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LSTM REGRESSION MODELS FOR REAL-TIME EARTHQUAKE SOURCE LOCALIZATION FROM SINGLE STATION

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Abstract

Real-time earthquake source localization plays a vital role in Earthquake Early Warning (EEW) systems, yet remains a significant challenge, especially in regions with sparse seismic station coverage. This study explores the potential of Long Short-Term Memory (LSTM) networks for estimating source-to-station distance and hypocentral depth from single-station three-component waveform data. We utilize the Stanford Earthquake Dataset (STEAD) and apply a rigorous preprocessing pipeline to extract a clean subset of over 100,000 labeled seismic event waveforms, ensuring completeness and consistency. We develop and tune three LSTM-based regression models using the Hyperband optimization algorithm. The best-performing model achieves a mean absolute error (MAE) of 26.1 km for distance and 10.1 km for depth. While these results are less accurate than those of baseline models based on Temporal Convolutional Networks and deep CNNs, our approach emphasizes architectural simplicity and operational efficiency. All LSTM models maintain a low number of parameters (as few as 6,098) and exhibit fast inference speeds under 60 ms on a standard GTX 1080 GPU with an Intel i7-7700K CPU. These findings suggest that LSTM-based architectures provide a promising lightweight alternative for rapid deployment in EEW systems, especially in low-resource or single-station scenarios. Future work will explore hybrid neural architectures and attention mechanisms to improve localization performance while maintaining real-time feasibility.

Keywords: *LSTM, machine learning, seismology*

Abstrak

Lokalisasi sumber gempa bumi secara *real-time* memainkan peran vital dalam sistem Peringatan Dini Gempa Bumi (Earthquake Early Warning/EEW). Terdapat beberapa tantangan yang signifikan terhadap lokalisasi ini, terutama di wilayah dengan cakupan stasiun seismik yang jarang. Studi ini mengeksplorasi potensi jaringan Long Short-Term Memory (LSTM) untuk mengestimasi jarak sumber ke stasiun dan kedalaman sumber gempa. Estimasi dilakukan dari data gelombang tiga komponen stasiun tunggal. Kami memanfaatkan Stanford Earthquake Dataset (STEAD) dan menerapkan alur prapemrosesan yang ketat untuk mengekstrak subset bersih dari lebih dari 100.000 gelombang kejadian seismik berlabel untuk memastikan kelengkapan dan konsistensi. Lalu, dikembangkan dan disetel tiga model regresi berbasis LSTM menggunakan algoritma optimasi Hyperband. Model dengan kinerja terbaik mencapai *mean absolute error* (MAE) 26,1 km untuk jarak dan 10,1 km untuk kedalaman. Meskipun hasil ini kurang akurat dibandingkan dengan model *baseline* berbasis Temporal Convolutional Networks dan CNN, pendekatan kami menekankan kesederhanaan arsitektur dan efisiensi operasional. Semua model LSTM mempertahankan jumlah parameter yang rendah (hingga 6.098) dan menunjukkan kecepatan inferensi cepat di bawah 60 ms pada GPU GTX 1080 standar dengan CPU Intel i7-7700K. Temuan ini menunjukkan bahwa arsitektur berbasis LSTM menyediakan alternatif ringan yang menjanjikan untuk penerapan cepat dalam sistem EEW, terutama dalam skenario sumber daya rendah atau stasiun tunggal. Pekerjaan masa depan akan mengeksplorasi arsitektur neural hibrid dan mekanisme atensi untuk meningkatkan kinerja lokalisasi sambil mempertahankan kelayakan sistem untuk diimplementasikan secara *real-time*.

Kata Kunci: LSTM, pembelajaran mesin, seismologi

1. Introduction

Earthquake source localization is a fundamental task in seismology, underpinning applications ranging from seismic monitoring to early warning systems. Accurate estimation of the origin of an earthquake, specifically its hypocentral distance and depth, is critical for assessing potential hazards, enabling rapid emergency response, and understanding geophysical processes.

Traditional approaches to earthquake localization rely on physics-based models, such as travel-time inversion techniques, which require well-calibrated velocity models and dense seismic networks (Thurber & Rabinowitz, 2000). These methods, while effective, often face challenges in real-time scenarios due to computational complexity, sensitivity to model assumptions, and limited spatial coverage. On the other hand, rapid estimation of some earthquake parameters is important for early warning system. Furthermore, accurate depth estimation remains particularly difficult with sparse or regional networks, and becomes especially challenging in single-station observations, where waveform information is more limited.

With the advancement of machine learning, particularly deep learning, new data-driven methods have emerged for seismic signal analysis. With the advancement of machine learning, particularly deep learning, new data-driven methods have emerged for seismic signal analysis. The recent review highlights that machine learning methods are becoming the dominant approaches for many tasks in seismology, particularly in earthquake monitoring where they enable the creation of much more comprehensive earthquake catalogs (Mousavi & Beroza, 2023). Convolutional and recurrent neural networks have been successfully used to detect events, pick phases, and even estimate locations from waveform data (Perol et al., 2018; Ross et al., 2018; Zhu & Beroza, 2019). Recurrent neural networks (RNNs), and more specifically Long Short-Term Memory (LSTM) networks, have shown strong potential for learning temporal dependencies in sequential data (Mousavi et al., 2020). These architectures are particularly well-suited to model seismic waveform sequences, which contain rich temporal patterns related to the earthquake source characteristics.

In this work, we propose an LSTM-based regression framework for real-time earthquake source localization from single-station waveform data, focusing specifically on estimating source-to-station distance and hypocentral depth. Our model operates directly on raw or minimally processed seismic signals and is designed to support rapid inference, making it suitable for early-warning applications or deployment in sparse seismic networks (Mousavi et al., 2020; Perol et al., 2018). We assess the effectiveness of our approach using a publicly available single-station seismic dataset (Mousavi et al., 2019), and benchmark its performance against baseline models in terms of localization accuracy and inference speed.

The main contributions of this paper are:

- We develop a deep learning model based on LSTM architecture to estimate the earthquake source distance and depth from input of a single station waveform.
- We assess the model's performance on real-world seismic data and compare it with other machine learning architectures.
- We demonstrate the feasibility of using this model for real-time earthquake monitoring applications.

2. Related Work

Traditional earthquake source localization methods typically depend on phase picking and travel-time inversion using data from multiple seismic stations. These techniques require well-established velocity models and dense station coverage to achieve accurate location estimates, particularly for earthquake depth. However, in many regions, seismic networks are sparse or unevenly distributed, limiting the effectiveness of such approaches (Lomax et al., 2014).

Recent advances in machine learning have opened new directions for seismic signal processing. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) have been employed for seismic event detection(Perol et al., 2018; Ross et al., 2018), arrival time picking (Zhu & Beroza, 2019), and direct localization (Mousavi & Beroza, 2020). In particular, Perol et al. introduced a CNN-based model that could estimate earthquake epicenters in real time using 2D waveform images, showing that deep learning can bypass some limitations of traditional geophysical inversions. Nonetheless, most of these advances require input or information from multiple seismic stations, which is not always the case.

A particularly relevant study proposed a Bayesian deep learning framework to estimate earthquake locations directly from single-station waveform data (Mousavi & Beroza, 2020). Their model captures uncertainty in the prediction and demonstrates promising performance in scenarios with limited station coverage. Another study also proposed a deep learning framework to estimate earthquake location and magnitude from single-station data (Ristea & Radoi, 2022). While effective, these two approaches primarily use convolutional and fully connected network components.

In contrast, we explore the use of sequence-based models, specifically Long Short-Term Memory (LSTM) networks, for earthquake source localization from single-station data. LSTMs are well-suited to capture the temporal structure of seismic waveforms and may provide complementary strengths to convolutional approaches. We apply LSTM regression to estimate source-to-station distance and depth from a single-station seismic trace.

3. Methodology

In this section, the methodology performed in this study is presented. This includes dataset and preprocessing, model architecture, and hyperparameter optimization.

3.1. Dataset and Preprocessing

We utilize the Stanford Earthquake Dataset (STEAD) (Mousavi et al., 2019), a high-quality, publicly available dataset that contains over one million manually verified three-component waveforms from globally distributed seismic stations. Each waveform is paired with rich metadata, including origin time, hypocentral coordinates, magnitude, and source-receiver information, making it suitable for supervised machine learning tasks in seismology.

Given our focus on real-time regression of source parameters from single-station observations, we apply a stringent preprocessing pipeline to ensure the relevance and quality of input data:

- **Missing Metadata Filtering**: Records lacking ground- truth labels for source-to-station distance or hypocentral depth are discarded.
- **Seismic Noise Filtering**: STEAD also contains ~100,000 seismic noise samples which are not incorporated in the model development.
- **Component Consistency**: Only events with all three orthogonal components (Z, N, E) are retained.
- **Signal Windowing**: Each waveform has 60–second time window.

This preprocessing step yields a clean and well-structured subset of single-station waveform data suitable for training regression models with deep learning. The result of this preprocessing is a curated set of around 150,000 waveforms that is ready to be used for model training and evaluation.

To facilitate model development, the dataset is randomly partitioned into three subsets: 70% for training, 15% for validation, and 15% for testing. The validation set is used for monitoring generalization performance and guiding hyperparameter tuning, while the test set is held out entirely for final evaluation.

3.2. Model Architecture

To capture the temporal dependencies inherent in seismic waveforms, we design a model based on Long Short-Term Memory (LSTM) networks (Hochreiter & Schmidhuber, 1997), a recurrent neural network (RNN) variant widely used in time-series applications. LSTM units maintain an internal memory cell and gating mechanisms that help retain information over long sequences and mitigate the vanishing gradient problem common in standard RNNs.

Each input instance consists of a time-series matrix with shape Tx3, where T is the number of time steps (samples) and the three channels correspond to the vertical (Z), north-south (N), and east-west (E) ground motion components. This raw or minimally processed data is fed directly into the network without requiring hand-crafted features.

As represented in Figure 1, our model architecture includes:

- One or more stacked LSTM layers (e.g., 64–128 units) to learn representations of the waveform's temporal structure. The LSTM layers act as the feature extraction layer.
- Optional dropout layers after each LSTM layer to prevent overfitting.
- A dense feedforward network (e.g., 1–2 layers with ReLU activation) for post-LSTM transformation.
- A final dense output layer with two units representing the regression targets: source-to-station distance and hypocentral depth.

This network is trained using the Adam optimizer with a Mean Squared Error (MSE) loss function. This objective encourages the model to minimize the squared deviations from the ground truth distances and depths. We monitor validation loss during training and implement early stopping to avoid overfitting.

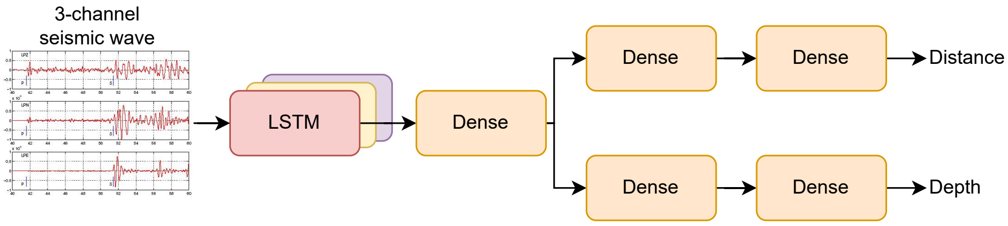

Figure 1 Model Architecture

3.3. Hyperparameter Optimization

We employ the Hyperband algorithm for efficient hyperparameter tuning. Hyperband is a multi-fidelity strategy that adaptively allocates more resources to promising configurations while pruning poor-performing ones early, making it particularly suitable for training deep neural networks with long training cycles (Li et al., 2018).

The hyperparameter search space includes:

- Number of LSTM layers: 1–3
- LSTM units per layer: 32–128
- Dropout rate: 0.0–0.5
- Dense layer units: 4–64

We perform the search using Keras Tuner's Hyperband implementation, with a maximum of 50 epochs per configuration and early-stopping patience of 5. The best-performing configuration is then retrained on the full training set for final evaluation. This methodology aims to balance model complexity, training efficiency, and generalization performance.

4. Experimental Results

In this section, we present the experimental results of our LSTM-based regression framework. We first report the outcome of the hyperparameter tuning process, followed by the performance metrics of the final selected model. Comparative analysis with prior works is discussed, and the feasibility of deploying our approach in real-time earthquake monitoring systems is also evaluated.

4.1. Hyperparameter Tuning and Final Model Selection

We employ the Hyperband optimization algorithm to explore the search space for optimal model configuration. The hyperparameters include the number of LSTM layers (1–3), LSTM units per layer (32–128), dropout rate (0.1–0.5), and the dense layer units. The search is conducted using the validation set, and the objective is to minimize the squared error (MSE) on distance and depth predictions. In this paper, we compare the performance of the top three models with the reference baseline models. The tuned hyperparameters for our best three models are presented in Table I.

All three models share the same LSTM layer depth (1 layer), but differ significantly in LSTM unit size, and dropout rate. Model 2, with 224 LSTM units and a relatively low dropout rate of 0.1, achieved the most favorable trade-off between performance and complexity.

From the model parameter counts, it is evident that Model 2 is the most complex (221,954 parameters), followed by Model 1 (115,186), and then Model 3 (only 6,098). This does not directly correlate with the inference speed shown in Table II, where Model 2 performs slightly faster than Model 1, and both outperform Model 3 in latency despite its minimal architecture. This is likely due to the relatively similar architecture.

Table I
Hyperparameter Tuning Result

Hyperparameter	Model 1	Model 2	Model 3
LSTM layers	1	1	1
LSTM units	160	224	32
Dropout Rate	0.1	0.1	0.5
Shared Dense Layer units	48	64	16
1st Dense Layer units	16	16	16
2nd Dense Layer units	8	8	8
#Parameters	115,186	221,954	6,098

4.2. Evaluation Metrics and Performance Analysis

We evaluate the model using Mean Absolute Error (MAE) for both target variables. Table II summarizes the results on the held-out test set. The model performs better in predicting distance compared to depth, which aligns with previous findings in earthquake localization using single-station data.

Table II also compares the performance of our LSTM-based models against two established baselines: Model A (based on Mousavi et al.'s TCN architecture) and Model B (from Ristea et al.'s complex CNN approach). Our LSTM models underperform in terms of raw MAE, especially in source-to-station distance estimation. The best LSTM model (Model 2) yields a distance MAE of 26.15 km and a depth MAE of 10.10 km, while Model B achieves 4.51 km and 6.15 km respectively.

This performance gap is not unexpected. Both Model A and Model B utilize architectures that are well-suited for learning spatial features across temporal patterns—TCN excels at capturing long-range dependencies through dilated convolutions, and CNNs are known for their high capacity in feature extraction. In contrast, LSTM models, while powerful for temporal sequences, are relatively lightweight and less expressive in capturing complex spatial dependencies in raw waveform data.

However, our models offer a critical advantage in terms of real-time feasibility. All LSTM models achieve inference speeds under 60~ms on CPU, measured on a system equipped with an Intel Core i7-7700K processor @4.20~GHz and NVIDIA GTX 1080 GPU. While GPU was available for training, inference measurements were strictly performed on the CPU to reflect realistic deployment conditions in edge devices if the edge devices do not have access to GPU. These results confirm the models' potential for deployment in latency-sensitive applications such as earthquake early warning systems.

These findings suggest that while LSTM-based architectures may not yet match the predictive accuracy of more complex deep networks for this task, they remain a strong candidate for real-time, deployable earthquake source localization—especially when simplicity, latency, and interpretability are prioritized.

Table II
Model Performance Comparison

Metric	Model A [6]	Model B [10]	Model 1	Model 2	Model 3
Distance MAE [km]	7.3	4.51	26.1	26.15	26.18
Depth MAE [km]	6.7	6.15	10.48	10.10	10.13
Inference Speed (ms)			52.84	50.50	56.07

4.3. Real-Time Feasibility

To assess the practical applicability of our model for early warning or rapid response systems, we benchmark the average inference time on a CPU-based setup. The LSTM model yields predictions in under 60 milliseconds per event (as presented in Table II), including preprocessing overhead, making it feasible for real-time deployment. This efficiency stems from the relatively low number of parameters and the simplicity of the model structure compared to deeper CNNs or attention-based architectures.

5. Discussion

The experimental results demonstrate that our LSTM-based models are capable of estimating earthquake source distance and depth from single-station waveform data in real time. However, the models underperform in terms of mean absolute error (MAE) when compared to more complex architectures, such as the TCN-based model by Mousavi et al. and the complex CNN-based approach by Ristea et al.. This performance gap can be attributed to the limited representational capacity of shallow LSTM networks and the absence of large convolutional receptive fields that are advantageous for capturing complex temporal patterns.

Nevertheless, our approach offers several practical benefits. First, the models maintain low inference latency (under 60 ms on CPU), which is critical for Earthquake Early Warning (EEW) systems. Second, the simplicity and lightweight nature of our architectures make them suitable for edge deployment in low-resource environments, including seismic stations in remote or underdeveloped regions. Moreover, the use of raw or minimally processed waveforms as input shows the potential for reducing preprocessing overhead in real-time systems. Future improvements may include integrating hybrid models (e.g., combining LSTM and CNN layers), incorporating attention mechanisms, or leveraging transfer learning with larger pretrained seismic models.

Finally, while this study focuses on single-station data, expanding the approach to incorporate sparse multi-station input without significant latency increase may provide a useful trade-off between accuracy and responsiveness.

6. Conclusion and Future Work

In this study, we proposed and evaluated LSTM-based regression models for real-time estimation of earthquake source distance and depth from single-station waveform data. Our approach emphasizes minimal preprocessing and efficient inference, making it suitable for rapid deployment in Earthquake Early Warning (EEW) systems, especially in regions with limited seismic infrastructure.

Although the proposed LSTM models underperform in terms of prediction accuracy compared to more complex architectures such as Temporal Convolutional Networks (TCN) (Mousavi & Beroza, 2020) and complex CNN-based models (Ristea & Radoi, 2022), they demonstrate several important advantages. Notably, our models offer fast inference times (under 60~ms on standard hardware), maintain low parameter counts, and exhibit structural simplicity, all of which contribute to their suitability for real-time and resource-constrained environments.

The results suggest that while LSTM architectures are not the optimal choice for highest accuracy in earthquake source localization, they remain valuable as part of a broader exploration of model architectures, particularly when computational efficiency and simplicity are prioritized.

Future work will focus on enhancing model accuracy through hybrid architectures (e.g., LSTM-CNN combinations), integrating attention mechanisms to improve temporal feature learning, and exploring domain adaptation or transfer learning strategies. Additionally, expanding the model to leverage sparse multi-station input with low latency may help balance the trade-off between accuracy and responsiveness, further improving the utility of machine learning models in real-time seismology applications.

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