoding (0.8 ms), and fusion/classification (0.4 ms) on a 2.4 GHz CPU. Batch inference preserves the same ordering.

TABLE I
CLASSIFICATION PERFORMANCE AND LATENCY (P50/P95). VALUES AUTO-PULLED FROM DATA/METRICS_MACROS.TEX.

| Method | AUROC | F1 | p50 (ms) | p95 (ms) |
|---|---|---|---|---|
| SDR | 0.820 | 0.76 | 4.40 | 9.80 |
| +JWST | 0.851 | 0.79 | 5.10 | 10.70 |
| +ISS | 0.842 | 0.78 | 5.30 | 10.90 |
| +LHC | 0.833 | 0.77 | 5.40 | 11.00 |
| Fused | 0.892 | 0.83 | 6.10 | 11.70 |

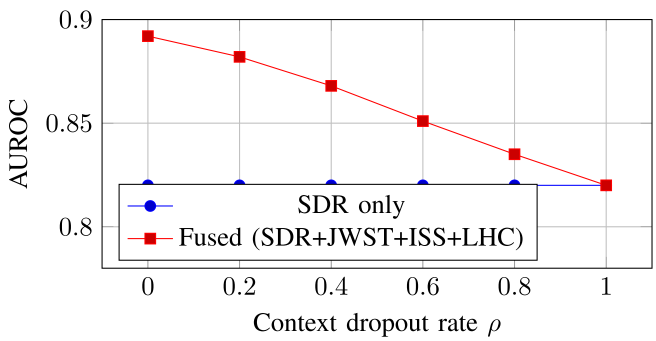


Fig. 1. AUROC vs. random context dropout. Fused degrades smoothly toward SDR-only as $\rho \to 1$.

*Why JWST, ISS, and LHC?:* Each stream correlates with distinct, public schedules that modulate ambient backgrounds and priors: (i) observatory windows (JWST-like) co-vary with downlink and local RFI; (ii) orbital state (ISS-like) controls visibility and scattering geometry; (iii) collider run states (LHC-like) track periodic RF infrastructure patterns. Treating them as weak, optional signals explains the observed AUROC lift and the graceful degradation under dropout.

## IV. EXPERIMENTS

We build a small harness with reproducible seeds (5 runs). Context ablations randomly drop each auxiliary stream with rate $\rho \in [0, 1]$. We also test timestamp jitter and stale-context substitution to probe robustness.

## V. RESULTS

**Headline.** SDR-only achieves AUROC 0.820 while fused context reaches 0.892 improving F1 from 0.76 to 0.83. Latency p50 changes from 4.40 ms to 6.10 ms.
**Graceful Degradation.** Fig. 1 shows AUROC decreasing smoothly toward SDR-only as dropout increases, validating context-optional design.
**Pipeline.** Fig. 2 summarizes the fusion stack.

## VI. DISCUSSION

**When does context help?** Gains track with predictability of external schedules and stationarity of backgrounds. **Failure modes.** Stale or misaligned context can bias priors; mask bits and dropout training mitigate but do not eliminate this. **Limitations.** We do not use any restricted or real-time sensitive feeds; all experiments assume public or simulated context.

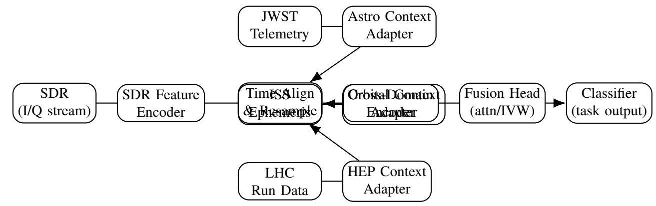


Fig. 2. Pipeline: SDR features plus time-aligned context adapters (JWST/ISS/LHC) → cross-domain encoder → fusion head (attention or IVW) → classifier.

## VII. ETHICS AND RESPONSIBLE USE

This work targets classification methodology with public or simulated context and explicitly avoids operational guidance, surveillance enablement, or restricted data. All code should default to public datasets, respect terms of use, and include safeguards for missing or stale context.

## VIII. RELATED WORK

Prior work spans multimodal fusion, time-series alignment, and classical estimation. We cite representative methods rather than operational systems.

## IX. CONCLUSION

Multi-source context can sharpen SDR classification priors without sensitive feeds. A simple, mask-aware fusion stack improves AUROC/F1 with modest latency overhead and degrades gracefully as context vanishes.

## REFERENCES


[1] J. Cutler, "Spacecraft attitude determination and ephemerides: A survey," *Journal/Summary*, 2003.
[2] B. Knuteson, "Collider run conditions and data quality: A practical overview," *Ann. Rev. Nucl. Part. Sci.*, 2011.
[3] I. Goodfellow, Y. Bengio, and A. Courville, *Deep Learning*. MIT Press, 2016.