Improving Earthquake Prediction with Artificial Intelligence and Machine Learning

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Overview

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Introduction



64,000 Lives Lost

In 2023, around 64 thousand lives were lost due to earthquakes



59% of Fatalities

Almost 59% of earthquake-related fatalities resulted from building collapses [1]



14.1 Billion

\$14.1 billion lost in 2023 due to earthquake-related damage

Introduction (cont.)

Detection Systems

- Shake Alert is one of various earthquake early detection systems working to detect incoming earthquakes
- One issue with this system is that the data pipeline for broadcasting alerts is racing against the seismic waves themselves

Problem Statement

- Earthquakes result in injuries, deaths, and have a serious economic impact
- Existing earthquake early detection systems do not provide enough time to prepare and evacuate
- Challenging to predict where and when earthquakes happen
 with current technology

Project Goals



Satellite Communication

Use satellites to allow seismographs and drones to communicate



Aerial Detection

Use aerial detection to expand seismic analysis



Artificial Intelligence

Using artificial intelligence and synthetic data to accurately forecast earthquakes

Seismic Data Pipeline



Telemetry Data Collection



- Data collection sources:
 - Drones
 - Seismographs
 - Satellites
- All data is used to make a prediction on oncoming earthquakes

Visual representation of seismic data pipeline

Seismic Data Overview

• Experimental data and preprocessing steps sourced from prior research into applying machine learning [2]



Test Waveforms

We use 2000 randomly selected waveforms for analysis where 1500 are P-waves and 500 are S-waves



We generate 5000 synthetic waveforms for both raw and preprocessed waveforms

Purpose of Wave Propagation

- P waves move parallel to the direction seismic activity is traveling
- S waves more perpendicular to the direction seismic activity is traveling
- P waves travel the fastest, thus reaching towns around the same time as the first alerts



Synthetic Data Generation



- Generative Adversarial Network (GAN): Uses existing real data to create synthetic (but fake) new data [3]
 - Consists of a generator and discriminator that train against each other to improve realism of fake data
 - Generator: Creates fake data to trick discriminator with it
 - Discriminator: Determines whether a given sample is real or fake

Machine Learning



• A **neural network** uses convolution (CNN) to upscale or downscale data (e.g., picture resolution, analog/digital waveforms) [4]

Machine Learning Results



85-90% Accuracy



85-90% total accuracy when classifying between P-waves and S-waves



41 min. & 31 sec.

Preprocessing - 34 seconds Seismic Analysis - 6 minutes Data Generation - 34 minutes

0.4 Magnitude Error

Magnitude predictions were on average 0.4 magnitudes off of the true value

P-Waves vs. S-Waves



Phase

A distinct type of seismic wave (e.g., P-waves, S-waves) generated by an earthquake can result in different patterns that lead to the same magnitude

85-90%

Accuracy when predicting phase

Magnitude Predictions



Magnitude

A measure of the energy released at the source of the earthquake, allowing for comparisons of earthquake sizes

0.4 Loss

When finding error of average earthquake prediction

Real & Synthetic Waveforms

PREP EXAMPLES TO MIMIC



- Left plot: Five waveforms used to train the preprocessed waveform GAN
- *Right plot*: The result of the training over 150 iterations of using data

Our Contributions

- First Design
 - Utilized an anomaly autoencoder + classification algorithms
 - Took two days to train 1000 waveforms
 - Magnitude accuracy was 50%
- Current Design
 - Utilized a custom window of only 50 seconds per 60 second sample
 - \circ Used Butterworth Filter (order 3, allowed 1 10 Hz frequencies)
 - Utilized CNN to regress waveforms into magnitude
 - Tailored GAN to work specifically with seismic waveforms
 - Took only 30 seconds to train 2000 waveforms
 - Average magnitude loss was only 0.4

Cost and Justification



Cost

Estimated development cost:

\$98 million

Yearly maintenance: \$61 million



mark 1

Community Impact

- Fewer injuries in earthquakes, more successful evacuations
- Less resources spent on EMS services
- Volunteers are enabled to focus on the injuries which do occur

Economic Impact

- \$320-960 million saved in economic value in 2023 based on death count
- Estimated that every \$1 in preventive measure correlates to \$11 spent in earthquake response [5]

Cost and Justification (cont.)

SUM of Cost	Year							
Cost Category	2025 (Testing)	2026 (Testing/Integration)	2027 (Integration)	2028 (Integration)	2029 (Validation)	2030 (Validation)	Yearly Maintenance	Grand Total
App Costs	\$25,000	\$25,000	\$25,000	\$25,000				\$100,000
Com Contract Cost						\$11,250,000	\$11,250,000	\$22,500,000
Cybersecurity Labor	\$868,000	\$868,000	\$868,000	\$868,000	\$868,000	\$19,220,000	\$19,220,000	\$42,780,000
Data Contract Cost						\$4,706,551	\$4,706,551	\$9,413,102
Geophone Drone Fleet						\$28,120,000		\$28,120,000
Production Team					\$761,000			\$761,000
Seismograph & Satellite Installations						\$259,000		\$259,000
Software Engineering Labor	\$761,000	\$761,000	\$761,000	\$761,000		\$25,847,000	\$25,847,000	\$54,738,000
Test Drones		\$380,000						\$380,000
Test Seismographs and Satellites		\$14 ,000						\$14,000
Grand Total	\$1,654,000	\$2,048,000	\$1,654,000	\$1,654,000	\$1,629,000	\$89,402,551	\$61,023,551	\$159,065,102

Table: A pivot chart of the distribution of costs by year and phase, shown in the dark blue boxes

Timeline to Deployment



Conclusion

<u>Summary</u>

- The approach presented here uses advances in technology to improve existing earthquake prediction and alert systems
- The results demonstrate the function of the proposed system and provide a preliminary proof-of-concept
- The solution has potential to help mitigate the consequences of earthquakes

Conclusion (cont.)

Key Takeaways

- Data from satellites, drones, and seismographs can be used together in a comprehensive prediction system
- We recorded 85-90% phase prediction accuracy and an average 0.4 loss for magnitude predictions

Future Work

- Search for other types of data (e.g., TEC perturbations) to use when training the model, to improve analysis
- Reconsider preprocessing steps to improve magnitude predictions
- Use newer APIs such as SeisBench to create real-time version of the solution
- Perform further cost analysis into the drawbacks of incorrect predictions
- Incorporate nuance into system to assess the type of incoming disaster (e.g., tsunami, earthquake)

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Thank You! To:









Any Questions?