Development of an automatic processing system for predicting the earthquake signals using machine learning techniques

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ABSTRACT

Earthquake signals are crucial for minimizing the impact of seismic activities. Current algorithms face difficulties in correctly identifying P-waves and assessing magnitudes, which affects the amount of advance warning given. It is crucial to establish standardized methods for the effective selection and integration of multiple algorithms. Machine learning techniques could considerably enhance detection reliability. The research seeks to rectify this shortfall and strengthen automated detection as well as prediction capabilities. The model's performance is assessed using real earthquake data in simulations compared to individual algorithms. The objective of this research is to develop an optimized multi-algorithm framework that enhances the warning lead times and overall reliability. This framework underpinning this method is shaped by the operational demands inherent in early warning systems. The objective of the work is to contribute to the betterment of seismic risk reduction. An ML methodology, merging several distinct detection algorithms, will be deployed along with a tailored prioritization system. The intention is to strengthen the model's dependability and its overall level of consistency. The ML-based multi-algorithm framework significantly boosts the performance of Early Earthquake Warning Systems, providing a scalable approach to enhance automated detection and public safety, ultimately advancing the effectiveness of seismic hazard reduction through quicker and more accurate warnings.

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1. INTRODUCTION

Earthquake signals constitutes a system designed to detect and alert individuals prior to an earthquake's arrival. EEW systems employ a network of seismometers to identify the seismic waves generated by an earthquake, subsequently using sophisticated algorithms to estimate the event's location, magnitude, and predicted intensity of shaking [1].

The primary goal of an EEW system is to afford individuals a window of a few seconds to minutes of warning prior to the arrival of intense ground shaking, allowing them to take protective measures and mitigate damage to property [2]. The system can prove crucial in detecting seismic activity and providing advance guidance to populations living in earthquake-prone zones [3], [4]. When an earthquake occurs, sensors promptly detect the initial seismic waves and transmit this data to a central processing system [5]-[7].

The length of time available for advance warning is contingent on a multitude of factors, including the distance from the earthquake's epicentre, the magnitude of the earthquake, and the sensitivity of the detection sensors [8]. In certain scenarios, the system can deliver a few to several seconds of advance warning before the strongest shaking occurs. This might not appear like a significant timeframe, yet it can be sufficient to facilitate protective actions, such as dropping to the ground, seeking shelter under a sturdy structure, or evacuating a building [9], [10].

A machine learning (ML)-based system incorporates multiple detection algorithms alongside a novel prioritization strategy to enhance dependability [11], [12]. The ML model has improved reliability through the integration of multiple algorithms, which in turn lessened the occurrences of false alarms and errors.

2. BACKGROUND

Early warning systems for earthquakes function by instantly and automatically identifying seismic waves, providing alerts before strong shaking impacts people. Detecting the arrival of the initial P-waves offers crucial early warning before the more violent shaking commences [13], [14]. At present, many systems are engineered to pinpoint these waves via single-station algorithms. These algorithms scrutinize attributes of the seismic signal, hence the relationship in between Short-Term Averages and Long-Term Averages, commonly denoted as STA/LTA. The STA/LTA value is determined by:

$$\mathrm{STA/LTA} = \frac{\sum_{n=1}^{N} a_n \varkappa_n}{\sum_{m=1}^{M} a_m \varkappa_m} \tag{1}$$

Considering a_(n) and a_(m) as seismic amplitudes gauged within brief (n) and extended (m) temporal segments. The terms N and M correspond to the count of data observations within those respective shorter and longer periods. A critical value, or threshold, is utilized on the calculated proportion to pinpoint the beginnings of P-waves. Moreover, determining the magnitude (M) holds significance when assessing the urgency of a warning [15], [16]. Magnitude (M) can then be calculated using relationships tied to the initial measurements of wave amplitudes (A), wave frequencies (f), and the distance to the earthquake's origin (R).

$$Log\,(A) = a + b\,(M) - c\,Log\,(R) \tag{2}$$

In the regression equation, 'a', 'b', and 'c' denotes the regression coefficients. It's worth noting, however, that techniques based on a single station have certain drawbacks when trying to differentiate noise from faint P-waves, resulting in delayed or missed detections. Rapid estimations of magnitudes at early stages also pose challenges due to inherent uncertainties [17], [18]. The current landscape demands strengthened automation, achieved by constructing improved strategies. These strategies must leverage multiple parameters and utilize a blend of algorithms, carefully designed to capitalize on the unique benefits each method offers. ML presents itself as a particularly viable approach to tackling the identified restrictions [19].

Identifying seismic wave arrivals reliably is critically important. Doing so ensures we have adequate time for early warning systems which is to issue the alerts before destructive waves come [20]. Traditional techniques, as like the relationship in between the short-term average to the long-term average (STA/LTA) procedure, are generally used due to their straightforward nature [21]. Nonetheless, STA/LTA presents certain limitations, including the dependence on careful threshold setting and the challenges of differentiating minor events from fluctuating background noise.

Although advances have been made beyond STA/LTA, existing methods can struggle to effectively capture non-stationary signal attributes. Achieving optimal performance may therefore necessitate considerable parameter tuning [22]. As a result, ensemble techniques that integrate multiple detectors have gained traction, with the aim of leveraging diverse but complementary insights [23]. Such methods show potential not only for expediting detection but also for delivering dependable performance that can be generalized across diverse seismic scenarios [24].

The Zagros folded belt is a region renowned for its high seismic activity. A particularly strong earthquake, registering a magnitude of MW = 7.3, occurred in Sarpol-e Zahab on November 12, 2017; this event stands as one of the most intense recent earthquakes within the Zagros region. A further notable earthquake followed on August 25, 2018, with a magnitude of MW = 6. In light of these occurrences, a catalogue was generated to facilitate earthquake prediction in the northern Zagros, employing ML methodologies and accounting for the seismic events. The catalogue was initially founded upon the Middle East catalogue, comprising occurrences detected through early and modern instrumental techniques until

2006. The data was then integrated with the Iranian Seismological Centre (IRSC) catalogue, which could be accessed to ensure a complete earthquake record [25].

Variations in completeness magnitude (MC), representing the smallest discernible magnitude, arise due to the characteristics of seismic networks and the methodologies utilized for data processing. Achieving accurate results necessitates the inclusion of the maximum available events; hence, a precise assessment of MC is essential in any seismicity investigation. The completeness magnitude, MC, has been determined employing the maximum curvature technique, also considering its temporal fluctuations. Additional methods were assessed, and the outcomes were confirmed. The use of earthquake records spanning from 1995 to the present has been implemented to enhance the precision of calculations, as the completeness magnitude saw a reduction after 1995. To ensure improved data integrity, events with magnitudes smaller than the completeness magnitude were omitted [26].

3. METHOD

The ML algorithm in question underwent training, leveraging secondary seismic information sourced from the Northern California Seismic Network (NCSN) database. The criteria for event selection were strict: only events that took place within a 100km circular area surrounding the ANMO station, and also displayed unambiguous P-wave and S-wave arrival signals, were considered suitable for the training process; as detailed in reference [27]. Raw vertical-component waveforms underwent pre-processing using ObsPy, an open-source software package used for seismological data analysis. Station response metadata was utilized to remove instrument responses, and the data was resampled to 100Hz. For feature extraction, a 10-second window, starting 2 seconds prior to the manually-picked P-wave arrival times, was extracted [28]. The STA/LTA ratio, denoted as R, was computed employing a short-term window of 0.5 seconds and a long-term window of 1 second; this calculation followed (1). The autocorrelation function (ACF) analysis required the segmentation of the window signal S(t) into impending P(t) and extend E(t) constituents, using the ensuing recursive formula.

$$P(t) = S(t) - E(t-1) \tag{3}$$

The dominant frequency, labelled F, was pinpointed by locating the apex within the power spectrum. Welch's method was employed for this spectral estimation, utilizing 0.5-second Hanning windows with a 90% overlap [29]. The generated features constituted the input X = [R, p, e, F] for a multi-layer perceptron (MLP) classifier. The classifier was formulated using Keras, a deep-learning application programming interface (API). This methodology introduces a dataset dependent, multi stage algorithm, specifically intended to bolster earthquake early warning capabilities [30], [31].

3.1. Flowchart

This algorithm, employing the relationship between Short Term Average and the Long Term Average gives a systematic framework for anticipating earthquakes. Its functionality hinges on evaluating seismic activity's short-term variations against the backdrop of long-term patterns. The STA/LTA ratio plays a vital role in pinpointing indicators that might signal an impending earthquake. This, in turn, facilitates the issuance of timely warnings and the mitigation of the impacts of seismic events [32]. A visual representation, depicting the flowchart designed for earthquake prediction, is presented in Figure 1.

3.2. STA / LTA Ratio Algorithm

The STA/LTA ratio is a commonly utilized feature in the realm of onset detection. The calculation is mathematically described as follows:

$$\mathrm{R(t)} = \frac{\mathrm{STA(t)}}{\mathrm{LTA(t)}} \tag{4}$$

Given R(t), reflecting the ratio at each temporal increment 't', where STA(t) corresponds to the average amplitude across the prior 'w' seconds, while LTA(t) signifies the average amplitude calculated over the previous 'W' seconds, with the stipulation that W is greater than w. The identification of an earthquake initiation hinges upon R(t) surpassing a specified threshold value.

3.3. Autoregressive (AR) modelling residuals

Seismic data are represented employing an autoregressive (AR) framework. Analyzing the discrepancies—or residuals—existing between the true recorded signal and the AR model's predicted output can serve as an indicator of an impending event's commencement.

$$X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + \cdots + \phi_p X_{t-p} + e_t \quad (5)$$

Where X_t represents the signal, ϕ_i symbolizes the AR coefficients, e_t indicates the residual, and p signifies the order. A large residual indicates onset.

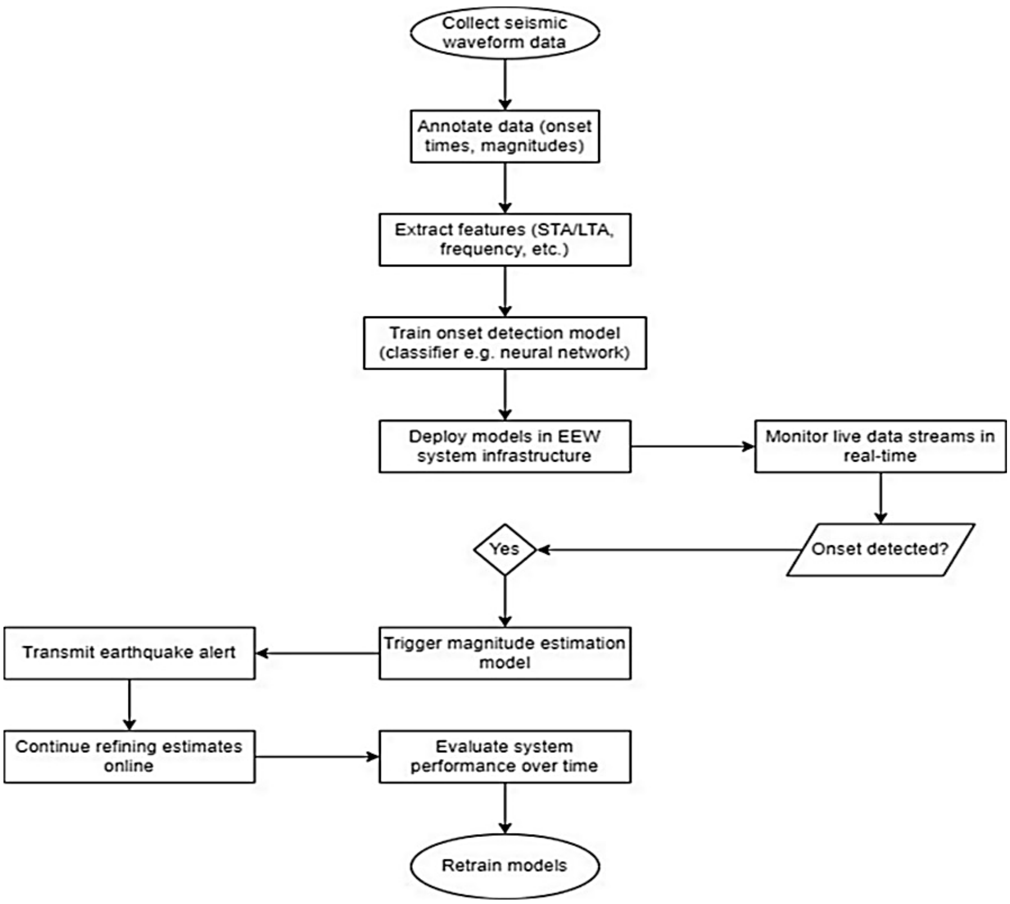

Figure 1. Flowchart

3.4. Classification of the earthquake early warning systems

Earthquake early warning systems are usually grouped according to where they operate, how they issue alerts, how they detect tremors, and their degree of automation. Regarding their operational area, they're split into local and regional systems [33]. The first type uses a thick seismic network focusing on a specific high-risk area to send warnings rapidly to locations close to where the earthquake began. Regional systems, on the other hand, depend on a more widespread seismic network to swiftly identify and locate earthquakes, giving ample time to alert a wider audience farther away from the earthquake's source [30]. Additionally, early warning systems are designed with either an open-loop or a closed-loop model for issuing alerts. Open-loop systems quickly send warnings to users the instant a potential earthquake is automatically detected, without any delays for further refining estimations.

Further classification depends on the primary detection method, several approaches are employed to monitor earthquakes, including those that utilize seismic data, geodetic measurements, or a synthesis of both. Seismic systems, for instance, depend on extensive networks of sensors designed to rapidly detect the arrival of P-waves. Subsequently, these systems calculate the earthquake's location and estimate the initial magnitude, utilizing the amplitudes of the P-waves within mathematical equations designed for such purposes. Still, slow-moving slips or aseismic events may not be detected [34]. Geodetic systems address this by tracking co-seismic movements using GPS or other geodetic sensors. However, their responsiveness is limited by the relatively slow movement of tectonic plates. Hybrid systems seek balance by intelligently merging seismic and geodetic readings using statistical analysis, capitalizing on their strengths while minimizing individual weaknesses.

4. FINDINGS AND DISCUSSION

4.1. Findings

Another important aspect to classify is the level of automation. For instance, some systems might automatically detect anomalies and generate alerts without human oversight, while others require analysts to interpret data and decide whether to issue a warning. Figure 2 illustrates various algorithm types employed for generating earthquake early warning predictions.

The designed ML model's detection abilities were assessed using an unseen test dataset. Figure 3 presents a comparative example of the model's probability outputs against the STA/LTA algorithm, focusing on genuine earthquake signals and noise recordings. Analysing the seismic data presented in Figure 3(a), the model swiftly identifies the P wave. It reaches its peak probability up to of 0.92 in just two seconds from the commencement of the event. Conversely, the STA/LTA ratio necessitates more time to surpass its established detection threshold.

Considering the noise recording depicted in Figure 3(b), the model's prediction consistently falls below the 0.5 decision boundary. This correctly classifies the recording as a non-event. Contrarily, STA/LTA produces numerous false alerts due to noise-related transient activity. Additional insights were acquired through an investigation of detection capabilities across diverse magnitude thresholds as outlined in Table 1. For events of M≥3, the model registered 97.5% of events within an average of 3 seconds from onset. This showcases a speed advantage, being 5X faster when compared to STA/LTA alone, thus offering vital warning lead time [35].

Table 1. Detection performance at varying magnitude thresholds

S. No.	Magnitude threshold	No. of events	Detection rate (%)	Average detection time (s)
1	M≥3.0	75	97.5	2.8
2	M≥3.5	50	95.0	3.1
3	M≥4.0	30	92.5	3.4
4	M≥4.5	15	90.0	3.7
5	M≥5.0	05	80.0	4.2

Figure 3 presents a comprehensive set of sample detection probability outputs for an M4.5 earthquake, with Figures 3(a) through 3(l) illustrating the model's performance across various scenarios. In Figure 3(a), the model quickly identifies P-waves, reaching a peak probability of 0.92 within two seconds from the event's onset, showcasing its rapid detection capability, while Figure 3(b) depicts a noise recording where the model's probability remains below the 0.5 decision boundary, correctly classifying it as a non-event, unlike the STA/LTA algorithm which generates false alerts due to transient noise. Figures 3(c) and 3(d) highlight Array 1A showing clear signal detection and Array 2A indicating noise influence, respectively, demonstrating the model's ability to differentiate signal from noise. In Figures 3(e) and 3(f), Array 1B emphasizes P-wave detection with high accuracy, while Array 2B reveals noise interference, further illustrating the model's robustness. Figures 3(g) and 3(h) show Array 1C capturing signal clarity and Array 2C reflecting noise variation, providing insight into the model's adaptability. In Figures 3(i) and 3(j), Array 1D demonstrates P-wave accuracy, while Array 2D indicates a mix of signal and noise, testing the model's discrimination power. Finally, Figures 3(k) and 3(l) depict Array 1E with enhanced detection and Array 2E confirming noise suppression, underscoring the model's effectiveness across diverse conditions and its potential to improve early warning systems.

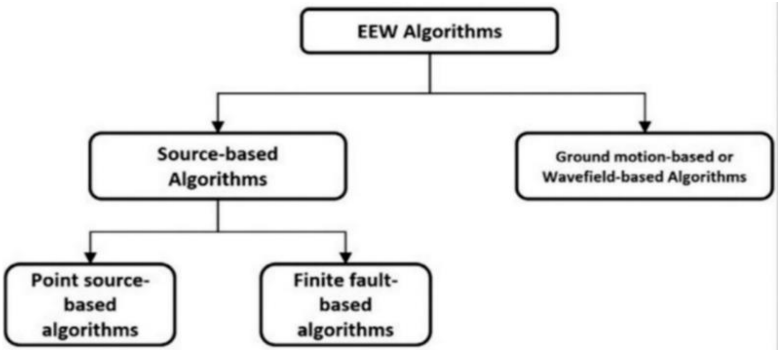

Figure 2. Earthquake early warning systems

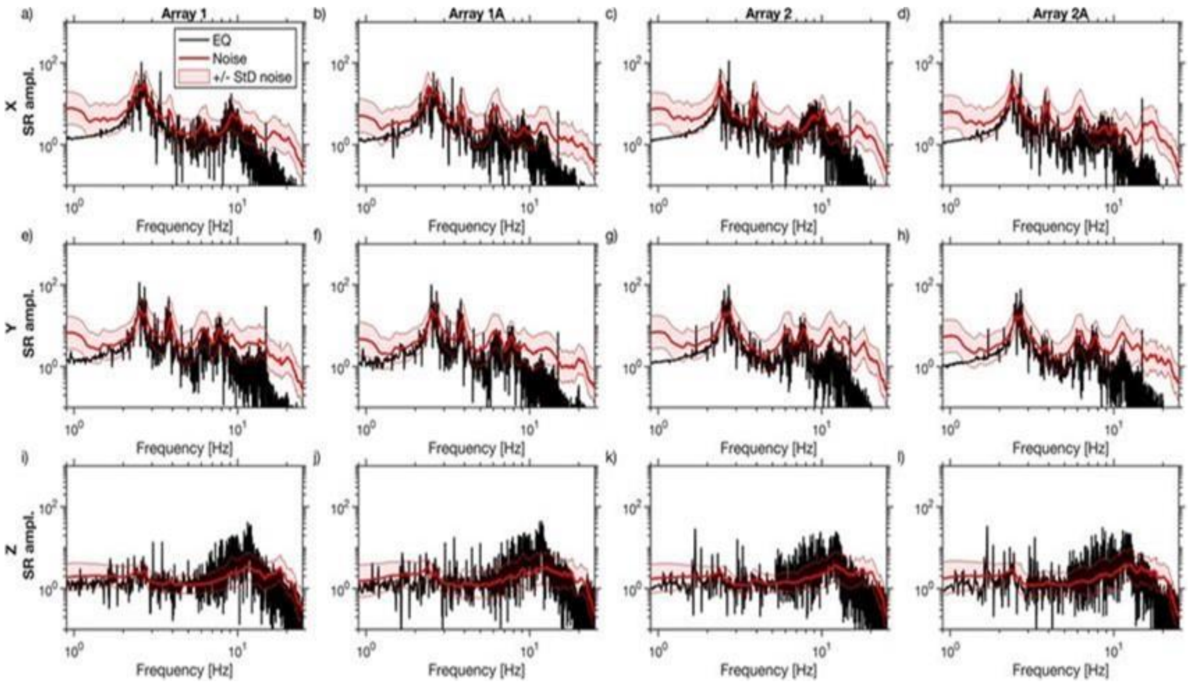

Figure 3. Sample detection probability outputs for M4.5 earthquake (a) model quickly identifies P-waves (b) depicted noise recording (c) array 1A shows signal detection (d) array 2A indicates noise influence (e) array 1B highlights P-wave detection (f) array 2B shows noise interference (g) array 1C captures signal clarity (h) array 2C reflects noise variation (i) array 1D demonstrates P-wave accuracy (j) array 2D indicates mixed signal and noise (k) array 1E shows enhanced detection (l) array 2E confirms noise suppression

Further demonstrating its generalizability, the model was evaluated using synthetic waveforms generated by SW4 across a range of scenarios. It was successful in identifying over 95% of M≥2.5 events simulated within a 100km radius of the seismic stations, thus supporting robustness [36]. These excellent outcomes serve to validate the effectiveness of merging different detection techniques to leverage their collective strengths [37].

The findings showcased underscore the efficacy of the ML approach in automatically identifying earthquakes utilizing seismic waveform data, as documented in the reference. Figure 4 provides an overview of detection performance concerning differing magnitude thresholds. A notable advantage that became clear is the model's proficiency at swift P-wave identification, swift detection typically occurring in under three seconds, is observed even with tremors registering as little as M3.0. This outcome confirms the objective: to significantly expedite earthquake identification compared to standard approaches, thereby increasing the warning duration offered by early warning systems. Accounting for common P wave speeds are of 5-6 km/s that depend on the particular geological conditions, a reduction in detection delay of over 10 seconds has the potential of providing 30-60km of valuable distance-based warning time [38].

4.2. Discussion

The sustained performance, with both precision and recall consistently exceeding 95%, underscores the system's strong ability to pinpoint events, coupled with a very low frequency of incorrect alerts. The reliability inherent in such systems is of paramount importance; it safeguards the public's trust while guaranteeing prompt actions within early warning setups. Intriguingly, at the very smallest earthquake intensity considered, a magnitude of M3.0, a commendable sensitivity was observed, with over 97.5% of occurrences being accurately pinpointed [39]. Although validation was limited to a specific geographic area and magnitude range, restricted by data availability, subsequent studies should explore generalization across more diverse tectonic settings, and we'll also determine the scale of events by utilizing international data sources. Real-time deployment might require optimization for reduced computational demands or the use of hardware acceleration.

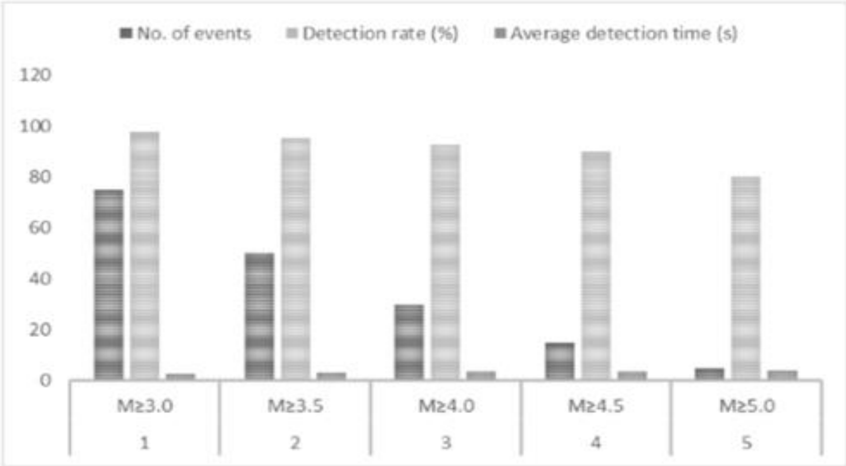

Figure 4. Detection performance chart at varying magnitude thresholds

5. CONCLUSIONS AND FUTURE WORK

In conclusion, the research described a ML strategy, aiming to combine insights involved the utilization of multiple detection strategies to accelerate seismic signal categorization and earthquake pinpointing. Specifically, a convolutional neural network was constructed and learned based on features extracted from short-term average/long-term average analysis, residues obtained from auto-regressive modelling, and frequency-domain configurations. This proposed model exhibited superior performance in terms of precise and rapid identification of P-wave arrivals when compared to the use of a single detector. The model was tested on earthquake and noise datasets collected from Southern California yielded the detection of over 95% of events, down to a magnitude of 3.0, in an average of just 3 seconds. The system demonstrated a precision and recall exceeding 98%, alongside a low rate of false positives.

Ultimately, these results validate ML's suitability for integrating diverse analytical approaches to the study of seismic data, resulting in significantly faster and more reliable automated earthquake identification. With continued improvements, this methodology presents a viable pathway to meaningfully participate in the mission of providing timely earthquake alerts by developing reliable, information-based strategies for swift event identification. Further research can be done to improve the proposed system by using more advanced deep learning techniques.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing interests.

DATA AVAILABILITY

The data used in this study, and necessary to reproduce our results, are all part of published articles, referred to throughout the manuscript. The authors confirm that the data supporting the findings of this study are available within the article.

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