QuakeWake: A Novel AI-Based Early Earthquake Warning and Post-Quake Building Safety Guidance System

Dhroov V Bharatia[a]
ACM Student Member, U.S.A.

Keywords: Earthquake, Earthquake Early Warning, Supervised Learning, Autonomous Learning, P-Wave, S-Wave, Building Damage, Dynamic Time Warping, User Collaboration.

Abstract: Millions of people around the world suffer from earthquakes every year. This research introduces an innovative, mobile device-based approach for real-time earthquake detection and prediction. By discerning quake patterns from users' regular usage patterns, a novel approach that prevents excessively draining battery uses an on-device neural network only when needed to detect earthquake tremors. Cloud servers running an AI module reliably predict the quake intensity and propagation pattern using signals from many users, enabling warning others who have yet to experience these tremors. It also detects buildings at high risk to reinhabit due to high relative floor displacement exceeding the building safety standards. A low-cost, affordable, and highly reliable optional adjunct device on the user's premise captures tremors with higher accuracy than mobile devices. This enables effective building-wide earthquake warnings and eliminates fatalities due to post-earthquake building structural integrity issues. With a neural network trained with many past earthquake patterns, the mobile devices reliably detected quakes and the AI module accurately detected its propagation with 99% accuracy, warning users along its path. Moreover, the adjunct device adequately captured shifts in the building's structure and reliably flagged the building as uninhabitable with more than 95% accuracy.

1 INTRODUCTION

Earthquakes are very dangerous as they cause tremendous damage and often there is not enough warning. Earthquake Early Warning (EEW) systems attempt to warn people to evacuate during an earthquake. However, earthquakes can strike at any time and at any place and it is not always possible to accurately predict or detect earthquakes. Today's earthquake detection methods using seismometers are too expensive, too few, and not always reliable and the current methods have proven to be inadequate as apparent from the many casualties every year. A system that can immediately and reliably warn a large number of people to evacuate during an earthquake can save lives.

Typical earthquakes emit two very common types of waves: Primary (P)-Waves and Secondary (S)-Waves. P-waves travel fast but are not very harmful whereas S-waves travel about half the speed, but are very harmful. Many EEW systems use sensors that detect the P-Waves and warn people before the harmful earthquake surface waves arrive. However, there are too few detection systems to immediately and reliably detect these P-Waves and warn a very large number of users in harm's way.

The purpose of this research is to create an intelligent earthquake system to reliably warn people before an earthquake arrives and if their building is unsafe after the earthquake. A novel collaborative earthquake early warning system is presented using the ubiquitous mobile smartphones. This helps overcome the two big issues faced by conventional EEW systems - the number of sensors providing coverage over populous areas and reliable means to notify affected users when an earthquake is detected. The accelerometer in a mobile device monitors the user's phone movements and a pre-trained neural network on the device helps determine if such movements may be due to an earthquake. Collaborating such detection across a large number of users in the vicinity adds accuracy and reliability to such detection. Additionally, by predicting the earthquake's path of progression, users in the path of the earthquake can also be warned even if they have not yet experienced any tremors. The ground shift and intensity recorded by each device further help in estimating if their building is safe to inhibit and hence

[a] https://orcid.org/0009-0003-1502-8081

Bharatia, D. V.
QuakeWake: A Novel AI-Based Early Earthquake Warning and Post-Quake Building Safety Guidance System.
DOI: 10.5220/0013123200003890

In *Proceedings of the 17th International Conference on Agents and Artificial Intelligence (ICAART 2025) - Volume 3*, pages 303-310
ISBN: 978-989-758-737-5; ISSN: 2184-433X

provides additional valuable safety guidance during and after an earthquake. Additionally, low-cost external accelerometer sensors mounted on the building structure can further ensure in providing such reliable building safety guidance.

1.1 Related Work

In 1868, the earliest front-detection EEW system (Cooper, 1868) was for the Hayward fault near San Francisco where telegraph cables signaled ground shaking to ring the city bell. (Aranda et al., 1995) more recently used front-detection to give 60s warning for Mexico City 320km away. But awaiting strong ground shaking loses valuable time and directional propagation prevents warnings for large areas around the epicenter leading to P-Waves based detection.

Reliably detecting P-Waves and using its amplitude to judge quake intensity poses big challenges due to limited detection time constraints as apparent in (Allen and Kanamori, 2003), (Allen et al., 2009) and (Wu and Kanamori, 2008). Most of EEW work still focuses on seismometers or a network of seismometers leading to two general categories of modern EEW systems: 1) regional and 2) on-site EEW.

Regional EEWs use a few seconds of initial ground motion data to provide intensity measure estimates over a region using pre-calibrated ground-motion models. As in (Bhardwaj et al., 2016), (Mu and Yuen, 2016), and (Münchmeyer et al., 2021) they face significant issues due to epistemic and aleatory uncertainties in modeling and epicenter proximity constraints. As in (Caruso et al., 2017), (Münchmeyer et al., 2021) and (Colombelli and Zollo, 2015) on-site EEWs focus on standalone single sensor estimating intensity and surface waves based on early P-Waves. They are limited to a locality and fail to help address structures in the area.

Building damage due to earthquakes involves a qualified inspector and since most buildings lack floor shift detection it prevents automated warnings. Recent machine learning techniques can detect certain cracks in structure such as in (Chen et al., 2024) but hidden building damage remains an unresolved issue.

(Reilly et al., 2013) used mobile device accelerometers to detect ground motion and transfer the accelerometer samples to a server for ground motion analysis. However, such continuous sever-based analysis is not pragmatic on a large scale. Instead, by having a very large number of user phones, acting as earthquake monitoring sensors, this paper demonstrates how to achieve very high reliability, accuracy, and coverage for earthquake detection without the aforesaid limitations of conventional EEW systems.

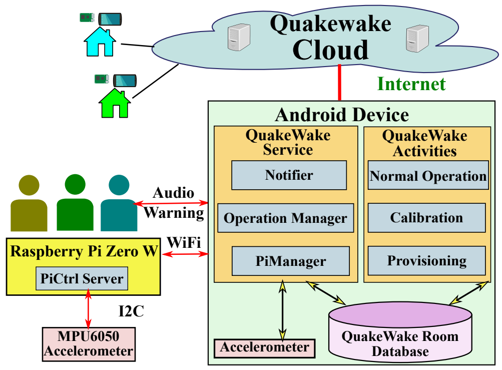

Figure 1: QuakeWake Overview.

2 PROPOSED APPROACH

QuakeWake leverages the pervasiveness of mobile phones equipped with an accelerometer to detect and collaborate earthquake tremors along with their location as shown in Figure 1. It reliably projects the path, intensity estimate, and time of the earthquake's arrival even for numerous users not yet in the earthquake's vicinity. Additionally, using the relative floor-shift data of a user's building gathered during the earthquake, it warns if the building is safe to reinhabit.

A mobile device is typically equipped with a micro-electro-mechanical system (MEMS) accelerometer that measures the acceleration in movement along the X, Y, and Z axis allowing analysis of the device's movement. Unlike other user activity-related movements, earthquake tremors caused by fast-moving P-waves produce a distinct pattern of this movement. A pre-trained convolution neural network (CNN) as in Figure 3 reliably detects this movement and warns users of the earthquake. The speed difference between these early detected P-waves and slow-moving harmful surface waves like S-waves enabled early warning. By extrapolating the location of detected tremors from many users, QuakeWake also warns users not yet in the vicinity, giving ample time to evacuate.

A building structure that experiences a large shift is prone to severe structural damage that could be hidden from view and extremely unsafe to inhabit. QuakeWake detects such shifts during the earthquake and based on collaborated data from similar buildings in the neighborhood, it uses a cloud-based neural network to predict building safety to warn users. An optional external accelerometer device powered by a low-cost Raspberry Pi Zero W can be mounted on the user's premise to further improve this building safety guidance. It improves reliability by providing better relative displacement detection and its low cost makes it a pragmatic user safety feature for all buildings.

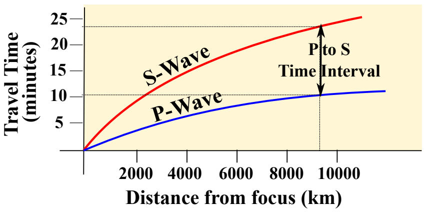

Figure 2: Wave Lag.

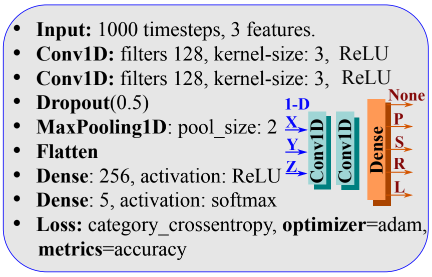

Figure 3: Detect-CNN.

2.1 Earthquake Waves

When an earthquake occurs, the shockwaves of released energy take the form of seismic waves. Seismic waves are categorized as primary waves (P-Wave), secondary waves (S-Wave), and additional surface waves (L-Wave/R-Wave).

Primary waves (P-Waves) are the least destructive type of seismic wave and have the fastest velocity. They are longitudinal waves that travel fastest at 6 km/s, pass through all matter, and cause objects to shift back and forth. P-Waves being the fastest arrive early and are used to detect earthquakes before the more destructive waves hit. As shown in figure 2, the distance of the user from the epicenter determines the fore-warning duration based on how early P-Waves arrive before other waves.

Secondary waves (S-Waves) are the more destructive large amplitude waves generated by tectonic plate movements. Other major destructive wave types include Love (L-Waves) and Rayleigh (R-Waves).

2.2 Detecting Earthquake

Earthquake causes prolonged shaking of the earth's surface proportional to the quake's intensity and this causes a phone resting on a surface to move with it. The acceleration of this movement is monitored by the phone's accelerometer and by analyzing the shake pattern, an earthquake is detected. Earthquakes can occur at any time, and there are many wave patterns depending on the type of waves and the user's relative position to the quake epicenter. Therefore, the QuakeWake app is provisioned to continuously monitor for tremors. Additionally, to rule out other shaking motions such as user movements, notifications with haptic vibrations, and other causes of seismic waves, it is essential to reliably detect an earthquake pattern. Direct point-wise comparison of waveforms fails to reliably discern shake patterns, especially for low quake intensity P-Waves. Therefore, a 1-dimensional (1-D) CNN is used to accurately detect the earthquake shake patterns.

The accelerometer motion data is sampled with a sliding window for motion along the X, Y, and Z axis. Overlapping 10s waves are sampled at 100Hz providing 1000 samples, representing a feature per channel which is fed as input to the CNN and the output predicts if a quake is detected. This detection CNN was trained using publicly available earthquake datasets such as STEAD (Mousavi et al., 2019). If an optional external accelerometer device is present, QuakeWake app also validates its results with it.

2.3 Activity Matching with Dynamic Time Warping

Frequent predictions using detection CNN are resource intensive and heavily drain the phone battery. To conserve battery, it is necessary to attempt such prediction only when there is something unusual as there is no earthquake most of the time.

Users tend to repeat a finite set A of common daily activities. A time-series t_x of an activity typically does not exactly match the time-series t_y for a known activity $y \in A$ but they do loosely match barring some temporal variations. So a simple point-wise Euclidean distance cannot correlate t_x and t_y. As shown in Figure 4, an optimal alignment between t_x and t_y needs non-linear "warping" (shown as green dotted lines between them) by stretching or shrinking along the time axis. A Dynamic Time Warping (DTW) algorithm non-linearly warp matches similar activities even if their time-series are out of phase along the time axis. As shown in (Salvador and Chan, 2007), $DTW(X,Y)$ provides distances between the i^{th} point in time-series t_x for waveform X to j^{th} point in time-series t_y for waveform Y aligning along optimal path P as:

$$DTW(X,Y) = \sqrt{\sum_{(i,j)\in P} (X_i - Y_j)^2} \tag{1}$$

DTW operates in linear time and space and can quickly correlate a current activity to an everyday known activity. Use of resource-intensive CNN can be restricted to only most likely unusual earthquake samples, significantly reducing the battery drain.

A time-series sample s comprises a tuple (s_{xi}, s_{yi}, s_{zi}) with $0 \leq i \leq w_N$, and w_N represents total intervals in s's capture window. s_{xi}, s_{yi}, s_{zi} is the acceleration along X,Y,Z axis for i^{th} interval with

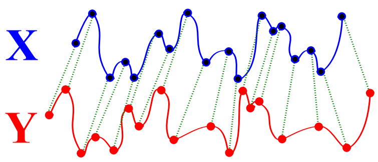

Figure 4: Dynamic Time Warping.

positive values when phone moves to right sideways: X axis, away from user: Y axis, vertically up: Z axis. At a 100Hz sampling rate, s of duration t has $w_N = t \times 100$ intervals. Early detection time-series spans $m\,sec$ and earthquakes confirming time-series spans $n\,sec, m < n$. As per Figure 2, forewarning needs at least $m \approx 2sec$ and $n \approx 10sec$.

The system manages time-series activity samples saved in three sets. An *Earthquake Set E* has $m\,sec$ samples of potential earthquake patterns $e \in E$. The *Activity Set A* for activity $a \in A$, each with first $m\,sec$ samples of a known user activity. The *Probable-activity Set P* has $m\,sec$ samples of activity $p \in P$ to be potential user activity known not to be an earthquake. A current sample is searched in a set using a novel DTW exact indexing technique based on (Keogh and Ratanamahatana, 2005). A query sample Q comprises a partial incoming time-series which is extended further only for high likelihood of a match. Consider each existing set sample C is n units long and N is the dimensionality of index space $1 \leq N \leq n$. U and L are upper and lower warping path envelopes around query Q with $\hat{U}_i$ and $\hat{L}_i$ being piecewise constant approximations of U and L for time-series represented as $c_i, 1 \leq i \leq N$. Lower bound piecewise aggregate approximation $LB\_PAA(Q,C)$ approximates the lower bound distance of query Q from sample C in an existing set as:

$$\sqrt{\sum_{i=1}^{N} \frac{n}{N} \begin{cases} (c_i - \hat{U}_i)^2 & \text{if } c_i > U_i \\ (c_i - \hat{L}_i)^2 & \text{if } c_i > L_i \\ 0 & \text{otherwise} \end{cases}} \qquad (2)$$

$$LB\_PAA(Q,C) \leq T_{LB}$$

The $MINDIST(Q,R)$ is the lower bounding measure between query Q and a minimum bounding rectangle (MBR) R that represents the smallest rectangle to spatially contain piecewise aggregate approximation points C_i under a node of a hierarchical MBR-based indexing structure, with MINDIST(Q, R) as:

$$\sqrt{\sum_{i=1}^{N} \frac{n}{N} \begin{cases} (l_i - \hat{U}_i)^2 & \text{if } l_i > U_i \\ (h_i - \hat{L}_i)^2 & \text{if } h_i > L_i \\ 0 & \text{otherwise} \end{cases}} \qquad (3)$$

$$MINDIST(Q,R) \leq T_{MD}$$

When $LB\_PAA(Q,C)$ exceeds T_{LB} there is no likelihood of match but when it is less, it is possible

foreach *user awaiting earthquake detection* **do**
$s \leftarrow$ **awaitMovement()**: Monitor time-series s captured with $< m\,sec$ window around every $m/8\,sec$ until 2 consecutive samples s for each interval $0 \leq i \leq w_N$ have $\{(s_{xi}, s_{yi}, s_{zi}) \mid |s_{xi}| > T_x, |s_{yi}| > T_y$ or $|s_{zi}| > T_z\}$, where T_x, T_y, T_z are minimum move thresholds.;
if $s \in W$ `// Known waking activity` **then**
awaitCalm(): Wait for $\{(s_{xi}, s_{yi}, s_{zi}) \mid |s_{xi}| < T_x, |s_{yi}| < T_y, |s_{zi}| < T_z\}$ for each sample interval $0 \leq i \leq w_N$;
continue;
end
if $s \in E$ ***or*** *detectCNN*(s) := *possible earthquake* `// Known tremor or suspected tremor detected` **then**
earthquakePossibleWarning();
confirmCNN(): Capture more samples and form $n\,sec$ time-series p, with each s as $m\,sec$ of *detectCNN*(s);
confirm $\leftarrow$ *detectCNN*(p);
if *confirm* = *earthquake* **then**
earthquakeConfirmedWarning();
inQuakeMonitorAndReport();
end
clearEarthquake();
continue;
end
if $s \in P$ `// Learn more waking activities` **then**
Increment counter associated with s in P;
if *counter*$(s \in P) > T_p$, *where* T_p *is activity inclusion threshold* **then**
Move s from P to A;
end
end
else
$P \leftarrow P \cup \{s\}$;
end
end

Algorithm 1: Earthquake Detection Algorithm.

that Q may match C and therefore additional sample intervals are retrieved if Q does yet have sufficient sample intervals as C. This technique is also applicable while computing $MINDIST(Q,R)$. It enables handling samples with time-axis warping with one or more time-series portions expanded beyond that of the target time-series. This technique allows to start aggressively indexing samples even when the full window of the query sample is not yet complete and once it is known to be highly probable for matching, it can be expanded to the full query time-series with minimal cost. It avoids awaiting query to be fully available saving valuable earthquake detection time.

Algorithm 1, detect earthquakes with very few computations. *awaitMovement*() helps avoid computation when the phone lies dormant as on a table. When a known user activity disrupts this dormant state, all samples during this activity are ignored until the phone is dormant, eliminating processing when the user is using the phone. In the dormant state, only if a known potential earthquake pat-

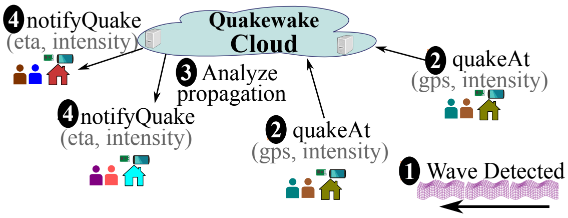

Figure 5: Collaboration Protocol.

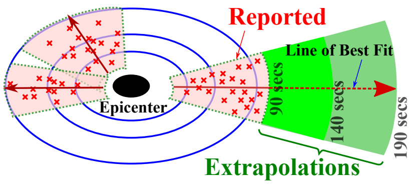

Figure 6: Predict Path.

tern or *detectCNN*() detects a possible earthquake, earthquake processing is launched. As it learns more non-earthquake activities that wake it from a dormant state, A expands, and it spends most of the time in *awaitMovement*() and *awaitCalm*() - both requiring very little computation, thereby conserving battery power. Moreover, earthquake warnings can be issued as early as $m = 2$ seconds which is a great improvement over today's EEW systems.

2.4 Collaborating Early Warning

A QuakeWake mobile application immediately warns its user when it detects earthquake tremors. Additionally, as shown in Figure 5, it also reports the detected earthquake intensity and its GPS location to QuakeWake cloud servers. QuakeWake cloud then creates an earthquake activity map and as shown in Figure 6, extrapolates the earthquake intensity, direction of propagation, and estimated time of arrival (ETA) to wider areas around the epicenter and notifies users in these affected areas giving them an additional 90 to 190 seconds of advance notification, potentially saving their lives. Reports from many users in highly populated urban areas significantly increase prediction accuracy for the path and ETA.

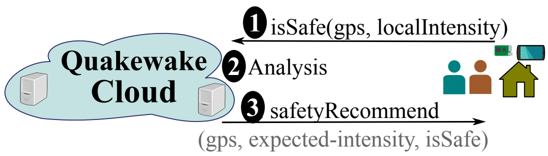

Figure 7: Building Safety.

2.5 Building Safety

Building safety standards and organizations such as the United States Geological Survey (USGS, 2024) specify a safe limit for floor movement relative to the structure below. Due to their high cost, most buildings are not equipped with the instrumentation that measures such a shift during an earthquake. The hidden structural damage due to such shift is extremely dangerous leaving the building residents vulnerable during and after major earthquakes.

Although no two buildings suffer the same damage, similar buildings in a neighborhood tend to experience similar floor shift patterns and tend to suffer similar earthquake damage. Therefore, a building-safety neural network is used to predict the quake intensity and shifts using regression as shown in Figure 8 and warn users of unsafe buildings. It can guide users even if they could not record the precise earthquake shift for their building. This neural network is pre-trained using historical datasets for earthquake damage and safety information, and continuously refined with current quake data using an adjunct network model. Building structures respond differently to different types of earthquake waves. Even for the same wave type, response changes based on whether the building was exposed to a rising or falling edge of the surface wave. Different buildings on the same path can be exposed to different cycles of the destructive S, R, or L waves. Therefore, the building-safety neural network must be retrained with actual reports from the affected buildings in the current earthquake to discern these variations of destruction patterns in the area. When a large number of users are concentrated in a small area, adequate training makes prediction reliable. Sparsely populated areas may need additional information such as ground shaking intensity ShakeMap published by the U.S. Geological Survey. QuakeWake also provides a means to use additional building information such as from OpenStreetMap (OSM) project (OpenStreetMap, 2024) based on the user's location and predict building safety as correlated with other similar buildings in the neighborhood.

The QuakeWake app records the building movements during an earthquake. When a user requests a building safety check, as shown in Figure 7 the app sends a request to the QuakeWake cloud server with the building type, building's GPS location, recorded intensity, and maximum local shifts recorded during the quake. QuakeWake server uses a building-safety neural network to predict the expected quake intensity and whether it is safe.

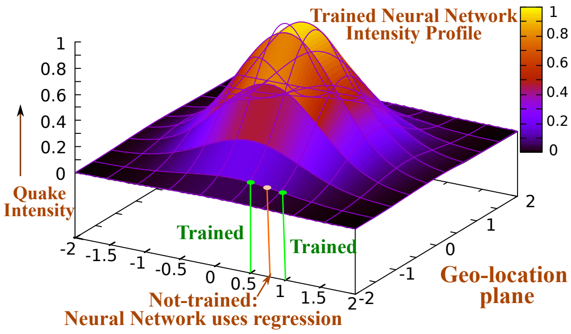

Figure 8: Building Safety Regression.

3 RESULTS AND DISCUSSION

3.1 Experimental Setup

A set of randomized time-series samples representing different activities and events was prepared and then used to test different aspects of QuakeWake as discussed below.

Earthquake Samples. Time-series data from the STEAD dataset as in (Mousavi et al., 2019) was captured along the three orthogonal seismograph component axes. 5 sets of local earthquake samples in randomized groups of 100,000 samples were extracted from the available earthquake samples worldwide within 350km of the earthquakes. Each earthquake sample window contained both P and S waves and began from 5 to 10 seconds prior to the P arrival and ended at least 5 seconds after the S arrival. The samples were conditioned by removing the mean and resampled at 100 Hz. Similarly, a randomized group of 100,000 non-earthquake seismic noise sample data was also used from this dataset to represent seismic conditions when there is no earthquake. Additionally, the building damage dataset from the Gorkha Earthquake of Nepal as in (Möbius, 2015) was used to build 10 sets of building safety samples in randomized groups of 50,000 samples.

User Activity Samples. The Bogazici University smartphone accelerometer sensor dataset as in (Davarcı and Anarım, 2022) was used in conjunction with other real-time data collection by the researcher for user movements during different activities. A custom app gathered time-series samples for different age groups and genders by sampling accelerometer data at 100Hz. 25 randomized groups of 10,000 samples were created for typical everyday activities.

Motion Test-Bed. A set of modern Android phone devices was used to test various aspects of QuakeWake. For accurate and repeatable test movements, custom directional stepper motors from a 3D-printer were repurposed to move a platform as per time-series input data. The test setup was calibrated to produce test device accelerometer data that matches the input time-series sample to produce the platform motion.

Battery Drain. QuakeWake was tested with varying duty cycles of any-activity, each cycle comprising a period of calm followed by a period of activity. The period of activity comprises a specific duty cycle of earthquake activity, wherein a random mix of earthquake and user activities are performed so as to achieve the required earthquake duty cycle. Tests were repeated with different any-activity duty cycles, each repeated with different earthquake duty cycles and intensities. The battery drain was recorded after an extended test duration depending on the any-activity duty cycle.

Earthquake Detection. Earthquake detection was tested by placing a test phone onto the motion test-bed described above and driven by a test time-series sample. Accuracy was determined based on whether QuakeWake correctly detected earthquake samples and did not detect other samples as earthquakes. Multiple trials were conducted with test samples for different earthquake shift distances, different earthquake powers resulting in different peak acceleration magnitudes, different contact surfaces of the table, different materials of the phone cover, and different earthquake wave types. Tests were repeated continuously with more than 98% user activity samples and the remainder as earthquake samples for a long time to ensure that Dynamic Time Warping mostly eliminated the resource-intensive detection CNN computations and conserved battery power.

Training Building Safety Neural Network. The building safety neural network was trained extensively using samples from the Gorkha Earthquake dataset. Testing for impact on building safety prediction by retraining with reports from the current quake was tested by retraining the preexisting trained model with an additional set of 50,000 test samples such that the test samples are localized in different high-density reporting areas with at least one region each of 100, 50, 20, and 10 reports per square kilometer.

3.2 Comparisons and Analysis

As shown in Figures 9, 10, 11, and 12, QuakeWake reliably detected an earthquake with very high accuracy for typical operating conditions. As shown in Figures 9 and 10, with a phone on a very smooth contact surface, it detected typical mild quakes with shifts exceeding 40mm and peak acceleration of $10m/s^2$. Figure 11 shows that for typical contact surfaces

Table 1: QuakeWake Test Summary.

Purpose	*Values*
Detect varying shifts	Mean:98.51% σ:0.96%
Detect varying power	Mean:96.37% σ:2.96%
Detect surfaces	Mean:89.01% σ:10.19%
Detect wave-types	Mean:93.26% σ:5.89%
Collab. forewarning	78-187s Mean:150s
Bldg. safety accuracy	Mean:90.43%, σ:2.09%
Bldg. retrain accuracy	Mean:97.12% σ:1.26%

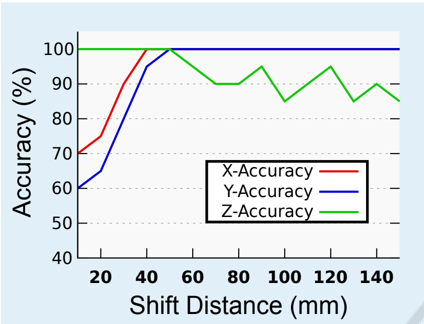

Figure 9: Detect varying shift.

of wooden furniture or with TPU, rubber, or silicone covers, accuracy increased drastically resulting in flawless earthquake detections even for very mild earthquakes. The typical contact surface does not result in excessive slippage and hence the ground motion during an earthquake tremor reaches the phone's accelerometer verbatim leading to a very high earthquake detection accuracy.

As evident from Figure 12, the earthquake detection accuracy is almost perfect for both the primary P-waves and secondary S-waves but goes down by around 15% for only the R-waves and by 8% when only L-waves are used. As R-waves and L-waves are not as common as the P-waves and S-waves, the neural network lacked training for L and R waves. This is less of a concern as R and L-waves rarely exist on their own and are always preceded by the P-waves.

Figure 13, shows results for any-activity duty cycle of 50% revealing that the battery drain percentage is mostly proportional to the duty cycle of the earthquakes, confirming that DTW-based activity detection and use of CNN only for earthquake samples works well. Severe earthquakes have less ambiguous patterns leading to lower battery drain. Battery drain for moderate earthquakes was not significantly worse especially when the duty cycle was low. Typically earthquake duty cycles are low and QuakeWake provides excellent performance with a very low battery drain allowing users to constantly use QuakeWake.

The baseline building safety neural network predicts with over 90% accuracy. As evident from Figure 14, when the earthquake passes through a densely populated area, the safety accuracy prediction is near perfect at 100 records/sq. km. and around 98% at 50 records/sq. km. As portrayed in Figure 8, more retraining samples from small populated areas lead to

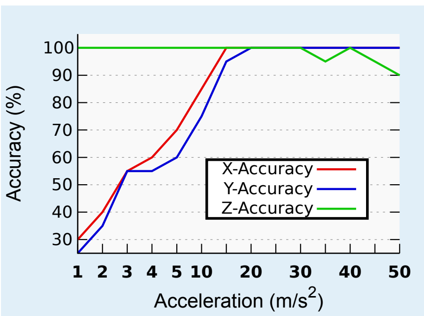

Figure 10: Detect varying power.

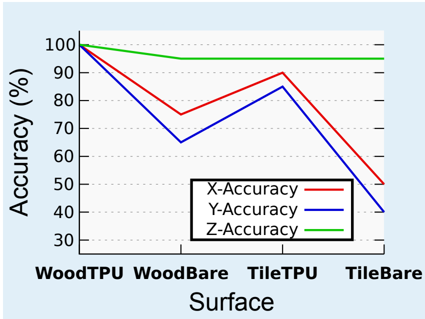

Figure 11: Detect varying contact surfaces.

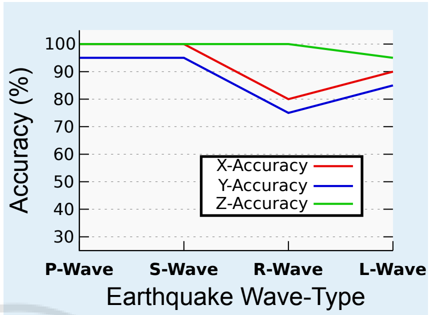

Figure 12: Detect varying wave-type.

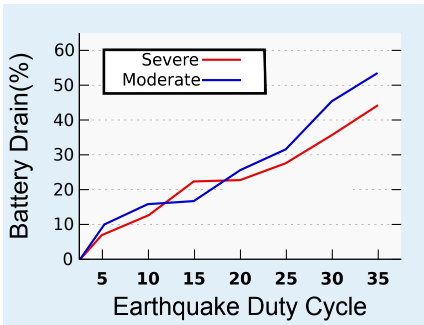

Figure 13: Battery Drain.

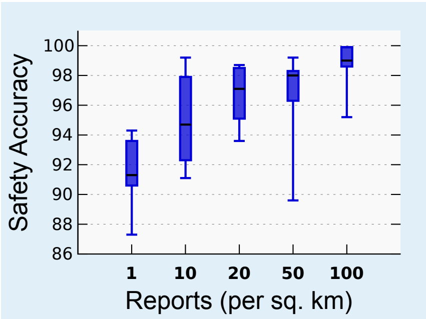

Figure 14: Building safety on retraining.

better regression and these retraining samples capture the unique destruction pattern of the current earthquake leading to highly precise predictions.

4 CONCLUSIONS

QuakeWake reliably detects quake vibrations using the accelerometer in phone devices and immediately warns its users when it detects earthquake tremors or if a user is in the path of an earthquake. Without an elaborate infrastructure of costly seismographs, it arms everyday users' smartphones to detect an earthquake and forewarn users in harm's way. It performs well with typical non-slipping phone covers and on wooden furniture. By using a novel Dynamic Time Warping algorithm, it discerns everyday activity motions and uses the resource-intensive CNN detection only when an earthquake is suspected, thereby conserving battery power. QuakeWake records the maximum shift experienced during an earthquake and uses this information to enable building safety warnings. By continuously retraining a building safety neural network, it learns to predict this safety based on patterns of the current earthquake. With its low-cost and simple but robust design, QuakeWake can help save numerous lives across the globe. In the future, QuakeWake can be integrated with other warning systems to greatly enhance its efficacy.

REFERENCES

Allen, R. M., Brown, H., Hellweg, M., Khainovski, O., Lombard, P., and Neuhauser, D. (2009). Real-time earthquake detection and hazard assessment by elarms across california. *Geophysical research letters*, 36(5).

Allen, R. M. and Kanamori, H. (2003). The potential for earthquake early warning in southern california. *Science*, 300(5620):786–789.

Aranda, J. E., Jimenez, A., Ibarrola, G., Alcantar, F., Aguilar, A., Inostroza, M., and Maldonado, S. (1995). Mexico city seismic alert system. *Seismological Research Letters*, 66(6):42–53.

Bhardwaj, R., Sharma, M. L., and Kumar, A. (2016). Multi-parameter algorithm for earthquake early warning. *Geomatics, Natural Hazards and Risk*, 7(4):1242–1264.

Caruso, A., Colombelli, S., Elia, L., Picozzi, M., and Zollo, A. (2017). An on-site alert level early warning system for italy. *Journal of Geophysical Research: Solid Earth*, 122(3):2106–2118.

Chen, W., Hou, J., Wang, Y., and Yu, M. (2024). Visualization analysis of concrete crack detection in civil engineering infrastructure based on knowledge graph. *Case Studies in Construction Materials*, page e03711.

Colombelli, S. and Zollo, A. (2015). Fast determination of earthquake magnitude and fault extent from real-time p-wave recordings. *Geophysical Journal International*, 202(2):1158–1163.

Cooper, J. (1868). Earthquake indicator. *San Francisco Bulletin*, 3.

Davarcı, E. and Anarım, E. (2022). Bogazici university smartphone accelerometer sensor dataset. *Data in brief*, 40:107833.

Keogh, E. and Ratanamahatana, C. A. (2005). Exact indexing of dynamic time warping. *Knowledge and information systems*, 7(3):358–386.

Mousavi, S. M., Sheng, Y., Zhu, W., and Beroza, G. C. (2019). Stanford earthquake dataset (stead): A global data set of seismic signals for ai. *IEEE Access*, 7:179464–179476.

Mu, H.-Q. and Yuen, K.-V. (2016). Ground motion prediction equation development by heterogeneous bayesian learning. *Computer-Aided Civil and Infrastructure Engineering*, 31(10):761–776.

Münchmeyer, J., Bindi, D., Leser, U., and Tilmann, F. (2021). The transformer earthquake alerting model: A new versatile approach to earthquake early warning. *Geophysical Journal International*, 225(1):646–656.

Möbius (2015). Earthquake magnitude, damage and impact: Gorkha earthquake 2015. https://www.kaggle.com/datasets/arashnic/earthquake-magnitude-damage-and-impact.

OpenStreetMap (2024). Openstreetmap project. https://www.openstreetmap.org.

Reilly, J., Dashti, S., Ervasti, M., Bray, J. D., Glaser, S. D., and Bayen, A. M. (2013). Mobile phones as seismologic sensors: Automating data extraction for the ishake system. *IEEE Transactions on Automation Science and Engineering*, 10(2):242–251.

Salvador, S. and Chan, P. (2007). Toward accurate dynamic time warping in linear time and space. *Intelligent Data Analysis*, 11(5):561–580.

USGS (2024). United states geological survey scientific research results. https://www.usgs.gov/products.

Wu, Y.-M. and Kanamori, H. (2008). Development of an earthquake early warning system using real-time strong motion signals. *Sensors*, 8(1):1–9.