Designing a Low-Cost Machine Learning-Based Early Earthquake Detection System for Developing Countries

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Abstract

Earthquakes are one of the most destructive types of natural phenomena. They cause massive loss of lives and leave large amounts of damage. This is especially the case in developing countries with inadequate technology that lack advanced detecting mechanisms which the already developed, wealthy countries possess. A big problem is that modern detection methods/systems are reliant on ultra-expensive, power intensive networks mapped out over a large area. As one can imagine, this makes it very complicated for developing regions to get the detection technology they need. Our project's goal is to design an affordable and energy efficient early earthquake detection device with the use of piezoelectric transducers (efficient and low-cost sensors suitable for low-power nodes), MEMS accelerometers, machine learning, and wake-on wireless radio communication (WOR). Earthquakes make quick, low-amplitude waves called Primary waves, or P-waves. This is then followed in quick succession by a large, damaging wave called the secondary wave, or S-wave. Detecting the P-waves in a swift and orderly fashion can save many lives and save a lot of infrastructure in the process. Ultimately, the main objective for our project is to provide a low-cost, energy-efficient early earthquake detector prototype for developing countries that cannot afford advanced equipment. This research is important since it combines aspects of various scientific fields such as electrical and mechanical engineering, a broad knowledge of seismology, and an understanding of machine learning. Societally, this will provide developing regions with an affordable way to warn their people of an earthquake, saving lives and money.

Introduction/Background

Our team wanted to solve a world problem involving developing countries and earthquakes that came to our minds. We researched developing countries that can't afford expensive EEW (Early Earthquake Warning) systems. An example of a country we researched can be Haiti. According to the *Haiti Earthquake Report,* earthquakes are very prevalent at approximately 31 per year and the latest was one recorded in the Haitian capital, Port-au-Prince, on December 2nd, 2025. The issue with this is that Haiti is one of the poorest countries in the world, which does not give them the luxury of affording expensive earthquake detectors. Unfortunately, the country's inability to effectively predict an earthquake leads to many deaths and large amounts of destruction. We want to build this device using low-cost options to save lives.

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 demonstration 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.

Piezoelectric transducer materials efficiently transfer mechanical waves to electrical energy, and the electrical energy transfers to motion. A piezoelectric transducer was used in real life in applications such as ultrasound, sonar, and microphone machines by Authors H. Jaffe and D. A. Berlincourt who used the equations $D = e^T E + dT$ and $S = d^T E + s^T T$ (D is the measure of electric charge movement, T is pressure/stress, E is electric field, and S is the quantity in which the material stretches) to describe the effect of piezoelectric transducer materials. Early transducers, according to the article, were Rochelle salt and quartz. The limitations of these materials, as discussed by the authors, were that they had low piezoelectric coupling, had a high acoustic impendence, had a limited output at low frequencies, and were very difficult to modify once set. The newer and improved materials, lead zirconate and lead titanate, also called PZT, checked all of the boxes in which the early transducers could not. This included characteristics such as a stronger piezoelectric effect and a High Curie Temperature point. In conclusion, the authors concluded that PZT works the best for most ultrasonic and sound applications. On the other hand, materials such as quartz work best for really high frequency devices/machines.

Authors Shih Lin Hung, Jiun Ting Ding, and Yung Chi Lu came up with a solution to reducing energy consumption in Wireless Sensor Networks (WSN) for Structural Health Modeling (SHM). The catch being they must still have a quick response to detect earthquakes. Earthquakes cause lots of damage, especially in places without advanced detective technology. In this study, a WSN was created using a technique called wake-on-radio (WOR) technology. What is important to note is that earthquakes release two different types of waves: Primary and secondary waves. Primary waves are faster and cause less damage, causing them to be perfect for early warning systems. The WSN system actually keeps most sensors in sleep mode in an effort to reduce the energy use and is only activated when the small number of sentry nodes detect any primary waves which are the earliest seismic signal of an earthquake. This study demonstrates a relationship between network delay time (T_d) and node activation time (T_a) showing that a balance of these two minimizes the response time further reducing energy use. The results of this study showed that the average standby current was $350\mu A$ and the wake-up delay was of <300 ms. This showed that the system works quickly and efficiently while using very little energy. In conclusion, this solution is really effective for on-site earthquake early warning systems.

Question

How can we build a low-cost, early earthquake warning system for developing countries that are not able to spend mass amounts of money on advanced technologies?

Hypothesis

Null Hypothesis: The integration of dual piezoelectric transducers and MEMS accelerometers with a wake-on-radio network and machine learning classifier does not significantly improve detection accuracy or reduce power consumption compared to traditional continuous-monitoring systems of developing countries that cannot fund an advanced detection system.

Alternative Hypothesis: The integration of dual piezoelectric transducers and MEMS accelerometers with a wake-on-radio network and machine learning classifier will significantly improve detection accuracy or reduce power consumption compared to traditional continuous-monitoring systems of developing countries that cannot fund an advanced detection system.

Computational Model: This prototype will combine physics-based signal processing with machine learning to classify vibration events. First, the raw data gets converted to numerical data. The data is then transferred into the computer of the system. Before feeding the data into the ML model, the computer will compute the numerical features from the raw signal such as frequency content, peak values, RMS acceleration, etc. Then, the features are input into the model that will predict whether an earthquake-like event has occurred. The event will be logged and will trigger a basic alert system.

Materials/Research Methods

The system will be built by using a dual sensor archetype of piezoelectric transducers and MEMS accelerometer alongside microcontroller-based components to detect earthquakes like vibrations. The first of the two sensors used is a Zirconate Titanate (PZT) piezoelectric disk. Which converts mechanical strain into readable electrical voltage, covering high-frequency vibration sensitivity. The ADXL355 MEMS accelerometer module will be used to detect low-frequency ground motion, additionally acting as a confirmation channel to reject noisy signals from the PZT sensor. Wires will be soldered onto the PZT disk and connected to an OPA2132 analog conditioning circuit component. This amplifies the PZT's voltage, making it readable to the microcontroller. The ESP32 development board will be used as the microcontroller due to its complex processing abilities. This component acts as the brain containing an input-output system which acts as an interface used to control electronic devices and collect data. Data collected would be stored on a 16GB microSD card. Twin LoRa SX1276 radio would be added to the system as it would enable the usage of Wake-On-Radio (WOR). This allowed communication between the 2 sensor nodes, allowing them to be in deep sleep until vibration was detected and triggered a system to wake up. The power source for this prototype design will be a rechargeable Li-ion lithium battery. An isolated ~3.3V buck converter will be used to distribute regulated power through components.

For testing, we will be using an APS 400, ELECTRO-SEIS® Long-Stroke vibration exciter. This is an electrodynamic force generator, the output of which is directly proportional to the instantaneous value of the current applied. We will use APS-400 as an arbitrary waveform input from online data sets to test our detector against real earthquakes. Additionally, A Raspberry Pi model 4 will act as a gateway into implementing machine learning. Data collected from the dual sensor is then sent through the microcontroller and stored in microSD card will be taken to the Pi which formats the data, so it is legible to the machine learning model.

During each trial which lasts 30 seconds, the sensors' voltage and acceleration are collected through the microcontroller while the shake table produces arbitrary vibration. This is then sent to a radio and triggers a WOR signal, subsequently waking up the other node and logging the time of activation. This allows the measurement of the efficiency of the system and how well it avoids background noise. After each trial, the data is sent to the Raspberry Pi, where the machine learning program is used to analyze the vibration recordings.

Data Analysis

The data we collect and analyze will be used to answer the research questions and hypotheses. Our objective is to use this data to evaluate the performance of the piezoelectric transducer network that is integrated with our machine learning classifier. We would then compare the results of our detection system with the performance of traditional continuous-monitoring systems, more specifically those that are in developing countries that are not able to afford advanced seismic detection.

The first step in analysis involves data collection from the dual sensor archetype. This network converts vibration to a proportional voltage whenever there is seismic activity. The OPA2132 circuit amplifies the voltage signal, making it readable data for the ESP32 microcontroller. All the sensor data is transferred from the ESP32 sensor node to the Raspberry Pi 4 wirelessly, via LoRa communication.

Once the data is stored into the Raspberry Pi 4, it processes the digital data and classifies parameters such as the root mean square amplitude, signal energy, zero-crossing rate, and the dominant frequency for each event. These features will then be organized into labeled datasets and evaluated as “false alarm”, “potential seismic activity", and "other environmental disturbances”. Then, model performance is measured using accuracy, precision, recall, and F1-score metrics. Additionally, the responsiveness of the system will be evaluated by measuring the detection-to-alert latency and communication delay of the two LoRa-connected sensor nodes.

To analyze the energy efficiency of this system, ESP32’s ability to measure current drawn will allow the system to log the amount of voltage and current drawn to calculate energy usage per event. From there, we will compare the statistical values of energy consumption between our wake-on-radio functionality to that of the continuous monitoring mode.

Lastly, all data is collected and summarized with graphs and statistics. Differences in energy consumption and alert latency between the two modes will be illustrated with bar graphs. Additionally, confusion matrices will be used to evaluate classification performance. From these analyzations, an evaluation will be made on the system as a whole. More specifically, we will determine if our early earthquake detection prototype design is an energy efficient system and capable of providing early earthquake warnings for developing regions of the world that lack such technology and funds to create their own.

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