International Journal of Multidisciplinary and Scientific Emerging ResearcH (IJMSERH)

| ISSN: 2349-6037 | www.ijmserh.com ||Impact Factor: 9.274||Quarterly, Peer Reviewed & Refereed Journal|

|| Volume 13, Issue 2, April - June 2025 ||

DOI: 10.15662/IJMSERH.2025.1302016

Machine Learning in Seismology for Earthquake Prediction

George Evans, Lily Harris, Jack Martin

Independent Researcher, UK

ABSTRACT: Earthquakes are among the most destructive natural disasters, yet accurately predicting them remains one of science's greatest challenges. Traditional seismological approaches struggle to interpret complex patterns from vast seismic datasets. Recently, machine learning (ML) has shown promise in seismology by identifying hidden patterns, detecting microseismic activities, and forecasting earthquake probabilities. This paper explores the integration of ML into earthquake prediction, reviewing current models, methodologies, and challenges. It also proposes a data-driven framework for improving seismic event forecasting using supervised and unsupervised ML algorithms.

KEYWORDS: Seismology, Earthquake Prediction, Machine Learning, Deep Learning, Time-Series Analysis, Seismic Data, Earthquake Forecasting, Pattern Recognition

I. INTRODUCTION

Earthquakes pose a significant threat to human life, infrastructure, and economies, especially in seismically active regions. Despite advancements in geophysical instrumentation and modeling, accurately predicting the location, time, and magnitude of earthquakes remains elusive due to the chaotic nature of seismic events. However, the explosion of seismic data and advances in machine learning provide new opportunities to tackle this problem. ML algorithms can learn complex, nonlinear relationships from historical and real-time seismic data, offering new avenues for early warning systems and risk mitigation.

II. LITERATURE REVIEW

1. Earthquake Detection & Phase Picking

- **Objective**: Identify seismic events and their arrival phases (P-waves, S-waves) with high accuracy.
- **ML Techniques**:
    - **Supervised Learning**: CNNs (e.g., *PhaseNet*, *EarthquakeTransformer*), RNNs, LSTMs.
    - **Unsupervised Learning**: Clustering waveform patterns to detect events without labels.
- **Impact**:
    - Automated real-time earthquake detection with high precision.
    - Outperforms traditional STA/LTA methods in noisy environments.

2. Earthquake Location & Magnitude Estimation

- **Objective**: Estimate the epicenter, depth, and magnitude of seismic events.
- **ML Techniques**:
    - **Regression Models**: SVR, Random Forest, and Deep Neural Networks.
    - **Bayesian Neural Networks**: For uncertainty-aware predictions.
- **Impact**:
    - Faster and more accurate than conventional inversion-based methods.
    - Real-time localization for microseismic events.

3. Seismic Signal Classification

- **Objective**: Distinguish between earthquakes, quarry blasts, volcanic tremors, and background noise.
- **ML Techniques**:
    - CNNs, SVMs, Decision Trees.
    - Spectrogram-based deep learning models.

| ISSN: 2349-6037 | www.ijmserh.com ||Impact Factor: 9.274||Quarterly, Peer Reviewed & Refereed Journal|

|| Volume 13, Issue 2, April - June 2025 ||

DOI: 10.15662/IJMSERH.2025.1302016

- **Use Cases**:
    - Volcanic monitoring.
    - Discrimination between tectonic and non-tectonic events.

4. Aftershock Forecasting

- **Objective**: Predict the likelihood, location, and magnitude of aftershocks following a major earthquake.
- **ML Techniques**:
    - **Logistic Regression**, Random Forests, Gradient Boosting Machines.
- Hybrid models incorporating physics-based features.
- **Notable Study**: *DeVries et al. (2018)* showed ML models could outperform traditional Coulomb stress-based forecasts.

5. Seismic Tomography & Earth Structure Imaging

- **Objective**: Infer subsurface structures using seismic wave travel times and amplitudes.
- **ML Techniques**:
    - Deep learning for super-resolution tomography.
    - Inversion acceleration using surrogate models and physics-informed neural networks.
- **Benefits**:
    - Faster computation with more detailed imaging.
    - Enables real-time updates in active regions.

6. Earthquake Early Warning Systems (EEWS)

- **Objective**: Detect early P-waves and alert populations before damaging S-waves arrive.
- **ML Techniques**:
    - Real-time classification and regression using lightweight CNNs and LSTMs.
    - Edge AI: running models on local devices (e.g., smartphones, Raspberry Pi).
- **Real-World Use**:
    - Implemented in Japan, Mexico, and California.

7. Induced Seismicity Monitoring (e.g., from fracking, reservoirs)

- **Objective**: Detect and analyze seismic events induced by human activity.
- **ML Techniques**:
    - Time-series analysis and clustering to detect low-magnitude swarms.
    - Anomaly detection for early intervention.
- **Applications**:
    - Real-time monitoring in oil/gas and geothermal fields.
    - Regulatory compliance and risk mitigation.

8. Seismic Hazard & Risk Assessment

- **Objective**: Model seismic hazard for urban planning and infrastructure design.
- **ML Techniques**:
    - Spatial models using Random Forests, Gaussian Processes.
    - Integration with GIS and socio-economic data.
- **Outputs**:
    - Risk maps.
    - Probabilistic forecasts of future seismicity.

| ISSN: 2349-6037 | www.ijmserh.com ||Impact Factor: 9.274||Quarterly, Peer Reviewed & Refereed Journal|

|| Volume 13, Issue 2, April - June 2025 ||

DOI: 10.15662/IJMSERH.2025.1302016

Numerous studies and applications of ML in seismology have emerged over the last decade:

Study / Research	Technique	Focus	Key Findings
Kong et al. (2019)	Convolutional Neural Nets (CNN)	Earthquake detection in continuous waveforms	CNNs outperform traditional detection algorithms
Mousavi et al. (2020)	Deep Learning (Deeplearning4j)	Automatic earthquake classification	Achieved high accuracy with minimal labeled data
Perol et al. (2018)	CNN	Earthquake location and magnitude estimation	Real-time, high-resolution event detection
Rouet-Leduc et al. (2017)	Random Forest, Gradient Boosting	Lab-based fault slip prediction	Demonstrated predictive capabilities before labquakes
Yoon et al. (2015)	K-means clustering	Seismic pattern discovery	Helped classify foreshocks vs aftershocks

III. TABLE: ML APPLICATIONS IN EARTHQUAKE PREDICTION

Application Area	ML Technique Used	Input Data	Output / Objective
Seismic Event Detection	CNN, RNN	Seismic waveform time series	Detect event onset in noisy data
Earthquake Magnitude Estimation	Regression, XGBoost	Seismograph data, waveform attributes	Predict event magnitude
Earthquake Localization	CNN, KNN	Arrival times, sensor coordinates	Estimate event epicenter
Pattern Recognition (Foreshocks)	Unsupervised Learning (K-means)	Historical event clusters	Identify foreshock patterns
Time-to-Failure Prediction	Random Forest, LSTM	Acoustic emissions, stress signals	Estimate time before rupture or quake

IV. METHODOLOGY

Step 1: Data Collection

- Collect seismic waveform data from global/regional networks (e.g., IRIS, USGS).
- Gather metadata: timestamp, epicenter coordinates, depth, and magnitude.

Step 2: Preprocessing

- Filtering noise, normalizing signals
- Converting time-series data into spectrograms for CNN input
- Feature engineering (e.g., frequency, amplitude, waveform shape)

Step 3: Model Selection and Training

- **Detection**: CNNs or RNNs trained on labeled seismic events
- **Classification**: Random Forest for foreshock vs aftershock differentiation
- **Regression**: Gradient Boosting for magnitude estimation
- **Forecasting**: LSTM for time-to-event prediction

Step 4: Evaluation

- Use metrics like accuracy, precision, recall, and F1-score
- ROC-AUC for binary classification of seismic events

Step 5: Deployment

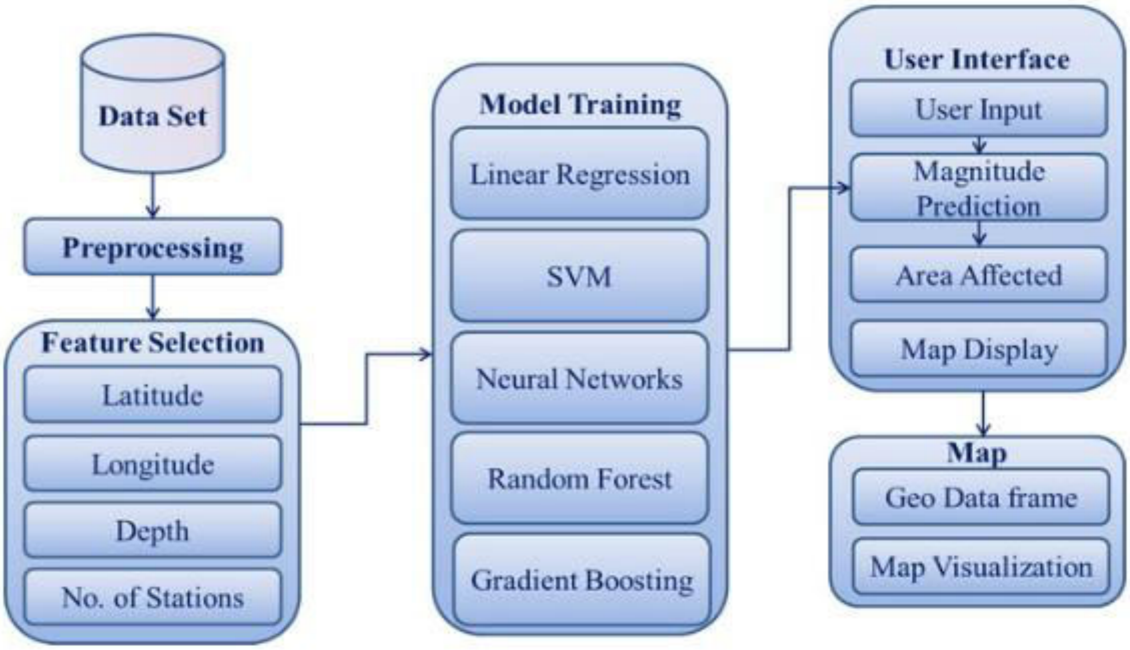
- Real-time integration into earthquake early warning systems (EEWS)
- Use cloud-based dashboards for live alerts and visualization

| ISSN: 2349-6037 | www.ijmserh.com ||Impact Factor: 9.274||Quarterly, Peer Reviewed & Refereed Journal|

|| Volume 13, Issue 2, April - June 2025 ||

DOI: 10.15662/IJMSERH.2025.1302016

FIGURE: MACHINE LEARNING PIPELINE FOR EARTHQUAKE PREDICTION



VI. CONCLUSION

Machine learning is rapidly transforming the field of seismology, offering tools that can detect, classify, and forecast seismic events with unprecedented accuracy. While predicting the exact time and location of large earthquakes remains complex, ML enhances our ability to interpret seismic patterns, assess risk, and issue timely warnings. Future work should focus on hybrid models combining physical and data-driven approaches, increased access to open seismic datasets, and the integration of AI into global early warning systems.

REFERENCES

1. Kong, Q., Trugman, D. T., et al. (2019). Machine Learning in Seismology: Turning Data into Insights. Seismological Research Letters, 90(1), 3-14.
2. Mousavi, S. M., et al. (2020). Earthquake Transformer – An attentive deep-learning model for simultaneous earthquake detection and phase picking. Nature Communications, 11, 3952.
3. Perol, T., Gharbi, M., & Denolle, M. (2018). Convolutional neural network for earthquake detection and location. Science Advances, 4(2), e1700578.
4. Chundru, S., & Mudunuri, L. N. R. (2025). Developing Sustainable Data Retention Policies: A Machine Learning Approach to Intelligent Data Lifecycle Management. In Driving Business Success Through Eco-Friendly Strategies (pp. 93-114). IGI Global Scientific Publishing.
5. Rouet-Leduc, B., et al. (2017). Machine learning predicts laboratory earthquakes. Geophysical Research Letters, 44(18), 9276-9282.
6. Yoon, C. E., et al. (2015). Earthquake detection through computationally efficient similarity search. Science Advances, 1(11), e1501057.
7. Mendhe, Vikas, Aamol Gote, and Roshan Mahant. "Comparative Analysis of Machine Learning Models for Credit Scoring: A Case Study on the South German Credit Dataset."
8. USGS Earthquake Catalog. https://earthquake.usgs.gov/
9. Madhusudan Sharma, Vadigicherla (2024). Enhancing Supply Chain Resilience through Emerging Technologies: A Holistic Approach to Digital Transformation. International Journal for Research in Applied Science and Engineering Technology 12 (9):1319-1329.