A Transformer-Based Classification System for Volcanic Seismic Signals

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Introduction

- Volcanic seismic signals are a key element in **volcano monitoring** to assess the state of unrest and a possible eruption style and timing
- Different sources generate **different types of events**, with somewhat distinct frequency content, envelope, and length
- Typical types of volcanic events classic to most volcanoes:
  - ***Long-period Earthquake (LP)*** → associated with fluid movement, due to hydrothermal activity, or gas/magma moving through cracks
  - ***Tremor (TR)*** → thought to be trains of LPs. A constant rumbling lasting from minutes to months
  - ***Volcano-tectonic (VT)*** → associated with fragile fracture around chambers and feeding dykes
  - ***Tectonic (TC)*** → also called Volcano Distal (VD), typical to crustal faults outside the volcanic edifice

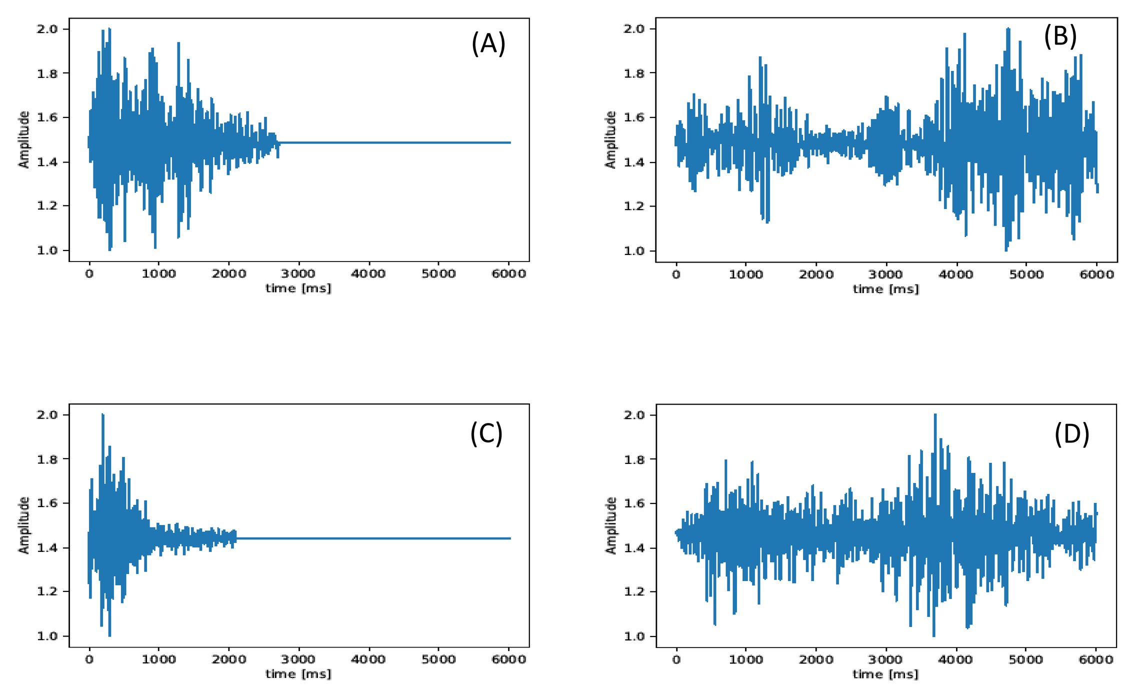

Figure 1. Examples of Volcanic Events. (A) LP event. (B) TR event. (C) VT event. (D) TC event. Events from Llaima volcano, dataset available from Canário et al. (2020).

The Problem:
In cases of unrest or an eminent eruption, the amount of events (data) generated would requires a fast and reliable source of classification, which is currently a labour intensive task mostly done by humans.

Our Proposal:
Create a Deep Neural Network (DNN) model that includes multi-head self-attention to automatically classify volcanic seismic signals, reducing human bias.

Data

Each event represents a one-minute signal sampled at 100Hz (10 milliseconds), resulting in 6,000 features

1. **Clean Llaima Data (Canário et al. 2020)** – 3592 events
   - Classes: 1488 TC, 1310 VT, 490 TR, and 304 VT
2. **Raw Llaima Data** – 1074 events
   - Classes: 1033 LP and 41 TR
3. **Raw St. Vincent Data** – 8,279 events
   - Classes: 7420 LP and 859 VT

$x_{i\,1}$	$x_{i\,2}$	…	$x_{i\,5999}$	$x_{i\,6000}$	$class_i$

Figure 2. Example of a single row in the data.

Methods

- We use the model proposed by **Canário et al. (2020)** as the baseline for comparison and propose a **novel model architecture** for the classification task

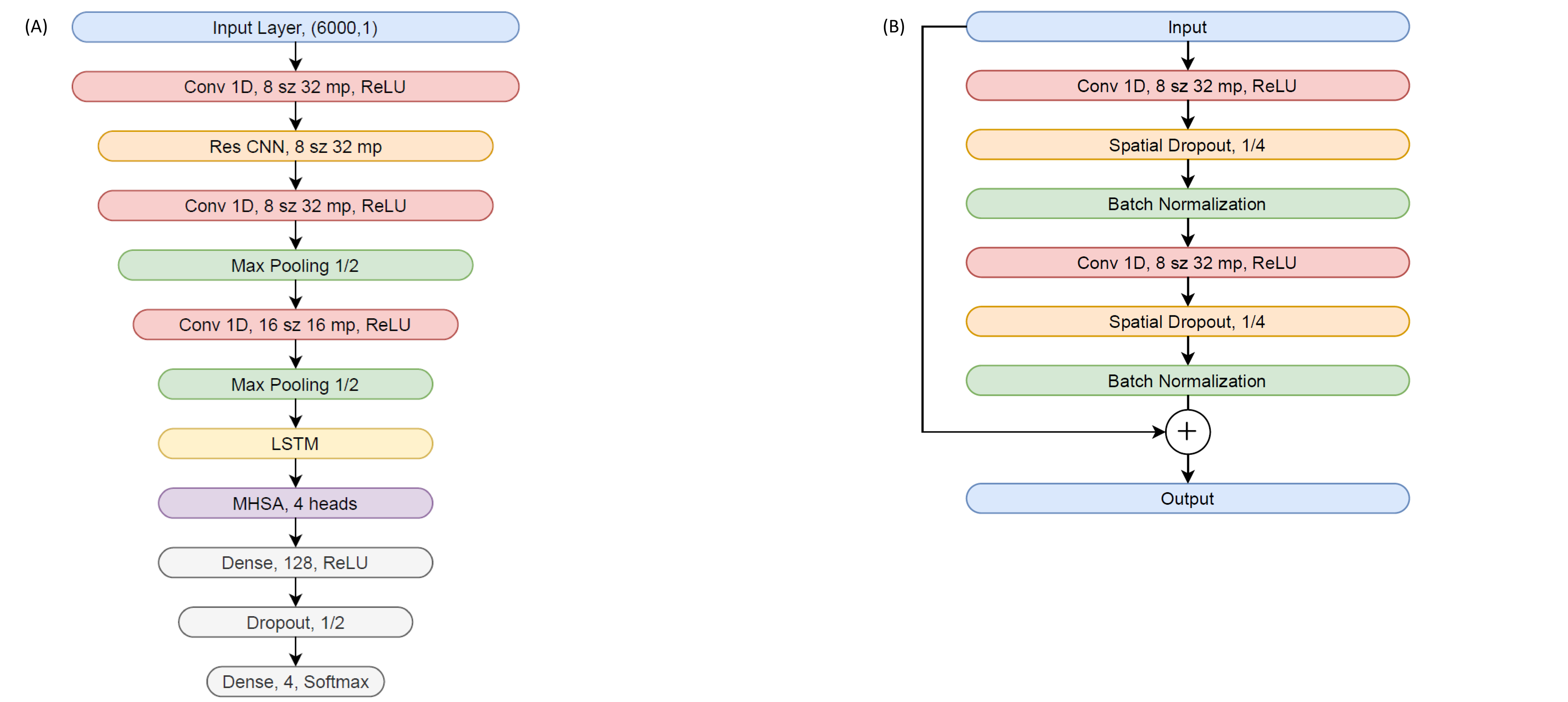

Figure 3. Proposed DNN Model Architecture. (A) DNN network including CNN layers, Residual CNN layers with skipped connections, LSTM block for positional encoding, and a multi-head self-attention block. X sz Y mp denotes a layer with filter size of X and Y filter maps. (B) Breakdown of the Residual CNN block used in the model architecture. Spatial dropout layers set ¼ of feature maps to zero.

- Models are compared using **accuracy** for dataset (1) and **AUC** (area under ROC) for datasets (2) and (3) due to the class imbalance
- Optimal number of training epochs is selected using **cross-validation** for dataset (2)

Results

- Our proposed model achieves **96.1% accuracy** with the benchmark model achieving **94.5% accuracy** on dataset (1)

(A)

	LP	TC	TR	VT
LP	242	13	0	3
TC	1	306	2	2
TR	0	4	89	0
VT	2	1	0	54

(B)

	LP	TC	TR	VT
LP	242	10	4	2
TC	1	298	10	2
TR	2	3	88	0
VT	5	0	0	52

Figure 4. Model Confusion Matrices. Rows represent the true classes from the data. Columns represent the predicted classes from the models. (A) Our proposed model. (B) Baseline model.

- The test set performance metric (AUC) is **bootstrapped** to understand its distribution since the severe class imbalance can result in misleading performance metrics

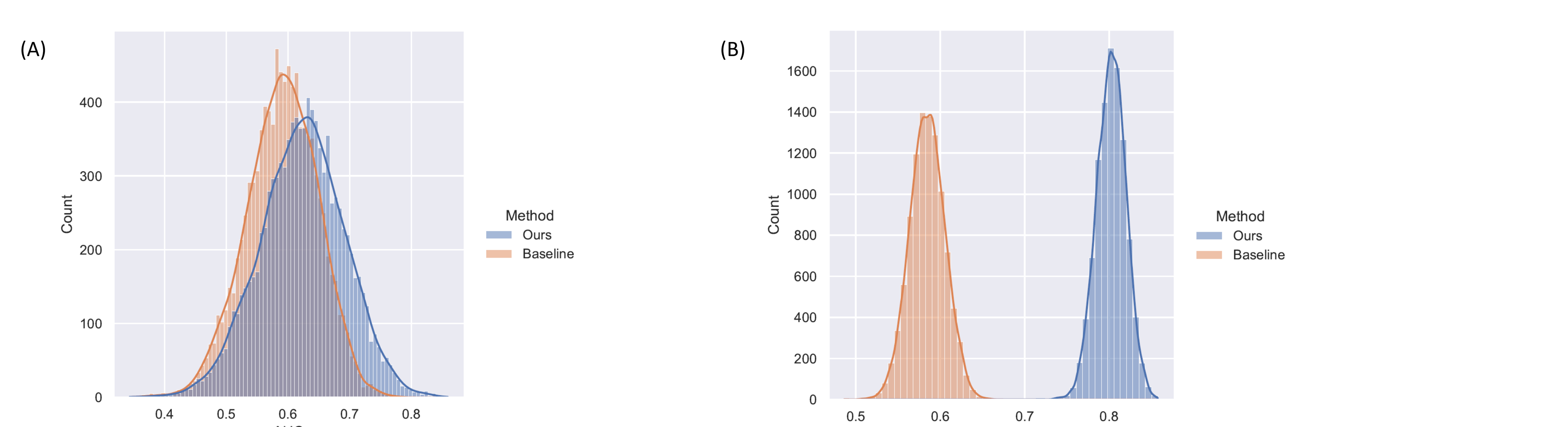

Figure 5. Bootstrap Distribution of Test Set AUC. Each dataset and model/method pair are bootstrapped 10,000 times. (A) Raw Llaima Dataset. (B) Raw St. Vincent Dataset.

Discussion

- We visualize the **attention heads** to better understand how the model attends to each of the four different classes of events
- **Attention plots** are a way to better understand the black-box methods of DNNs

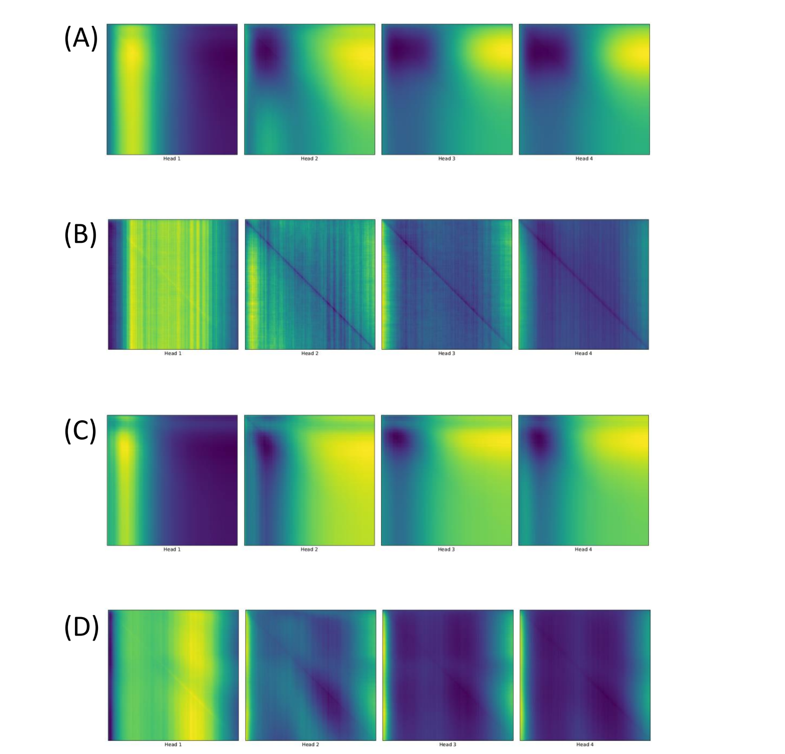

Figure 6. Attention plots for clean Llaima data. (A) LP attention. (B) TR attention. (C) VT attention. (D) TC attention.

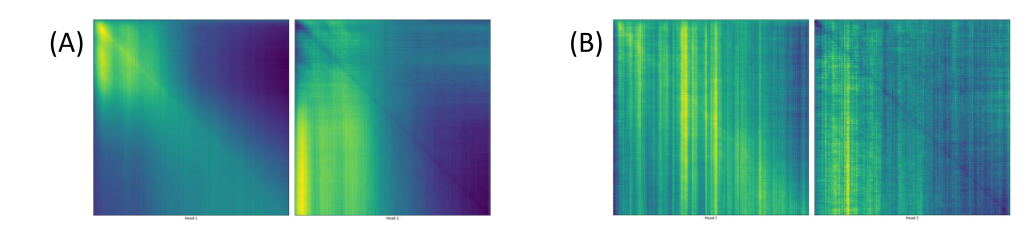

Figure 7. Attention plots for raw Llaima data. (A) LP attention. (B) TR attention.

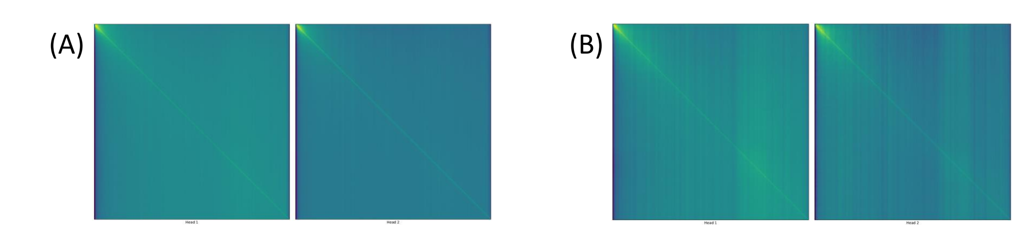

Figure 8. Attention plots for raw St. Vincent data. (A) LP attention. (B) VT attention.

- Attention plots are similar for LP and VT events, and are similar for TR and TC events, aligning nicely with the visual shape of the events
- Attention plots are similar for the same event types across different datasets, indicating that the multi-head self-attention mechanism is attending to similar information across different volcanoes

Conclusion

- Our proposed model architecture provides **minor improvements** over existing approaches on **pre-processed data**
- When considering **raw signals** coming directly from monitoring stations, **our model outperforms** existing approaches by a great margin
- Where our model will **excel** is in stations where **human capital is limited** and there is difficulty in identifying all volcanic events

References
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