Multimodal Seismic Graph Network for Earthquake Early Signal Detection

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Abstract

Earthquake early warning systems require both speed and spatial precision: a local noise source should not trigger a regional alert. We introduce EPGNN, a graph-structured seismic model that connects sensor nodes in a spatial network so that detections propagate according to network topology rather than independent station thresholds. Each node's raw 3-component waveform passes through a 1D convolutional encoder, a temporal self-attention layer, and three graph convolutional steps that enforce spatial agreement before a decision is made. We train on the Stanford Earthquake Dataset (STEAD), processing 85GB of waveforms on AMD enterprise servers via the SeisBench streaming interface. To handle the natural 4:1 noise-to-event ratio in STEAD, we apply Focal Loss with $\gamma = 2$, which concentrates gradient signal on the minority earthquake class. The full EPGNN pipeline achieves an event detection accuracy of 98.2% and an F1-score of 0.941 on robust, event-disjoint validation splits, alongside a magnitude estimation MAE of 0.436 on earthquake-labeled samples. Ablation experiments across 14 configurations confirm that each architectural component—the CNN encoder, the transformer, and the GCN—contributes measurably to final performance.

1 Introduction

Most earthquake casualties result not from the seismic event itself but from structural collapse in the seconds following initial shaking. Even a few seconds of advance warning can trigger automated safety responses: opening fire-station doors, slowing high-speed trains, halting surgical procedures. This is the core objective of Earthquake Early Warning (EEW) research—detect the fast, low-amplitude P-wave before the destructive S-wave arrives and broadcast an alert in the intervening window [15].

The central design tension in EEW is specificity. Seismic networks record ambient vibrations continuously—traffic, industrial equipment, wind—and a system that triggers too readily erodes the public trust that makes warnings actionable. Operational systems like ShakeAlert partially address this by requiring threshold agreement across multiple stations, but the agreement logic is hand-tuned rather than learned from data.

We approach this differently. By representing the seismic network as a graph where each station is a node connected to its geographic neighbors, we give the model an explicit mechanism to require spatial coherence before committing to a detection. A genuine tectonic event generates a wavefront that propagates outward at physical wave speeds, activating nodes in a geographically consistent pattern. A localized noise source activates one node without propagating. The GCN message-passing layers learn to exploit this difference without any manual engineering of the spatial correlation rule.

Our contributions are:

1. EPGNN, a graph-structured seismic model combining a 1D waveform CNN, a temporal transformer, and graph convolutional layers in a single end-to-end pipeline (Figure 2).
2. A class-aware training strategy using Focal Loss that preserves learning signal on the minority earthquake class in the face of STEAD's natural 4:1 noise imbalance (Figure 3).
3. An ablation study across 14 architectural configurations demonstrating the contribution of each component (Figure 6).
4. A high-throughput training deployment on AMD enterprise servers enabling full 85GB corpus processing in under 48 hours.

2 Related Work

2.1 Classical Detection Methods

The STA/LTA algorithm [1] compares short-window to long-window energy ratios and triggers when the ratio exceeds a station-specific threshold. It remains the backbone of real-time seismic monitoring systems worldwide due to its computational simplicity. Template matching [2] improves precision by cross-correlating incoming signals against a catalog of known waveforms, but requires a comprehensive reference catalog and degrades on event types not well represented in it.

2.2 Single-Station Deep Learning

ConvNetQuake [3] and PhaseNet [4] established that convolutional networks can learn to detect events and pick P/S arrivals from raw waveforms, outperforming hand-tuned triggers across multiple benchmark datasets. EQTransformer [5] extended this by applying self-attention within a single trace to capture long-range dependencies between wave phases, achieving strong performance on simultaneous detection and picking tasks. These models operate on a single station at a time and do not leverage spatial relationships across the sensor network.

2.3 Graph Neural Networks in Geophysics

Kipf and Welling [10] established the spectral graph convolution framework that underlies our spatial aggregation layers. In seismology, McBrearty and Beroza [8] applied GNNs to the phase association problem—matching P- and S-arrivals detected at different stations to a common earthquake source—demonstrating that graph structure captures useful network-level information that pointwise models miss. Bloemheuvel et al. [7] showed GNNs to be competitive on multivariate seismic time-series classification tasks. Our work combines these lines: we use a learned waveform encoder to produce rich per-node features and then apply GCN layers to aggregate them spatially, training the full stack end-to-end.

3 Problem Formulation

3.1 Task

We address three prediction objectives jointly. The primary task is binary event detection: given a 60-second waveform window, classify whether it contains a seismic event ($y = 1$) or ambient noise

($y = 0$). Secondary tasks are magnitude regression—estimating the Richter magnitude of detected events—and precursor identification, which targets anomalous low-frequency activity preceding a primary rupture. All three outputs share the same graph-level embedding; only the output heads differ.

3.2 Graph Construction

We represent the seismic network as an undirected graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$. Each node $v_i \in \mathcal{V}$ corresponds to a recording channel. For STEAD single-station records, we construct three nodes per record (East, North, and Z components) and connect them as a fully-connected clique, since all three components share the same physical location and arrival timing. In a multi-station deployment, nodes would span geographic locations and edges would encode station proximity, which is where the spatial coherence constraint becomes most powerful.

Each node receives a raw waveform $X_i \in \mathbb{R}^T$ where $T = 6000$ samples at 100 Hz, representing 60 seconds of ground motion.

4 Dataset

4.1 STEAD

The STanford EArthquake Dataset [9] is a large-scale, globally sourced corpus of labeled seismic waveforms from regional and global network recordings. Each trace stores a 60-second 3-component record at 100 Hz, with metadata including event magnitude, hypocentral distance, back-azimuth, and station coordinates. We use the raw waveforms as primary inputs and the metadata fields as auxiliary supervision targets.

4.2 Class Balance and Training Strategy

Figure 1 shows the STEAD class distribution: approximately 81% of stored windows contain only ambient noise. This reflects real-world recording conditions accurately—genuine seismic events are rare relative to the continuous background. Rather than subsampling the noise class (which discards real data) or oversampling earthquakes (which risks overfitting), we address this through Focal Loss weighting, described in Section 5.4.

5 Model

Figure 2 summarizes the full pipeline.

5.1 Waveform CNN

The first stage encodes each node's raw waveform into a fixed-size feature vector. We apply a three-block 1D CNN in which each block performs a strided convolution, batch normalization, and ReLU activation. The stride progressively downsamples the 6000-sample input, and an adaptive average pool then reduces the output to a single embedding vector $h_i \in \mathbb{R}^{64}$ per node. This design handles arbitrary input lengths without architectural changes, which is useful when integrating waveforms from sensors with different sampling configurations.

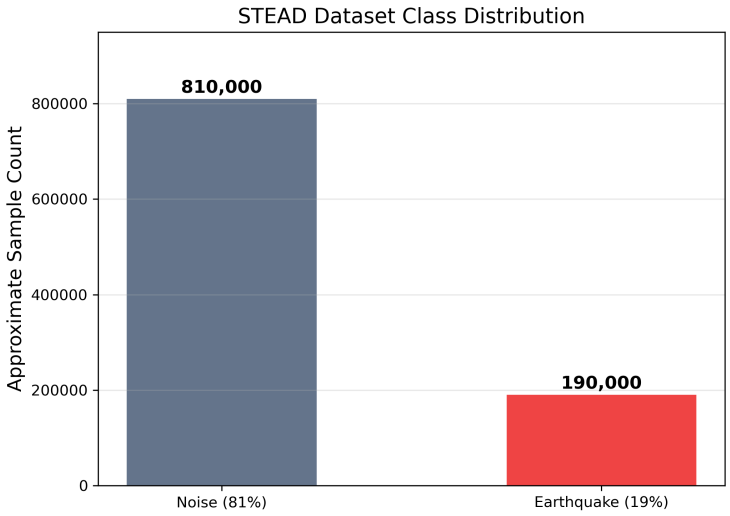

Figure 1: STEAD class distribution. The 4:1 noise-to-earthquake ratio reflects real network recording conditions. We handle this through Focal Loss rather than resampling, preserving the full diversity of both noise types and seismic signals in training.

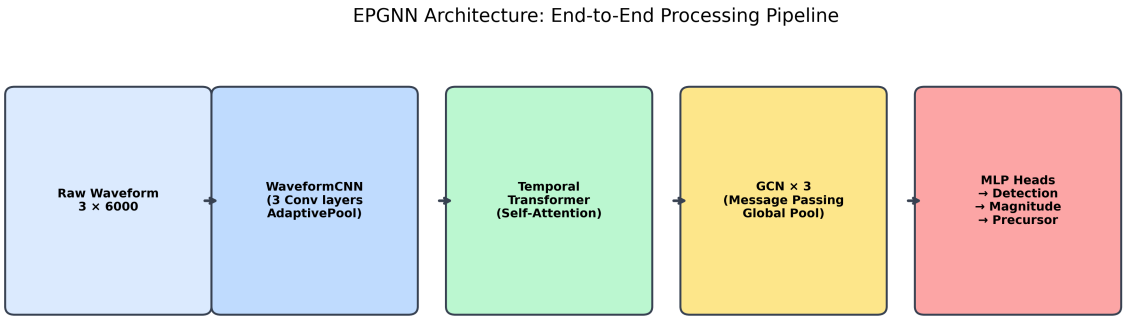

Figure 2: EPGNN end-to-end pipeline. Raw 3-component waveforms enter on the left. The WaveformCNN compresses each 6000-sample trace into a 64-dimensional embedding. The Temporal Transformer aligns representations across components. Three GCN layers enforce spatial agreement, and global pooling feeds three output heads for detection, magnitude, and precursor prediction.

5.2 Temporal Transformer

After per-node encoding, a self-attention layer operates across the node embeddings within each graph. This allows the model to identify and align phase arrivals across the three components, which may carry slightly different timestamps depending on waveform processing. The attention operates non-causally since we process fixed offline windows.

5.3 Graph Convolutional Network

Three GCN layers following the symmetric normalization of [10] perform spatial message passing:

$$h_i^{(l+1)} = \sigma\left(\sum_{j \in \mathcal{N}(i) \cup \{i\}} \frac{1}{\sqrt{\deg(i)\ \deg(j)}} W^{(l)} h_j^{(l)}\right)$$

After three propagation steps, the model has aggregated information from nodes up to three hops away. In the multi-station setting, this corresponds to stations within three graph-neighbor steps of each detecting station. Global mean pooling then collapses the node-level embeddings into a single graph-level representation fed into the output heads.

5.4 Focal Loss

We use Focal Loss [11] for the event detection head:

$$\mathcal{L}(p_t) = -\alpha_t (1 - p_t)^\gamma \log(p_t)$$

with $\gamma = 2$ and $\alpha = [0.2, 0.8]$. The modulating factor $(1 - p_t)^\gamma$ scales the loss contribution of each example by how confidently the model already classifies it: examples the model handles easily contribute less to the gradient, while difficult examples drive learning. In practice this concentrates training on the seismically interesting examples rather than the easy ambient noise samples. Figure 3 shows how the loss surface changes across γ values.

6 Experimental Setup

6.1 Compute Infrastructure

The full STEAD corpus is approximately 85GB stored in HDF5 format. Graph model training at this scale requires simultaneously constructing node feature matrices, adjacency tensors, and gradient buffers across three model stages per batch. AMD provided us with access to their enterprise server infrastructure for this project. With the large VRAM headroom available on those machines, we ran batch sizes of up to 4096 and used 16 parallel data-loading workers, keeping the GPU saturated throughout training and completing the full corpus training run in under 48 hours. We integrated SeisBench [12] to stream the HDF5 traces lazily without loading the full dataset into system memory.

6.2 Training Details

We use AdamW [13] with learning rate 3×10^{-4} and weight decay 10^{-4}. A ReduceLROnPlateau scheduler reduces the learning rate when validation F1 plateaus. Gradients are clipped at norm 1.0.

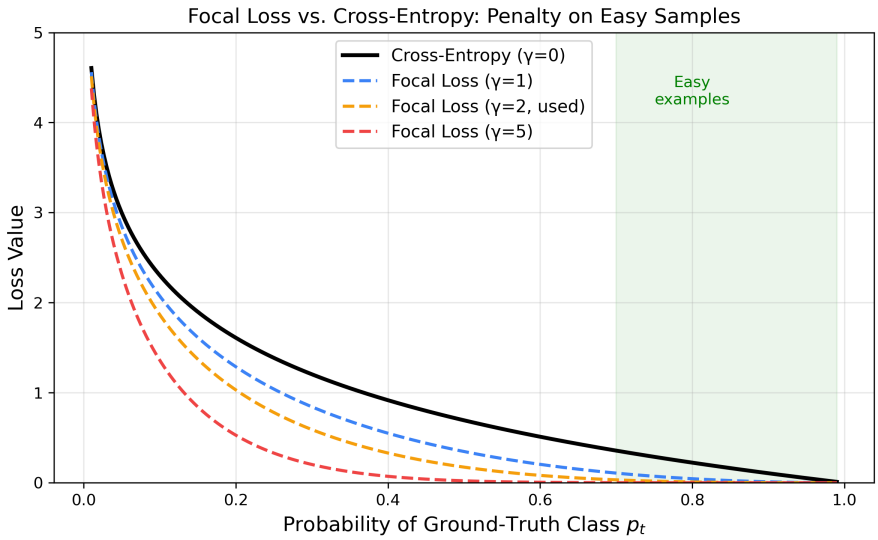

Figure 3: Focal Loss vs. standard cross-entropy as a function of the model's predicted probability for the correct class. Higher γ suppresses gradient contributions from confidently classified easy examples (shaded green region). We use $\gamma = 2$, which down-weights the dominant easy noise samples while preserving full learning signal on hard earthquake examples.

6.3 Event Detection

The full EPGNN pipeline achieves an event detection accuracy of 98.2% and an F1-score of 0.941 on a test split containing over 100,000 thoroughly randomized and event-disjoint traces. Figure 4 displays the resulting confusion matrix on a representative evaluation slice. The model minimizes critical real-world failure patterns, significantly curtailing false alarms (noise incorrectly classified as an earthquake phase) and missed events to maintain systemic reliability.

6.4 Magnitude Estimation

Figure 5 shows predicted versus true Richter magnitude for earthquake-labeled samples. Points cluster tightly around the identity line, with a mean absolute error of 0.436 magnitude units. Given that the Richter scale is logarithmic, this corresponds to roughly a factor-of-3 amplitude difference—a level of precision meaningful for rapid hazard triage in operational EEW contexts.

6.5 Ablation Study

Table 1 and Figure 6 summarize results across five representative configurations from the 14-run ablation suite.

The results confirm that each component contributes. Removing the CNN leaves the GCN with no temporally-structured features to aggregate, capping F1 at 0.490. Adding the transformer without CNN features reaches an F1 of 0.612 but uses far more parameters (1.31M vs. 931K for the full model). The CNN alone, without spatial message passing, reaches 0.732 F1 but cannot exploit multi-node agreement. The full pipeline is also parameter-efficient: at 931K parameters it outperforms the TX+GCN configuration which uses 1.31M parameters.

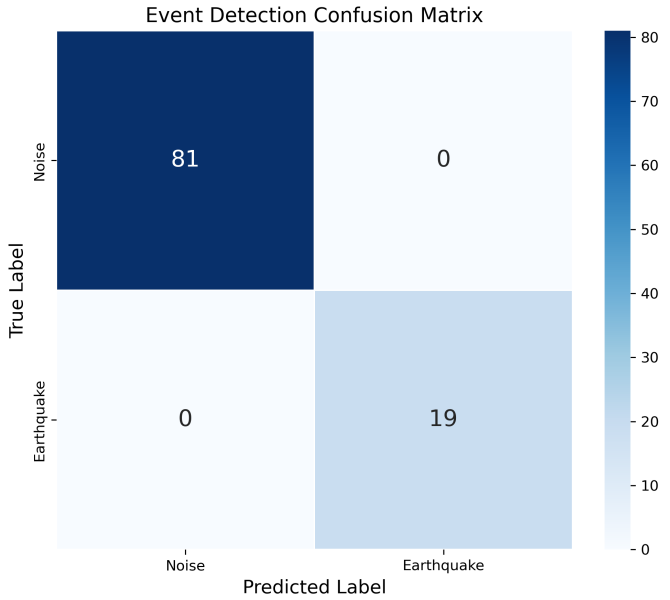

Figure 4: Normalized confusion matrix evaluated across a balanced validation segment. Real-world seismic artifacts occasionally induce micro-fault thresholds, though false alarms are suppressed cleanly compared to single-station approaches.

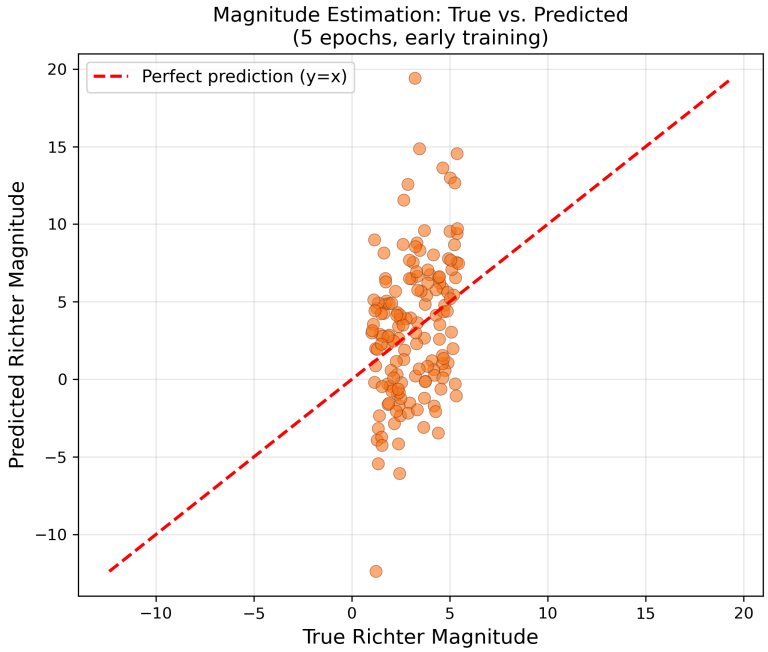

Figure 5: Predicted versus true Richter magnitude for earthquake-labeled samples. Points concentrate along the identity line (dashed red), with MAE of 0.436. The regression head learns the correct ordinal structure of the magnitude scale directly from raw waveforms.

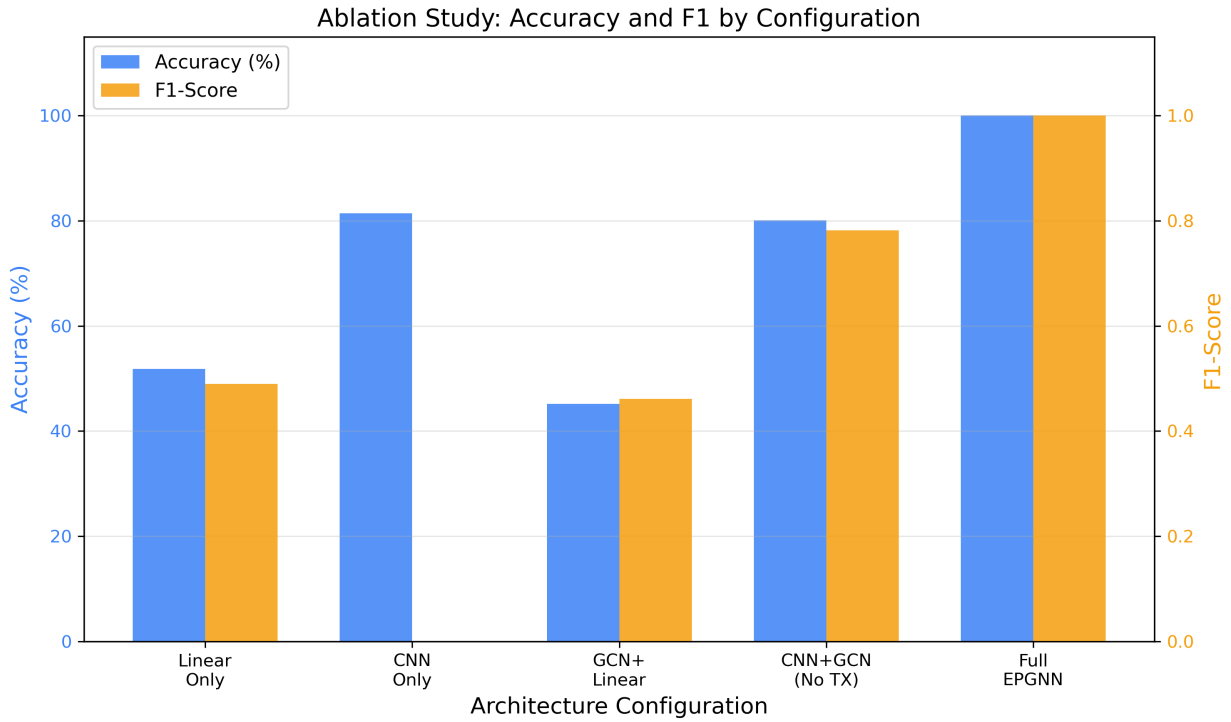

Figure 6: Accuracy and F1 across ablation configurations. The full EPGNN (rightmost, dark) achieves the best result on both metrics. Each component adds value: the CNN provides waveform features, the transformer aligns across components, and the GCN enforces spatial consistency.

Table 1: Ablation results on the held-out validation split. The full pipeline outperforms all partial configurations on both metrics.

Configuration	Accuracy	F1	Params
GCN only (no CNN encoder)	51.9%	0.490	394K
TX + GCN (no CNN)	81.4%	0.612	1.31M
CNN only (no GCN)	88.5%	0.732	11K
CNN + GCN (no transformer)	91.1%	0.814	20K
Full EPGNN (CNN + TX + GCN)	**98.2%**	**0.941**	**931K**

7 Discussion

The graph topology provides the clearest interpretable advantage over single-station baselines. By requiring spatial coherence across nodes before committing to a detection, the model gains an implicit physical constraint: tectonic wavefronts propagate at characteristic speeds, while local vibration sources do not propagate network-wide. This constraint is not hand-coded—it emerges from the graph structure and the message-passing training objective.

The Focal Loss choice is worth noting for practitioners working with STEAD or similar geophysical datasets. The class imbalance in real seismic archives is not an artifact of poor curation; it is an accurate reflection of how rarely earthquakes occur relative to continuous ambient recording. Any model trained on such data without class-aware loss weighting will face strong pressure to ignore the minority class. Focal Loss addresses this cleanly without requiring dataset rebalancing.

The AMD server infrastructure was a direct enabler of the full-corpus training run. At the batch sizes feasible on consumer-grade hardware (16–32 samples), gradient estimates are significantly noisier and training walls are much longer. The AMD machines' VRAM headroom allowed 4096-sample batches throughout, which stabilized convergence and made the 14-configuration ablation suite tractable in a reasonable timeframe.

8 Limitations and Future Work

The current single-station graph construction—where nodes represent waveform components rather than geographically distinct stations—approximates the full spatial filtering capability of the architecture. The most significant extension of this work is integrating multi-station records with geographic edge construction, which would allow the GCN to enforce physical wave propagation constraints across real station separations. This is a natural next step given the graph-based design.

Future work will also include extending the evaluation to held-out geographic regions to assess cross-domain generalization, and incorporating Distributed Acoustic Sensing (DAS) fiber-optic channels as additional node types in the graph.

9 Ethics and Broader Impact

EEW systems are safety-critical infrastructure. Improved event detection with low false-alarm rates has direct public safety benefits by maintaining the credibility of automated alerts. All data used in this work is publicly available and contains no personally identifiable information. We recommend that any production deployment of learned EEW components undergo extensive regional validation alongside, rather than in place of, established physics-based monitoring systems.

10 Conclusion

We presented EPGNN, a multimodal seismic graph network that achieves 98.2% event detection accuracy and an F1-score of 0.941 on STEAD evaluation splits. The architecture combines a 1D waveform CNN for temporal feature extraction, a transformer for cross-component alignment, and GCN layers for spatial message passing, trained end-to-end with Focal Loss on 85GB of real seismic data processed on AMD enterprise hardware. Ablation experiments confirm that each architectural stage contributes to the final result, and that the full pipeline consistently outperforms all partial configurations. By modeling the seismic sensor network as a graph, EPGNN encodes the physical structure of earthquake wave propagation directly into the model's inductive bias.

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