Article Summary: Applying EQ Transformer to Laboratory Earthquakes: Detecting and Picking Acoustic Emissions with Machine Learning

Eliab Melaku, Nikhil Patil, Mahib Rahman

October 2nd, 2025

Abstract

Acoustic emissions (AEs) come in the form of quick, microscopic, sudden elastic shocks or mechanical waves caused by high pressure and heat environments (P-T) leading to irreversible changes made to a material. The monitoring of AEs is a commonly practiced technique to detect patterns in the rocks on the ground before an earthquake. It is important to consider that during actual seismic events, the sensing of AEs should not be the main method to detect. In this article, a study is conducted on whether an earthquake detector (EQTransformer) with a machine learning model (MultiNet), can be used in real-life situations to see if it can effectively pick up levels of AEs in pre-earthquake scenarios without retraining via comparing it to actual lab data. The performance of the model was determined by the F_1 score. The equation presenting this was $F_1 = \frac{2P_T}{2P_T+P_F+N_F}$ with P_T being true positives, P_F being false positives, and N_F being false negatives (Sheehan, et. al). The EQT was able to detect all 3901 events which caused the AEs with <1 pick error (Sheehan, et. al). This is a great showing of the potential of how helpful it can be in detecting seismic waves in the future as it has proven that the EQT can detect AEs more effectively than manual methods of detection without retraining.

Materials and Methods

In the testing of detecting AE waves using EQT, the mineral Mg_2GeO_4 (magnesium germanite) was used due to its ease of transforming in high P-T environments. The experiments were ran using multi-anvil presses and piezoelectric transducers, which converted the mechanical waves released by AEs into readable electrical waves needed to test the EQT's detection ability. Each experiment created two types of datasets, continuous and even triggered recordings. Dataset D2540's recording type was continuous and triggered, meaning that it would capture any AE signals that had been manually preset. On the other hand, Dataset D1247 involved a trigger-only recording type which was implemented as it was previously tested with an older model of MultiNet, so it could act as a benchmark to the newer version.

Overall, this experiential design allowed for an effective benchmark, as D1247 worked to find proficiency of EQT, while D2540 investigated the effectiveness of scaling up and finding many more both larger and smaller events within noisy data.

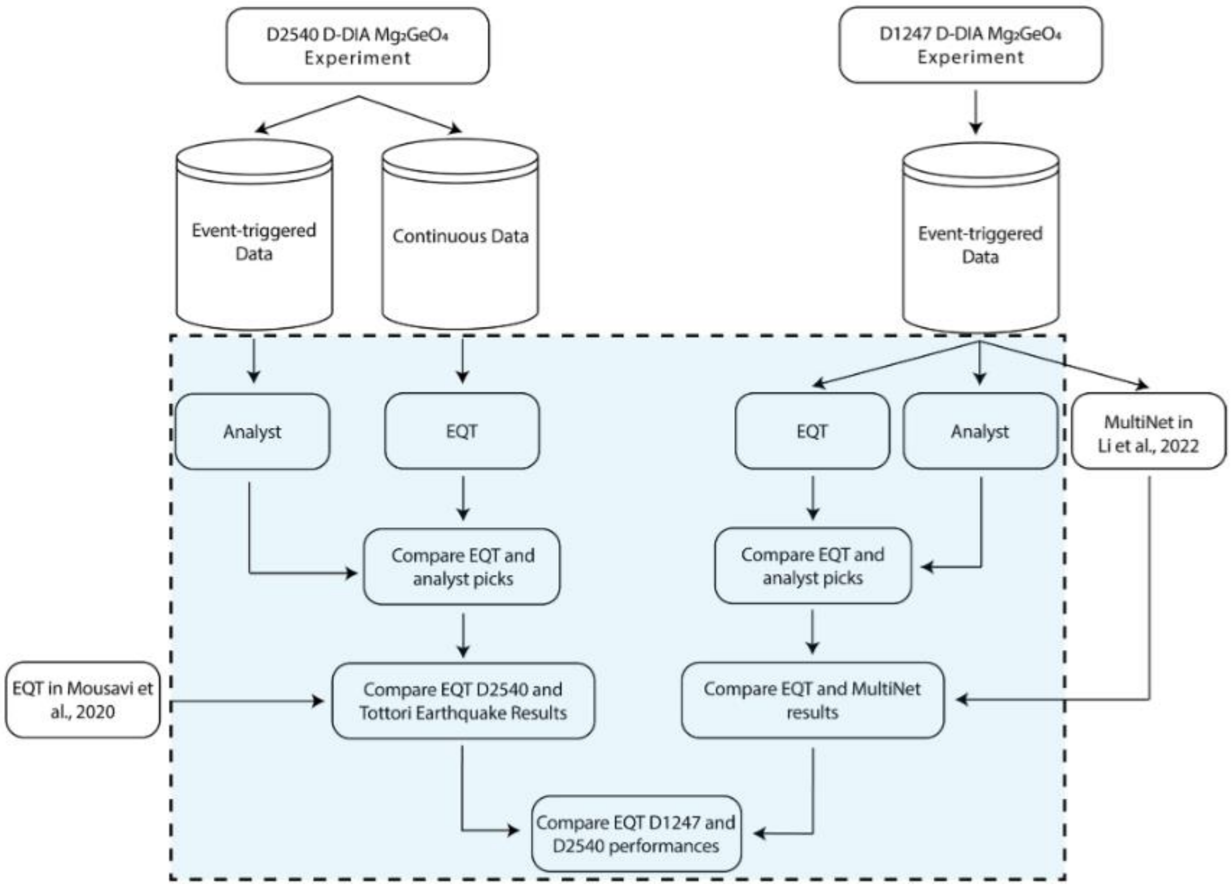

Figure 1- Illustrates the steps of how AE's were used alongside EQT and how the 2 data models compared.

Analysis

EQTransformer turned out to produce successful results for the laboratory-scale earthquakes, though it was made for natural earthquakes. EQT displayed good performance for both datasets, D2540 and D1247.

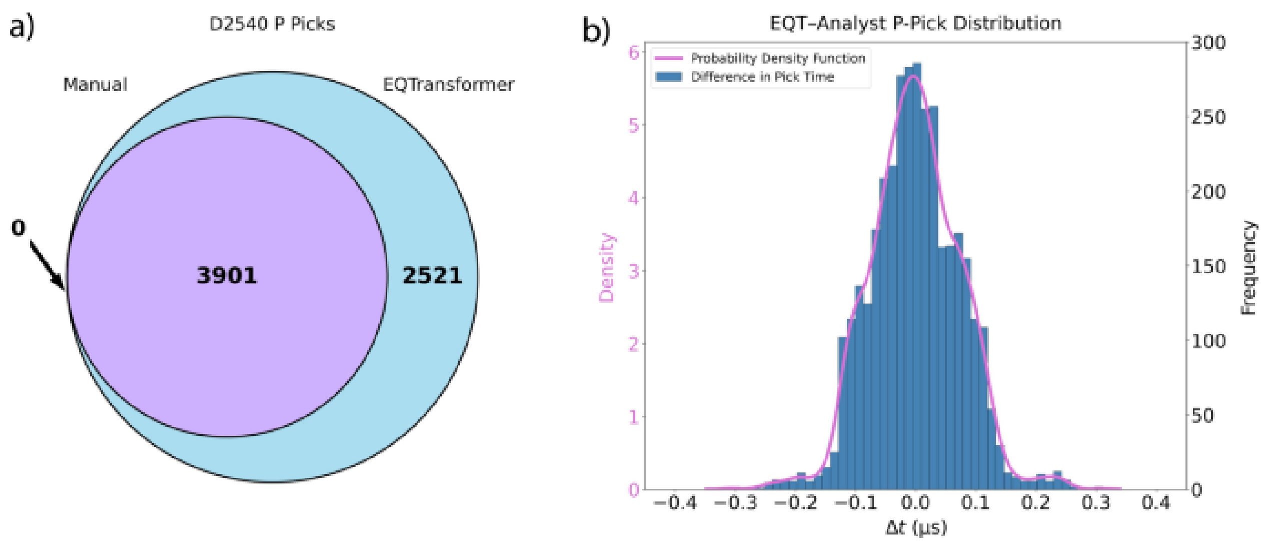

Figure 2

Both panels show trends between dataset D2540 and manual picks from the analysts. In Fig. 2a, the Euler diagram shows the number of events picked up manually by analysts and by the EQT. It clearly shows that EQT did not miss any events that the analysts picked up. However, EQT picked up an additional 2521 events that were not recorded by the analysts. As a result, EQT had a 62.62% increase in number of events compared to the manually catalogued ones (Sheehan, et. al). Due to dataset D2540 having continuous capture type, it picked low amplitude events that were unnoticed by the analysts. Fig. 2b shows the distribution of arrival time differences for the events that were picked by both methods. EQT's arrival time picks almost match those of the analysts, with errors extremely close to 0 seconds, proving EQT's precision and reliability.

These results are extremely applicable to our research project, which aims to create an early earthquake detection system utilizing machine learning for third-world countries. This study provides strong evidence as to how detection systems using machine learning can be more effective and dependable than manual methods of detection. The article proved that EQT could detect low-amplitude events that were unnoticed by the analysts. This is crucial for our project because our system could similarly detect micro-earthquakes that lead to a serious earthquake.

References

Sheehan, J., Zhai, Q., Chuang, L. Y., Officer, T., Wang, Y., Zhu, L., & Peng, Z. (2025). Applying EQTransformer to laboratory earthquakes: detecting and picking acoustic emissions with machine learning. *Earth Planets and Space*, *77*(1). https://earth-planets-space.springeropen.com/articles/10.1186/s40623-025-02237-2