Earthquake Depth and Magnitude Prediction using Dense Neural Networks

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***Abstract*—This study investigates the use of deep learning models for predicting earthquake magnitude and depth using the USGS Earthquake Database comprising 23,595 global seismic events. We developed three Dense Neural Networks (DNNs) and one Long Short-Term Memory (LSTM) model. The best-performing DNN achieved a Mean Absolute Error (MAE) of 0.3092 for magnitude prediction, while the LSTM model outperformed all others in depth prediction with an MAE of 55.19 km. Compared to a baseline mean-value predictor, these models reduced error by over 25%. Results demonstrate the effectiveness of neural networks in modeling complex seismic patterns, offering promising tools for real-time seismic risk assessment and early warning systems.**

***Index Terms*—Earthquake prediction, deep learning, dense neural networks, LSTM, USGS, magnitude estimation, depth prediction, geophysical modeling.**

I. Introduction

Earthquakes are highly destructive natural disasters, causing over $40 billion in global losses annually due to infrastructure damage and economic impact (National Earthquake Information Center, 2021). Accurate estimation of earthquake parameters, particularly magnitude and depth, is crucial for real-time alerts, damage assessment, and evacuation planning. Early detection can save lives, as seen in significant events like the 2004 Indian Ocean tsunami and the 2011 Tōhoku earthquake, which caused $235 billion in losses (Fukushima, 2011).

Traditional seismological models rely on physical simulations and signal processing techniques, but these methods are computationally intensive and struggle to capture complex, nonlinear relationships in large-scale seismic data. As global seismic data grows, the limitations of these models become evident.

Deep learning methods, particularly Dense Neural Networks (DNNs) and Long Short-Term Memory (LSTM) networks, offer a more efficient approach to predicting earthquake parameters. These models excel at identifying patterns in high-dimensional data without needing explicit feature engineering. This paper leverages the USGS Earthquake Database to train deep learning models for earthquake magnitude and depth prediction, offering a scalable solution to traditional approaches.

II. Related Work

Recent advancements in machine learning have significantly improved earthquake prediction models. Traditional seismological methods rely on physical simulations but often struggle with large-scale datasets and complex nonlinear patterns. To address this, machine learning models, particularly deep learning, have shown promise in capturing these complexities.

Jain et al. (2021) demonstrated the use of machine learning techniques like Support Vector Machines and Random Forest to predict earthquake magnitudes, showing better performance than traditional methods. Wang et al. (2023) explored artificial neural networks (ANNs), finding that deep learning models, especially DNNs, outperformed traditional models in predicting both magnitude and depth.

Sadhukhan et al. (2023) proposed hybrid models combining DNNs with Long Short-Term Memory (LSTM) networks, which capture long-term dependencies in seismic data. Joshi et al. (2024) further improved predictions by integrating CNNs with LSTMs, excelling in accuracy and generalizability.

Patil et al. (2023) incorporated real-time seismic data into deep learning frameworks, enhancing early warning systems. These works collectively highlight the growing potential of deep learning in earthquake prediction, providing the foundation for our approach using Dense Neural Networks (DNNs) and LSTMs on the USGS Earthquake Database.

III. Dataset Description

The dataset used in this study is sourced from the **USGS Earthquake Database** on Kaggle, which contains global seismic event records with the following details:

- **Total Records**: 23,595 earthquake events
- **Total Features**: 22 columns
- **Data Range**: Early 20th century to present
- **File Format**: CSV

A. Key Features

For more information, visit the USGS Earthquake Database on Kaggle

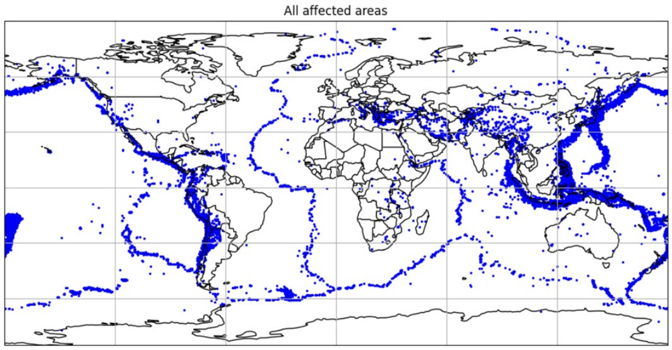

Fig. 1. Dataset Description on Map

Feature	Description
time	Timestamp of the earthquake event
latitude	Latitude of the earthquake epicenter
longitude	Longitude of the earthquake epicenter
depth	Depth of the earthquake (km)
mag	Magnitude of the earthquake
location	Location description
region	Region or country of occurrence

TABLE I
KEY FEATURES OF THE EARTHQUAKE DATASET

IV. DATA PREPROCESSING

The raw dataset undergoes several preprocessing steps to prepare it for use in training predictive models. These steps ensure the data is clean, relevant, and formatted properly for machine learning algorithms.

A. Handling Missing Values

The dataset contains some missing values, particularly in columns such as `location` and `region`. These missing values are handled in the following manner:

- **Numerical features** such as `depth` and `mag` have their missing values imputed with the mean or median of the respective columns, depending on the feature's distribution.
- **Categorical features** such as `location` and `region` are filled using the mode or by replacing missing values with a placeholder value (e.g., "Unknown").

B. Feature Engineering

New features are created to improve the predictive power of the models:

- **Date Features**: Extracted day, month, and year from the `time` column to help the model identify trends based on time.
- **Magnitude Classes**: The `mag` feature is converted into categorical classes such as "Minor", "Light", "Moderate", "Strong", and "Great" based on predefined magnitude ranges.
- **Distance from the Epicenter**: The dataset is enriched with additional features such as the distance from the earthquake epicenter to major fault lines or cities.

C. Normalization and Scaling

To ensure the proper performance of the machine learning models, certain numerical features are normalized or scaled:

- `depth` and `mag` are scaled using standardization (zero mean, unit variance) to handle the differences in their magnitudes.
- `latitude` and `longitude` are scaled between 0 and 1 to reduce their impact on the model, especially when dealing with large geographic datasets.

D. Encoding Categorical Features

Categorical features such as `region` and `location` are encoded using:

- **One-hot encoding**: For non-ordinal categorical variables, each unique value is converted into a separate binary feature (e.g., "Asia", "America", etc., become individual columns).
- **Label encoding**: For ordinal variables such as `magnitude class`, numerical values (0, 1, 2, etc.) are assigned to each category.

E. Data Splitting

The dataset is split into training and testing sets using a 70:30 ratio. 70% of the data is used for training the models, and the remaining 30% is reserved for evaluating model performance. Additionally, 10% of the training data is set aside for cross-validation.

The preprocessed data is then ready for use in training the predictive models, ensuring the dataset is free from inconsistencies and well-structured for machine learning applications.

V. MODEL DEVELOPMENT

In this study, four models were employed to predict earthquake magnitude and depth: three Dense Neural Networks (DNNs) and one Long Short-Term Memory (LSTM) network. Each model was trained on the preprocessed dataset and aimed to estimate two output variables: magnitude and depth.

A. Dense Neural Network (DNN) - Model 1

The first DNN model was constructed with two hidden layers, each consisting of 16 neurons. The activation function used in these layers was ReLU, which is effective in preventing the vanishing gradient problem. The output layer utilized a softmax activation function to predict both magnitude and depth simultaneously. Hyperparameter tuning was performed using GridSearchCV to optimize various parameters, ensuring the best performance for this model.

B. Dense Neural Network (DNN) - Model 2

The second DNN model had a similar architecture to Model 1, but with significant improvements. It featured 64 neurons per layer, increased complexity to capture more intricate patterns, and incorporated Dropout regularization (0.2) to prevent overfitting. The Adam optimizer was used with a learning rate of 0.001 to adjust the weights during training.

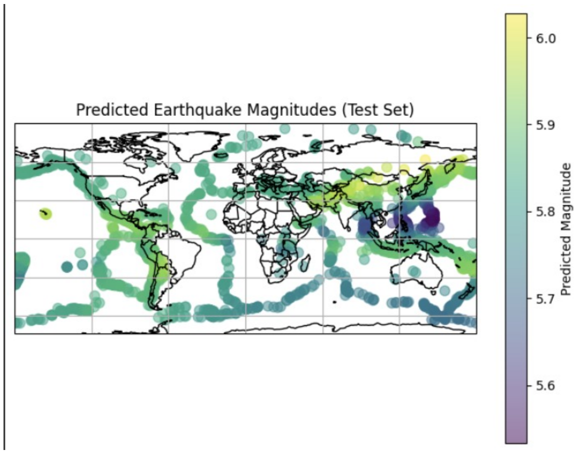

Fig. 2. Model 1 - Magnitude

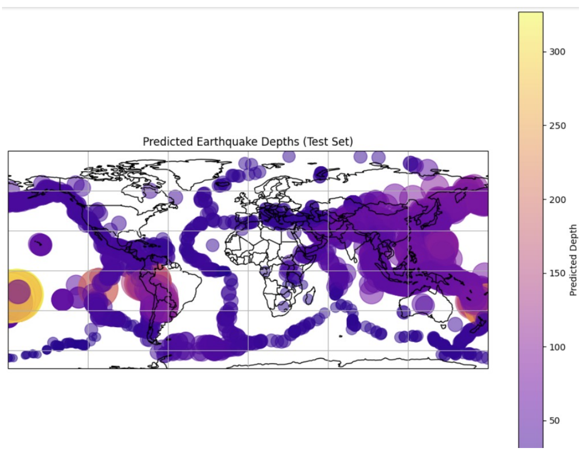

Fig. 3. Model 1 - Depth

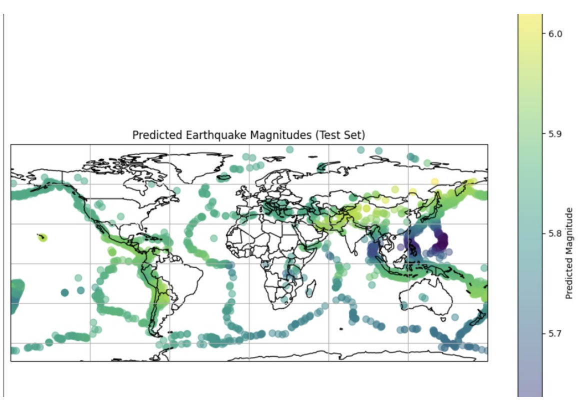

Fig. 4. Model 2 - Magnitude

C. Dense Neural Network (DNN) - Model 3

Model 3 was also a DNN, but with a focus on preventing overfitting through early stopping. Similar to Model 2, it had 64 neurons per layer and Dropout layers, but it included an early stopping callback to halt training when the validation performance stopped improving. This mechanism helped retain the best-performing model weights and avoid unnecessary training.

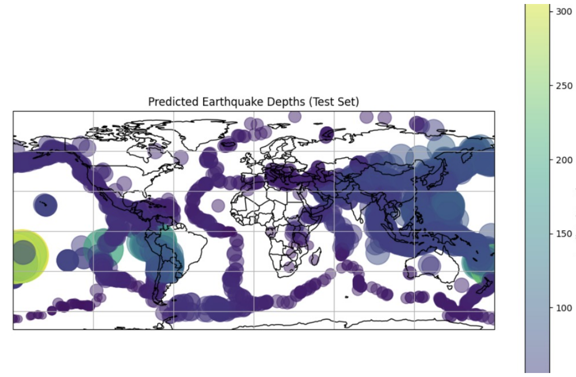

Fig. 5. Model 2 - Depth

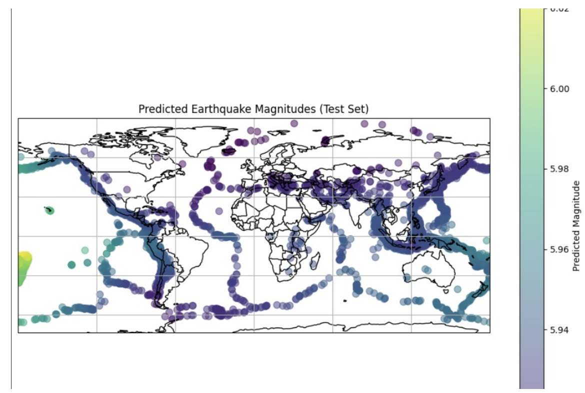

Fig. 6. Model 3 - Magnitude

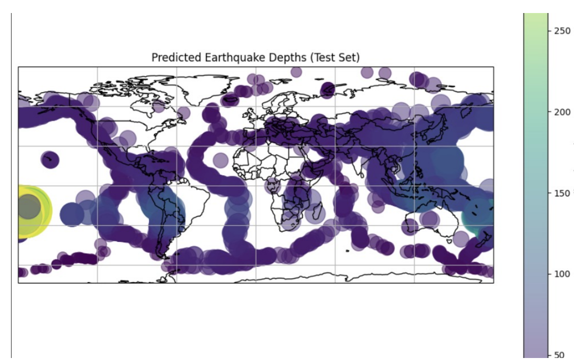

Fig. 7. Model 3 - Depth

D. Long Short-Term Memory (LSTM) Model

For the LSTM model, the input data was reshaped into sequences to match the model's requirements, taking advantage of the LSTM's ability to capture temporal dependencies. The model consisted of two LSTM layers followed by Dropout layers for regularization. The output layer used a linear activation function to predict both magnitude and depth, suitable for regression tasks.

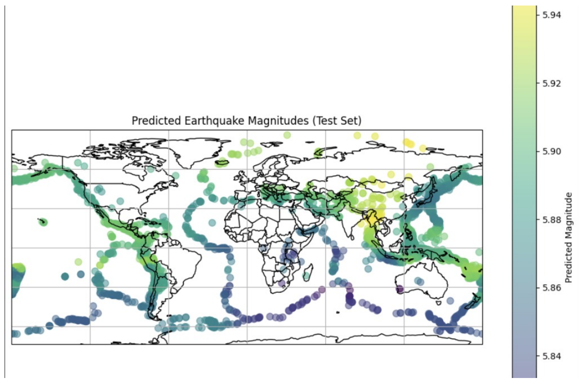

Fig. 8. LSTM - Magnitude

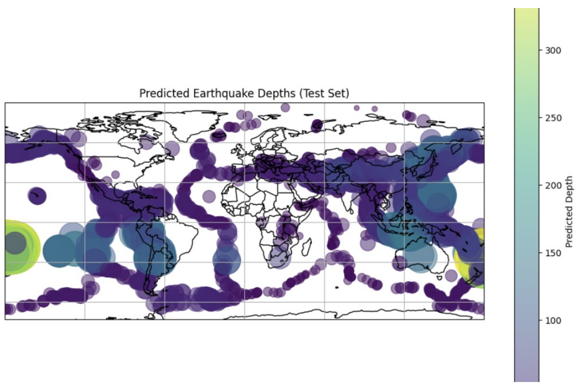

Fig. 9. LSTM - Depth

VI. Model Training

Each of the aforementioned models was trained on the preprocessed dataset using the Adam optimizer. Training was conducted over 100 epochs with a batch size of 32, and the models were evaluated based on two key metrics: Mean Absolute Error (MAE) and Mean Squared Error (MSE). These metrics were used to assess the models' performance in predicting earthquake magnitude and depth.

VII. Experimental Setup

- Train/test split: 80/20
- Batch size: 32
- Epochs: 100 with EarlyStopping (patience = 10)
- Validation data used for monitoring overfitting

Hardware: 3050 RTS GPU on Google Colab

VIII. Results and Evaluation

To assess model performance, we benchmarked four neural network architectures against a simple statistical baseline model that predicts the mean magnitude and depth values from the training set. The performance metrics used were Mean Absolute Error (MAE) and Mean Squared Error (MSE) for both magnitude and depth predictions.

A. Baseline Model (Mean Predictor)

This baseline serves as a reference for evaluating the effectiveness of the neural networks.

Metric	Magnitude	Depth
MAE	0.3162	70.5687
MSE	0.1859	15138.5096

TABLE II
Baseline Model Performance Metrics

B. Neural Network Performance Summary

Model	MAE (Mag.)	MSE (Mag.)
Dense NN - Model 1	0.3385	0.1924
Dense NN - Model 2	0.3285	0.2020
Dense NN - Model 3	0.3092	0.1874
LSTM Model	0.3196	0.1864

TABLE III
Magnitude Prediction Performance Metrics

Model	MAE (Depth)	MSE (Depth)
Dense NN - Model 1	57.8882	11165.5490
Dense NN - Model 2	65.1040	13052.0351
Dense NN - Model 3	59.1810	11301.7834
LSTM Model	55.1929	10175.4363

TABLE IV
Depth Prediction Performance Metrics

C. Interpretation

- All four models outperform the baseline in depth prediction, significantly reducing both MAE and MSE, particularly the LSTM model which achieves the best results with a 21.8% lower MAE and 32.8% lower MSE compared to the baseline.
- For magnitude prediction, the improvement over the baseline is more modest. Model 3 (Dense NN with Early Stopping) yielded the lowest MAE of 0.3092 and the LSTM had the lowest MSE of 0.1864, slightly better than the baseline.
- These results indicate that while predicting magnitude is more challenging due to its lower variance, deep learning models still capture meaningful patterns beyond the statistical average.

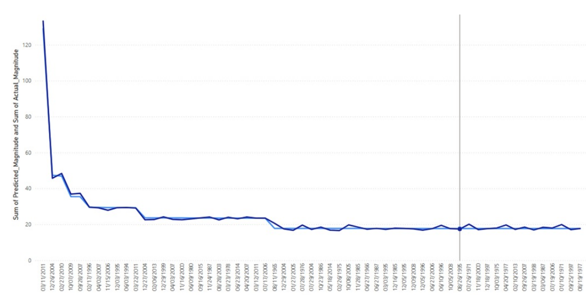

Fig. 10. Line Graph Comparison - Magnitude

IX. Real-World Applications

The ability to accurately predict earthquake magnitude and depth has profound implications for disaster preparedness,

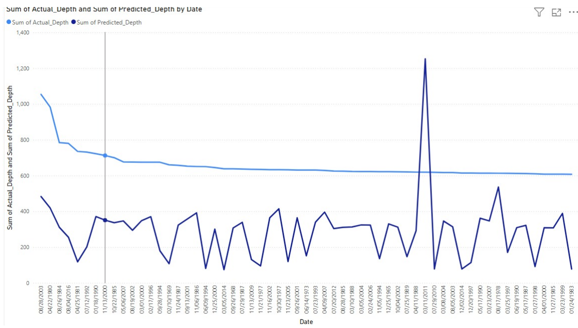

Fig. 11. Line Graph Comparison - Depth

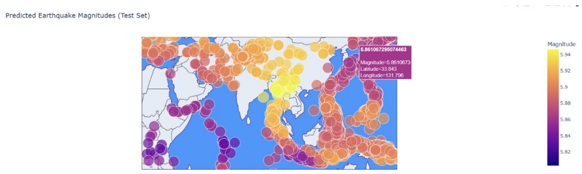

Fig. 12. Final Predictions - Map

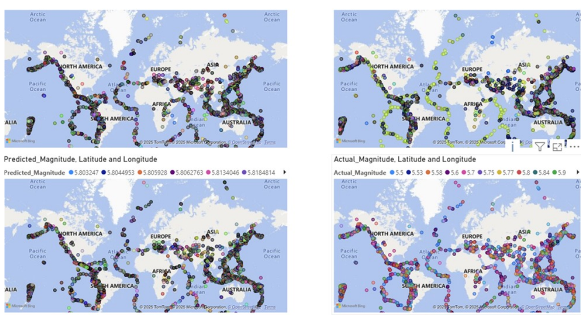

Fig. 13. Dasboard

infrastructure resilience, and public safety. The methods explored in this study using deep learning can significantly enhance the early-warning systems, providing timely alerts for high-risk regions and enabling proactive responses to mitigate damage.

- Earthquake Early Warning Systems
- Seismic Hazard Assessment
- Infrastructure Resilience
- Insurance and Risk Management
- Real-time Monitoring

X. Conclusion and Future Work

This research demonstrates the potential of deep learning models, specifically Dense Neural Networks and LSTM, for earthquake prediction. While DNN models were effective for predicting magnitude, the LSTM model provided superior results for depth prediction. Future work could explore hybrid models or integrate additional features such as time-series data to further improve prediction accuracy.

Future work includes:

- Incorporating tectonic plate boundaries and fault line proximity as features.
- Using attention mechanisms for better temporal learning.
- Deployment of lightweight models on edge devices for low-latency predictions.
- Investigating the use of transfer learning to leverage pre-trained models on seismic data for better generalization across different regions.

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