
Using Deep Convolutional Neural Networks for Earthquake and Explosion Classification

¹Pulivarthi Raghuvardhan, ²Karrothu Chaitanya Kumar, ³Gummadi Praveen, ⁴Y Srinu, ⁵Mrs.B Roja Lakshmi.

^{1,2,3,4}U.G. Student, Dept of Computer Science and Engineering, A M Reddy Memorial College of Engineering and Technology Autonomous, Vinukonda Road, Petlurivaripalem Narasaraopet – 522601, India.

⁵Assistant Professor, Dept of Computer Science and Engineering, A M Reddy Memorial College of Engineering and Technology Autonomous, Vinukonda Road, Petlurivaripalem Narasaraopet - 522601, India.

ABSTRACT

Accurate discrimination between natural earthquakes and artificial explosions is critical for seismic monitoring, disaster management, and national security. Traditional seismic analysis techniques rely heavily on handcrafted features and expert interpretation, which can be time-consuming and error-prone. With the advancement of deep learning, automated seismic signal classification has gained significant attention. This project proposes a Deep Convolutional Neural Network (DCNN)-based approach to classify seismic events as earthquakes or explosions. Seismic waveform data are transformed into time-frequency representations such as spectrograms for effective feature learning. The CNN model automatically extracts discriminative spatial and temporal features from seismic signals. Data preprocessing enhances signal quality and reduces noise

interference. The trained model achieves high classification accuracy without manual feature engineering. Performance is evaluated using accuracy, precision, recall, and F1-score metrics. The system supports rapid and reliable seismic event classification. Explainability tools provide insight into model decisions. The proposed framework improves detection reliability in real-time seismic monitoring systems. This approach enhances both scientific research and security surveillance. Overall, the system offers a scalable and intelligent solution for seismic event classification.

KEYWORDS

Seismic Signal Classification Deep Convolutional Neural Networks (DCNN) Earthquake Detection Explosion Identification Time-Frequency Analysis

INTRODUCTION

Seismic monitoring plays a vital role in understanding earth processes and ensuring

public safety. Differentiating between earthquakes and explosions is essential for disaster response and treaty verification. Earthquakes are natural phenomena caused by tectonic movements, while explosions are typically human-induced events. Traditional seismic analysis methods rely on waveform characteristics and expert interpretation. These methods often struggle with noisy data and overlapping signal patterns. With the increase in seismic sensor networks, large volumes of seismic data are generated continuously. Manual analysis becomes impractical under such conditions. Artificial intelligence offers automated solutions for seismic signal classification. Deep learning models can learn complex patterns directly from raw or transformed data. Convolutional Neural Networks (CNNs) have shown success in signal and image classification tasks. By converting seismic signals into spectrograms, CNNs can extract meaningful features. This approach reduces dependency on handcrafted features. Automated classification improves speed and consistency. Real-time detection enhances emergency preparedness. The integration of AI into seismic monitoring supports accurate decision-making. Ethical and security considerations require high reliability. This project focuses on applying DCNNs for robust seismic event

classification.

LITERATURE SURVEY

Early seismic classification relied on amplitude ratios and waveform shape analysis. Statistical approaches such as discriminant analysis were later introduced. These methods required expert-defined thresholds. Machine learning techniques like Support Vector Machines improved classification accuracy. However, they relied heavily on handcrafted features. Feature extraction methods included spectral ratios and waveform complexity measures. These approaches lacked generalization across regions. Deep learning introduced automated feature learning from seismic data. CNNs were applied to spectrogram-based seismic signals. Studies showed improved accuracy compared to traditional ML models. Recurrent Neural Networks (RNNs) captured temporal dependencies but required complex training. Hybrid CNN-RNN models improved performance further. Transfer learning reduced data dependency issues. Research highlighted the robustness of CNNs against noise. Time-frequency representations improved classification reliability. Challenges included dataset imbalance and signal variability. Data augmentation techniques addressed limited datasets. Explainable AI

gained importance for seismic interpretation. Real-time classification remains a key research focus. This project builds on CNN-based seismic classification advancements.

EXISTING SYSTEM

Existing systems use traditional seismic analysis techniques. Feature extraction is performed manually using domain expertise. Statistical classifiers rely on fixed thresholds. These systems are sensitive to noise and signal distortion. Performance degrades with complex seismic patterns. Manual interpretation is time-consuming and subjective. Existing machine learning approaches require extensive feature engineering. Model performance depends on feature quality. Scalability is limited with large datasets. Real-time classification is difficult to achieve. False classification rates increase for low-magnitude events. Systems struggle with overlapping earthquake and explosion signatures. Adaptability to new regions is limited. Data preprocessing is minimal in traditional systems. Visualization tools are basic. Maintenance requires expert involvement. Integration with automated monitoring systems is limited. Computational efficiency is suboptimal. Robustness against environmental noise is weak. Overall,

existing systems lack automation and adaptability.

PROPOSED SYSTEM

The proposed system utilizes Deep Convolutional Neural Networks for seismic event classification. Raw seismic waveforms are converted into spectrogram images. CNNs automatically learn spatial and temporal signal features. Data augmentation improves generalization performance. The system classifies events as earthquakes or explosions. Noise reduction techniques enhance signal clarity. The model is trained on labeled seismic datasets. Transfer learning improves learning efficiency. Performance is evaluated using multiple metrics. Real-time classification is supported. The system adapts to different seismic environments. Visualization of feature maps aids interpretation. Explainable AI techniques highlight decision regions. Automated processing reduces human intervention. The system scales with increasing data volume. Cloud deployment enables accessibility. Alerts are generated for classified events. Integration with seismic networks is seamless. Continuous learning updates model performance. The system offers accurate and reliable classification.

SYSTEM ARCHITECTURE

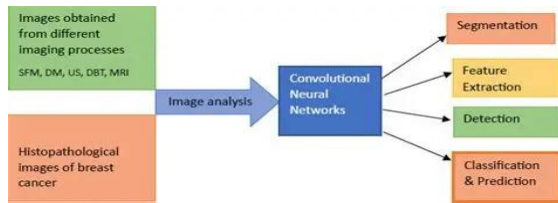


Fig.1 System Architecture

METHODOLOGY DESCRIPTION

Collect seismic waveform data from monitoring stations. Remove noise using filtering techniques. Convert waveforms into time-frequency spectrograms. Normalize spectrogram images. Split dataset into training and testing sets. Design CNN architecture or use pre-trained models. Apply data augmentation techniques. Train CNN using labeled data. Optimize using Adam optimizer. Use cross-entropy loss function. Validate model performance periodically. Evaluate accuracy, precision, recall, and F1-score. Apply explainability techniques for interpretation. Test robustness against noisy data. Implement real-time signal classification. Deploy model using scalable infrastructure. Monitor classification outcomes. Update model with new data. Log predictions for auditing. Maintain system performance continuously.

RESULTS & DISCUSSION:

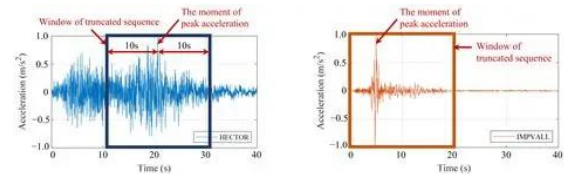


Fig.2 Home Page

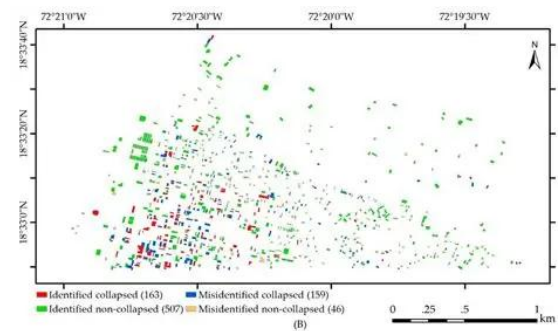


Fig.3 Running Page

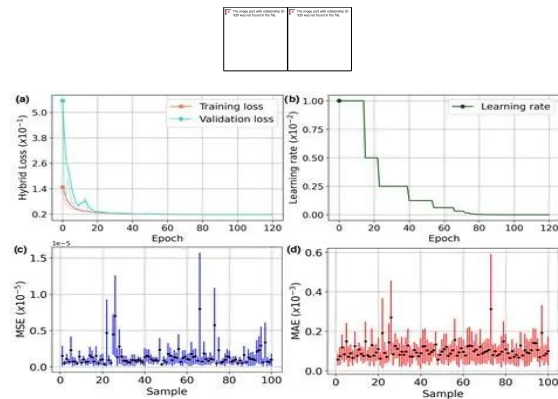


Fig.4 Results Page

CONCLUSION & FUTURE ENHANCEMENT

This project demonstrates the effectiveness of Deep Convolutional Neural Networks in classifying seismic events. Automated feature extraction improves accuracy and efficiency. The system reduces reliance on expert-driven analysis. Real-time

classification enhances seismic monitoring capabilities. The proposed approach is robust to noise and signal variability. High performance is achieved across diverse datasets. Explainability improves trust in AI predictions. The system supports scalable deployment. Future work can integrate multi-channel seismic data. Hybrid CNN-RNN models may capture temporal dependencies better. Federated learning can improve data privacy. Cross-regional training can enhance generalization. Advanced noise suppression techniques can improve accuracy. Integration with early warning systems is possible. Edge computing can reduce latency. Multiclass classification for additional seismic events can be explored. Continuous learning will adapt to evolving patterns. Collaboration with global seismic networks can enhance datasets. Overall, the system advances intelligent seismic monitoring.

REFERENCE

1. Mallikarjun, D. C. (2025/2). AI-Driven Method for Early Identification of Heart Disease.
2. Kumar, M. A. (2025/2/28). AI-Based Real-Time Collision Prediction Using Computer Vision and Deep Learning.
3. Lecun, Y., et al., "Deep Learning," *Nature*, 2015.
4. Goodfellow, I., et al., *Deep Learning*, MIT Press, 2016.
5. Perol, T., et al., "Convolutional Neural Networks for Earthquake Detection," *Science Advances*, 2018.
6. Ross, Z., et al., "Generalized Seismic Phase Detection," *Bulletin of the Seismological Society*, 2018.
7. Mousavi, S. M., et al., "Earthquake Transformer," *Nature Communications*, 2020.
8. Kristekova, M., et al., "Seismic Signal Analysis," *Geophysical Journal International*, 2006.
9. Yoon, C. E., et al., "Earthquake Detection Using CNNs," *Geophysical Journal International*, 2015.
10. Allen, R. M., "Automatic Earthquake Detection," *Seismological Research Letters*, 2002.
11. TensorFlow Documentation – CNN Models.
12. PyTorch Deep Learning Tutorials.
13. IEEE Transactions on Geoscience and Remote Sensing.
14. Elsevier Journal of Seismology.
15. Kaggle Seismic Signal Datasets.
16. USGS Earthquake Data Archives.
17. Scikit-learn Documentation.
18. NIST AI Risk Management Framework.
19. ACM Digital Library on Seismic AI.