View Reviews

Paper ID
47

Paper Title
Earthquake Prediction Using Deep Learning with Spatiotemporal Priors

Track Name
Others

Reviewer #5

Questions

2. Does the paper describe an original work?
Yes

3. Is the paper technically sound ?
Yes

4. In your opinion, does the paper show technical novelty ?
Yes

5. Are the title and abstract satisfactory ?
Yes

6. Is paper organised as per IEEE standard format and style?
Yes

7. Are all the tables, figures and references properly cited in the text?
Yes

8. Strength and Weakness of the Paper
Kindly see the attached general comments and incorporate in the camera ready paper.

9. Contributions: What are the major issues addressed in the paper? Do you consider them important? Comment on the degree of novelty, creativity and technical depth in the paper.
Kindly see the attached general comments and incorporate in the camera ready paper.

10. Your overall recommendation
Accept with minor revision

11. Overall evaluation and comments to authors
Kindly see the attached general comments and incorporate in the camera ready paper.

Reviewer #6

Questions

2. Does the paper describe an original work?
Yes

3. Is the paper technically sound ?
Yes

4. In your opinion, does the paper show technical novelty ?
Yes

5. Are the title and abstract satisfactory ?
Yes

6. Is paper organised as per IEEE standard format and style?
Yes

7. Are all the tables, figures and references properly cited in the text?
Yes

8. Strength and Weakness of the Paper
Strengths:

Tackles a high-impact real-world problem: earthquake early warning.

Proposes a unified deep learning framework that predicts multiple earthquake parameters (magnitude, epicentral distance, azimuth, focal depth) simultaneously.

Strong technical architecture: combines CNNs (local features), BiLSTMs (sequential patterns), and Transformers (long-range dependencies).

Incorporates handcrafted statistical features (e.g., Pd, skewness, kurtosis) with deep features, enhancing robustness.

Includes uncertainty estimation via Monte Carlo dropout, which is critical in safety applications.

Provides explainability using SHAP values and Transformer attention maps—important for trust in real-world deployments.

Extensive experiments on K-NET and KiK-net datasets with competitive MAE values (e.g., 0.18 for magnitude, 5.21 km for distance).

Clear structure, thorough methodology, and meaningful comparisons with baselines.

Weaknesses:

The contribution is mainly an integration of existing models (CNN, BiLSTM, Transformer), rather than a fundamentally new algorithm.

Limited validation: performance is demonstrated only on Japanese datasets; transferability to other seismic regions is not shown.

Some baseline comparisons (CNN-only, BiLSTM-only) are relatively weak; comparison with state-of-the-art EEW systems would strengthen claims.

The paper would benefit from real-time deployment experiments (latency benchmarks on actual edge devices).

Certain figures (e.g., 18 in results) are incomplete or lack detailed explanation.

Minor language and formatting issues reduce readability.

9. Contributions: What are the major issues addressed in the paper? Do you consider them important? Comment on the degree of novelty, creativity and technical depth in the paper.

Major Issues Addressed:

Traditional EEW systems suffer from latency, noise sensitivity, staged pipelines, and lack of generalization.

This paper addresses these by proposing an end-to-end multi-task model with spatiotemporal priors and interpretable outputs.

Importance:

The problem is highly important—accurate and fast EEW systems can save lives and infrastructure.

Joint prediction of multiple parameters in a single pass is both novel and practical for deployment.

Novelty, Creativity, and Technical Depth:

Novelty: Moderate. The model integrates known architectures rather than introducing a new algorithm, but the joint multi-task framework + uncertainty + interpretability makes it distinctive.

Creativity: High in combining different techniques (deep + handcrafted features, SHAP + attention, Monte Carlo dropout).

Technical Depth: Good balance of theory and practical implementation; experiments are solid, though further comparative evaluation could enhance credibility.

10. Your overall recommendation

Accept with major revision

11. Overall evaluation and comments to authors

This paper presents a technically strong and application-relevant contribution to earthquake early warning. The integration of CNN, BiLSTM, and Transformer modules with handcrafted features, uncertainty estimation, and interpretability tools is well-executed. Results on large seismic datasets demonstrate good predictive accuracy across multiple tasks.

Suggestions for Improvement:

Strengthen baseline comparisons with more recent state-of-the-art EEW models.

Discuss real-world deployment considerations such as latency on embedded hardware, energy efficiency, and data transmission delays.

Expand the evaluation to cross-regional datasets to prove generalization.

Improve clarity in figures and fix missing captions/details.

Streamline some sections to make the narrative more concise.