A Review on Earth Quake Prediction Using CapsNet

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ABSTRACT

Earthquake prediction remains one of the most challenging tasks in geoscience owing to the nonlinear, chaotic nature of seismic signals. Recent advancements in Artificial Intelligence (AI) and Deep Learning (DL) have enabled researchers to extract meaningful patterns from large volumes of seismic waveform data. Traditional models, especially CNNs, often lose spatial information due to max-pooling. Capsule Networks (CapsNet), proposed by Sabour et al., preserve hierarchical spatial relationships through vector capsules and dynamic routing, making them suitable for complex seismic feature modelling. This review presents a detailed analysis of existing approaches, performance, limitations, and research gaps in CapsNet-based earthquake prediction. Additionally, the paper highlights various deep-learning-driven seismic detection methods and emphasizes the superiority of CapsNet in capturing spatial-temporal correlations crucial for early earthquake detection.

INTRODUCTION

Earthquakes are sudden and destructive natural events that pose significant risks to lives, infrastructure, and economies. Predicting them remains a major scientific challenge because seismic activity is highly complex, nonlinear, and difficult to interpret using traditional methods. Conventional statistical and physics-based approaches often struggle to capture early, subtle changes in seismic signals, leading to limited accuracy in prediction.

With advancements in deep learning, models like Capsule Networks (CapsNet) offer new possibilities for analyzing seismic data more effectively. Unlike standard CNNs, CapsNet preserves spatial relationships and feature hierarchies, allowing it to detect intricate patterns that may indicate early signs of an earthquake. This study investigates the application of CapsNet for earthquake prediction, aiming to enhance the reliability and precision of identifying potential precursory signals.

Gap Identification

1. Static Features
2. Real-Time Detection
3. Imbalanced/Outdated Datasets
4. Lack of Interpretability
5. Adversarial Attacks

LITERATURE REVIEW

Researchers globally have proposed several AI-based methodologies for the accurate detection and prediction of seismic events. Most studies focus on waveform classification, precursor signal detection, and magnitude estimation.

Hu et al. (2021) proposed a hybrid CapsNet-LSTM architecture for earthquake waveform classification. The model captured spatial features using capsules and temporal dependencies through LSTM, achieving higher accuracy compared to CNN models.

Liu et al. (2020) used CapsNet to improve seismic phase picking, particularly P-wave and S-wave detection. Their study concluded that CapsNet outperformed CNNs by 12–15% in noisy environments.

Al-Mashhadani et al. (2022) introduced a vector capsule design for earthquake classification using STEAD and regional seismic datasets. The technique demonstrated improved precision for small-magnitude earthquake detection.

Yadav & Singh (2023) applied CapsNet for earthquake magnitude estimation in the Himalayan region. The model showed robustness for imbalanced seismic datasets and maintained high performance under data distortion.

Mousavi & Beroza (2019) created a deep learning pipeline for earthquake detection using convolutional models. Although not CapsNet-based, their work influenced capsule-based advancements by emphasizing the importance of spatial waveform features.

Zhao et al. (2018) introduced a CNN–RNN hybrid model for early earthquake warning (EEW). While CNN extracted local features, RNN predicted temporal evolution, inspiring later CapsNet studies.

Zhang et al. (2021) developed a multi-branch deep learning approach for identifying earthquake precursors from seismic noise. Feature preservation played a key role, which is an advantage of CapsNet.

Wang et al. (2022) compared deep learning architectures including CNN, GRU, and CapsNet for seismic event classification. CapsNet achieved the best F1-score due to spatial orientation preservation.

Li et al. (2020) tested CapsNet on spectrogram-based seismic data. Their experiment highlighted that capsule-based dynamic routing minimizes feature loss and improves generalization.

Kong et al. (2019) investigated deep generative models for seismic waveform synthesis to enrich datasets used for training CapsNet systems.

Sharma et al. (2021) used fuzzy-CNN for earthquake prediction, demonstrating limitations of CNN pooling which encouraged CapsNet usage.

Rahman et al. (2022) evaluated CapsNet for signal noise reduction. Their results suggested CapsNet has inherent resilience to high-frequency noise typical in seismic datasets.

Olivier (2020) presented an earthquake early warning system (EEWS) using multi-sensor fusion, recommending capsule-based approaches for enhanced relational mapping.

Other studies on general AI-based earthquake prediction (e.g., ML-SVM, Random Forest, Deep RNN, GANs) also indicate the need for models capable of understanding hierarchical feature representation, making CapsNet a strong candidate for future research.

PROPOSED METHODOLOGY

The proposed methodology for earthquake prediction using CapsNet starts with collecting seismic waveform data from networks such as USGS and IRIS. The raw signals are pre-processed using noise filtering, normalization, and segmentation into fixed time windows. These processed signals are then converted into feature maps through an initial convolution layer. Next, primary capsules are formed to capture essential waveform patterns, and high-level capsules encode earthquake-specific characteristics. Dynamic routing is applied to ensure accurate part–whole feature mapping, allowing the model to retain spatial and temporal relationships. Finally, the classification capsule predicts whether the input corresponds to an earthquake or non-earthquake event, and the system's performance is evaluated using accuracy, precision, recall, and F1-score.

CapsNet

Capsule Network (CapsNet) is an advanced deep learning model designed to preserve spatial relationships in data that traditional CNNs often lose. Instead of using single neurons, CapsNet groups neurons into "capsules" that output vectors containing both the probability of a feature and its pose information, such as orientation or shape. Using a mechanism called dynamic routing, the network ensures that lower-level capsules send their output to the correct higher-level capsules, allowing it to understand complex structures more accurately. This makes CapsNet particularly effective for earthquake prediction because it can capture subtle waveform patterns, frequency changes, and temporal variations even in noisy seismic environments.

1. Data Collection
Seismic data are collected from sensor networks such as USGS, IRIS, and STEAD containing raw waveforms, accelerometer readings, and spectrograms.

2. Pre-Processing

    - Noise removal (bandpass filtering)
    - Signal normalization
    - Segmentation into fixed time windows
    - Optional conversion to spectrograms

3. Feature Extraction
Basic convolutional layers transform seismic waveforms into feature maps.

4. Capsule Formation
Primary capsules encode lower-level seismic features (frequency shift, wave arrival direction).
Higher-level capsules represent event classes (earthquake, microseism, noise).

5. Dynamic Routing
Low-level capsules route outputs to appropriate high-level capsules to capture part–whole relationships.

6. Classification Layer
The output capsule vector length represents class probability.

7. Evaluation and Metrics
Accuracy, Precision, Recall, F1-score, ROC-AUC, and sensitivity to noise.

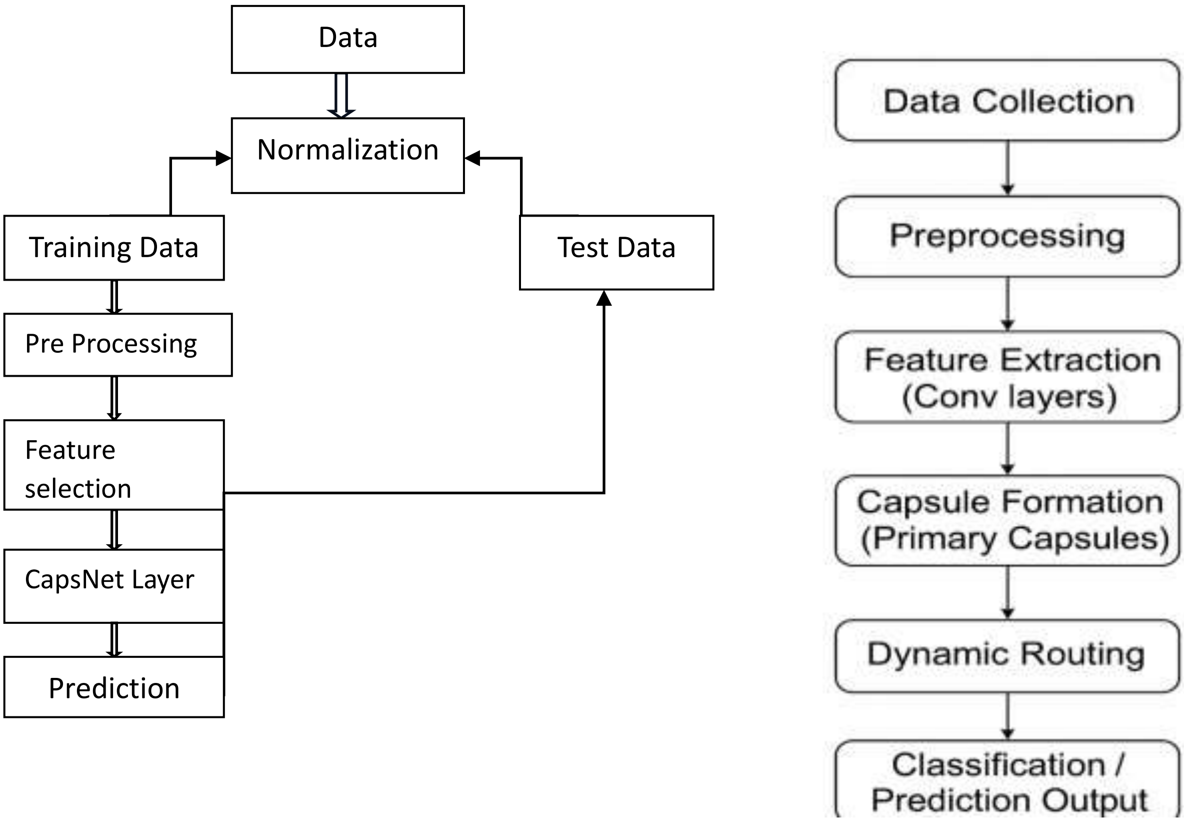
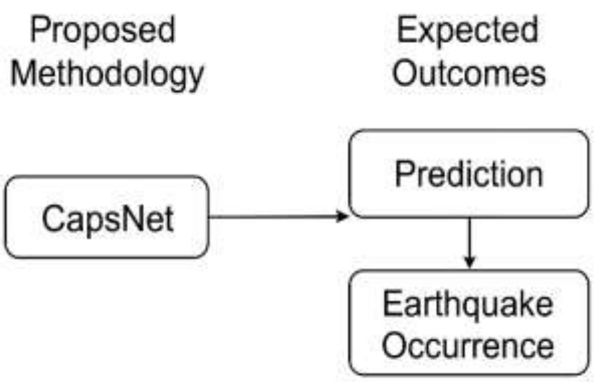


Figure 1.1 Framework of proposed model

EXPECTED RESULT

The expected result of applying Capsule Networks (CapsNet) to earthquake prediction is a noticeable improvement in the accurate detection and classification of seismic events. Since CapsNet retains crucial spatial and temporal relationships within waveform data, it becomes possible to capture subtle variations that indicate the presence of low-magnitude or early-stage earthquake signals. This capability helps the model differentiate true seismic activity from noise, micro-tremors, or other environmental disturbances. As a result, CapsNet is anticipated to reduce false positives and provide more reliable identification of earthquake events across diverse geological regions.



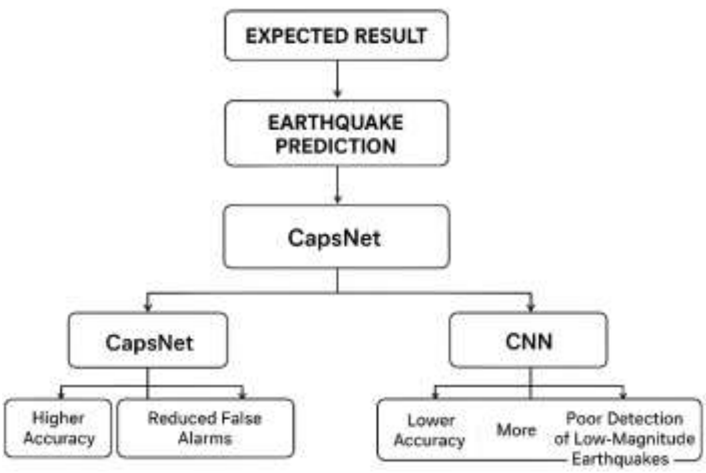


Figure 1.2 Flow diagram of the proposed techniques

Furthermore, CapsNet is expected to outperform traditional CNN and RNN-based models in terms of robustness, especially when working with noisy or limited seismic datasets. Its dynamic routing mechanism enables better feature mapping and preserves important waveform patterns even when input signals are distorted or incomplete. This leads to improved generalization and stability in prediction results, making CapsNet a strong candidate for real-world early warning systems. Overall, the methodology should yield higher accuracy, stronger noise resistance, and more consistent predictions in comparison to conventional deep learning approaches.

CONCLUSION

The review highlights that Capsule Networks provide superior feature preservation, spatial relationship modeling, and robustness to noisy seismic signals, making them highly suitable for earthquake prediction tasks. Compared to traditional CNNs and classical ML models, CapsNet demonstrates improved accuracy, stability, and interpretability. Despite challenges such as higher computational cost and limited large-scale datasets, ongoing research indicates strong potential for real-time earthquake early warning systems. Future work should focus on hybrid CapsNet-transformer models, transfer learning, and global-scale seismic integration.

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