# Forecast of Earthquake Magnitude for North-West (NW) Indian Region Using Machine Learning Techniques

Aditya Gupta[1], Babita Sharma[2] and Prasanta Chingtham[3]

[1] University of Illinois, Urbana-Champaign IL 61801, USA
[2] National Centre for Seismology, New Delhi, India
[3] National Centre for Seismology, New Delhi, India

**Abstract.** Earthquakes have posed significant hazards to human lives and infrastructure for as far back as can be recalled. This paper presents a Machine Learning (ML) based approach for earthquake magnitude forecasting spatially using the earthquake clustering in five selected zones of NW Indian region. Previous research efforts have primarily relied on empirical relationships and statistical models, which often struggled to capture the complex dynamics associated with earthquakes. However, with the emergence of ML techniques, the ability to analyze large datasets and uncover hidden patterns has significantly improved. We propose ML models to forecast earthquake magnitudes in the five identified earthquake zones present in NW Indian region using Random Forest and Support Vector techniques. For each earthquake, we utilize the latitude, longitude, depth, and zone information for model prediction. Our models obtain a cumulative weighted average (Root Mean Square Error) RMSE of 0.407 for the Random Forest Regressors and a cumulative weighted average RMSE of 0.420 for the Support Vector Regressors. Our results improve over previous results in the field due an emphasis on zone-based models. This study demonstrates the potential of machine learning techniques in earthquake magnitude forecasting which may be utilized for proactive measures in mitigating the impact of seismic events.

**Keywords:** Earthquake magnitude forecasting; Earthquake Magnitude Prediction; Machine Learning; Earthquake clustering; Random Forest Regressors; Support Vector Regressors; Seismic event mitigation.

*Non peer-reviewed preprint submitted to EarthArxiv on August 23, 2023*

## 1 Introduction

Earthquakes are amongst the significant hazards to human lives and infrastructure. They have resulted in widespread destruction, causing buildings to collapse, earthquake induced landslides, and tsunamis in coastal areas (Cardona, 2019). The violent shaking during an earthquake can lead to injuries, loss of life, and long-term psychological trauma for survivors, making preparedness, early warning systems, and robust construction practices essential in earthquake-prone regions. Therefore, forecast of earthquake magnitudes plays a pivotal role in mitigating the potential devastation caused by seismic events. Over the years, extensive research has been conducted to develop methodologies and models for earthquake forecasting (Yadav et al, 2011; Chingtham et al, 2014; Chingtham et al, 2016; Chingtham et al, 2017; Chingtham and Sharma, 2022), aiming to provide early warning systems and inform effective disaster management strategies.

Early attempts to predict earthquakes primarily relied on empirical relationships and statistical models, which often struggled to capture the complex and nonlinear dynamics associated with seismic events (Jackson 1996, Rikitake 1968, Mogi 1985). However, with the advent of Machine Learning techniques, researchers have gained access to powerful tools capable of analyzing vast amounts of data and identifying intricate patterns that were previously unattainable. Machine Learning algorithms excel at discovering hidden relationships between input variables and target outputs, thus leading to their increased use in other fields i.e finance and game theory (Gupta et. al 2023). This makes these algorithms well-suited for earthquake forecasting as well, which is influenced by numerous interconnected factors such as fault characteristics, historical seismicity, and related parameters (Narayanakumar et. al., 2016).

The study of earthquake forecasting dates back several decades, with early attempts focused on empirical approaches and statistical models. These methods relied on historical seismic data, attempting to identify patterns and correlations between precursor events and subsequent earthquake magnitudes, as seen in Gusiakov (2011). While these initial efforts provided valuable insights, they often lacked accuracy and robustness. In recent years, the emergence of machine learning techniques has revolutionized earthquake magnitude forecasting. Researchers have leveraged advanced algorithms such as artificial neural networks in Adeli et al. (2009) to analyze vast amounts of seismic data and extract meaningful patterns out of them. These methods have demonstrated improved predictive capabilities, surpassing traditional approaches in accuracy and reliability, as shown in Galkina and Grafeeva (2019).

A critical aspect of earthquake magnitude forecasting lies in the identification and selection of relevant features. Researchers have explored various techniques for feature extraction, ranging from basic statistical parameters to more complex wavelet transforms and time-frequency analyses, as seen in Zhou et al (2019). The challenge lies in balancing the complexity of feature extraction with the efficiency and effectiveness of the forecasting model. Seismic data is often plagued by noise, outliers, and missing values, which can adversely affect forecasting accuracy. To address this, researchers have focused on developing robust data preprocessing and cleaning techniques. These methods involve filtering, denoising, and imputation algorithms to enhance the quality and reliability of the input data as seen in Asim et al (2018).

Deep learning, a subfield of machine learning, has gained significant traction in earthquake magnitude forecasting. Recurrent neural networks (RNNs) and convolutional neural networks (CNNs) have shown promising results in analyzing temporal and spatial dependencies that exist within seismic data. Moreover, the integration of deep learning with transfer learning and ensemble methods has further improved forecasting performance as shown in Bao et al (2021). While significant progress has been made in earthquake magnitude forecasting, several challenges persist. The scarcity of labeled data, the inherent complexity of seismic processes, and the occurrence of rare, high-magnitude events pose obstacles to accurate forecasts. Additionally, the interpretability of deep learning models remains a concern. Future research should focus on developing hybrid models, incorporating physical principles and domain knowledge to enhance forecasting accuracy and reliability as highlighted in the survey by Galkina and Grafeeva (2019).

The utilization of machine learning techniques, advancements in deep learning, and the exploration of innovative feature extraction methods have significantly enhanced forecasting accuracy (Asim et. al 2017). However, several challenges and opportunities for improvement of such models remain unresolved. By addressing these challenges, further refining of forecasting models may be achieved. Consequently, researchers can provide critical insights to assist in disaster preparedness and risk management, ultimately contributing to the safety and well-being of communities affected by earthquakes.

This paper proposes a Machine Learning-based earthquake forecasting model, highlighting the importance of this task in enabling proactive measures and minimizing the impact of earthquakes on human lives and infrastructure. Specifically, we propose a model to forecast earthquakes in the NW Indian region based on key characteristics like the location, depth, and zone of occurrence of the Earthquake. NW Indian region is seismically very active due to the collision of Indian plate with that of the Eurasian plate (Ni and Barazangi, 1984). Major part of the seismicity is from the Hindukush region where the subduction of Indian plate takes place beneath the Eurasian plate (Billington et al, 1977). Also, the tectonic setup of the Himalayan region in form of several thrusts (Coward et al., 1987) makes the NW Indian region tectonically active. It is very important to study this area as large populations are residing in NW India which poses a threat from the devastating earthquakes time to time. Therefore, an attempt has been made to study the seismic hazard in form of the earthquake magnitude forecasting using the earthquake catalog of previous years.

## 2 Dataset Preparation

The original dataset consists of an earthquake catalog that occurred in the NW part of Indian subcontinent(Gupta et al., 2014, Mishra 2014). Each earthquake contains features such i.e time, depth, latitude, longitude and magnitude. These earthquakes are reported for the time in between 1975 and 2010. Earthquake datasets typically contain different magnitude scales, such as local magnitude (ML), body wave magnitude (mb), surface wave magnitude (MS), and moment magnitude (MW). Unfortunately, these scales have distinct magnitude distributions. To combat this, the earthquakes in the catalogue were transformed into a singular scale of magnitude. In the present study a homogenized earthquake dataset for moment magnitude (Mw) for the period 1975-2010 have been used (Chingtham et al. 2014; Yadav et al, 2011). All earthquakes in the dataset are located within the latitude boundaries of 25°N - 40°N and the longitude boundaries of 65°E - 85°E. Each earthquake is plotted based on its location in **Figure 1**. Additionally, by using the Maximum Curvature approach to fit the power law to the frequency magnitude distribution of the earthquakes in the dataset, the thoroughness of the magnitude completeness (MC) assessment for the complete dataset was ensured, as seen in **Figure 2**. As part of our analysis, we performed the construction of a correlation matrix to investigate the existing relationships among the different features present in the dataset. This correlation matrix allows us to quantify the degree of association between pairs of variables and gain insights into the interdependencies within the data.

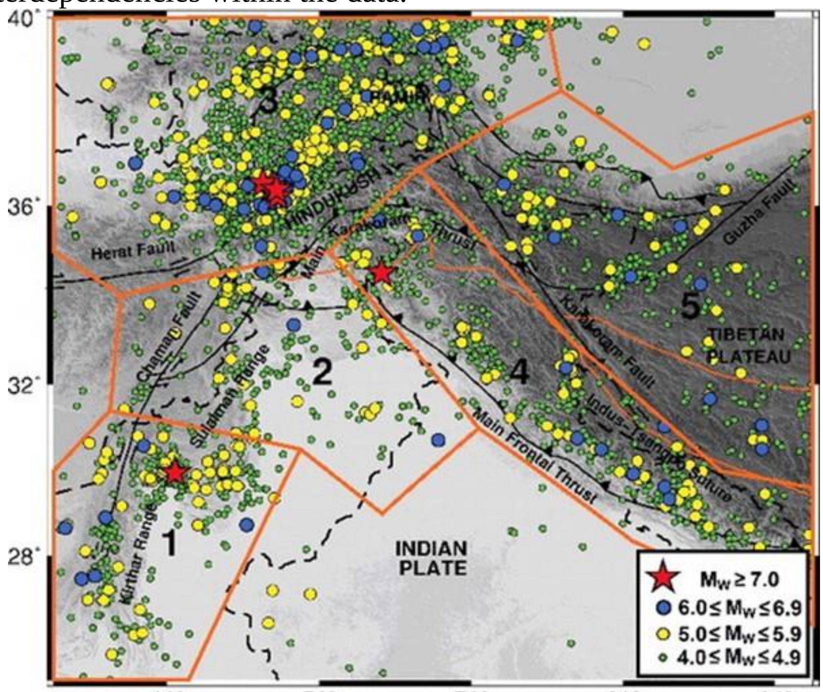



**Fig. 1:** Map to represent the study area along with the major tectonic features of the NW part of the Indian subcontinent. Five earthquake zones dividing the region as per occurrences of the seismic events are depicted (after Chingtham et al, 2017).

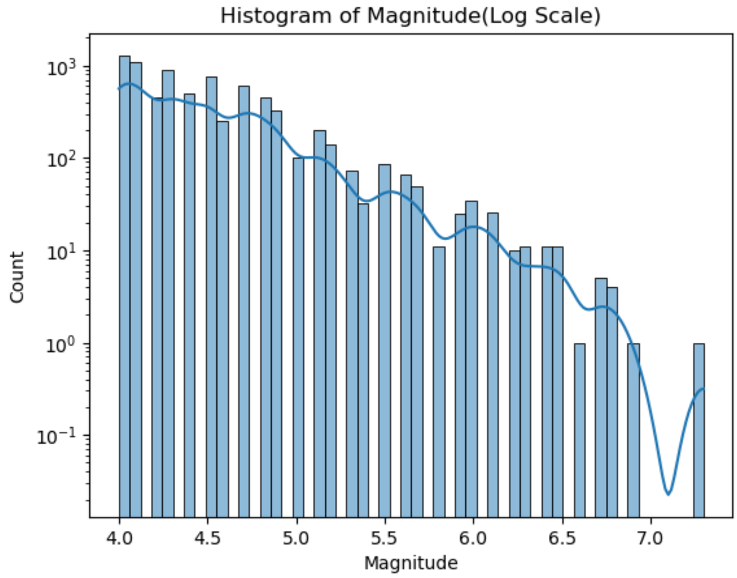



**Fig. 2:** Distribution of Magnitude in Dataset (Log Scale) and the Power Law

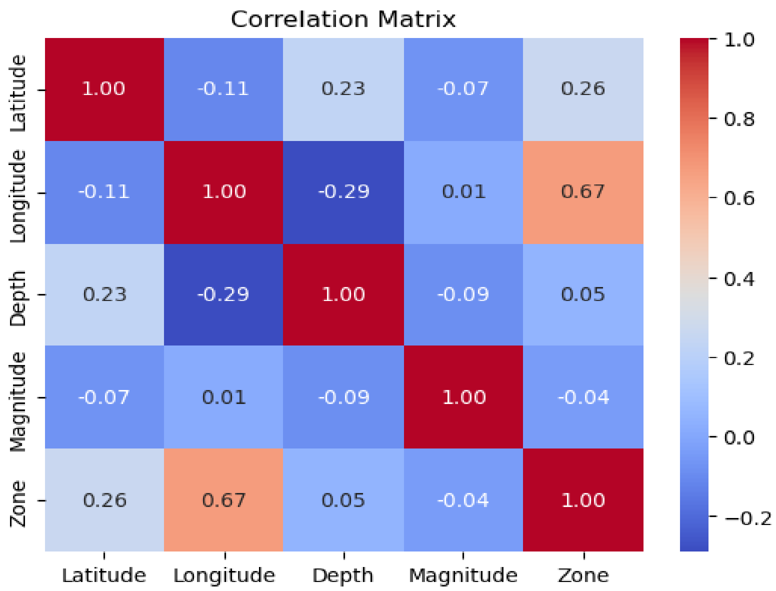



**Fig. 3:** Correlation Matrix of Prepared Earthquake Dataset Features

In particular, we found it intriguing that the depth variable exhibited correlations with both the magnitude and location parameters. The correlation between depth and magnitude indicates that there may be a relationship between the depth at which an earthquake occurs and the corresponding magnitude of the event. This finding suggests that the depth of seismic activity could potentially influence the intensity or strength of the earthquake (**Figure 3**). Furthermore, the correlation between depth and location parameters suggests that the geographical location of an earthquake may be linked to its depth. This implies that certain regions or areas may experience earthquakes at specific depths more frequently than others as shown in **Figure 3**. By uncovering these correlations, we gain a deeper understanding of the relationships that exist within the dataset, providing valuable insights for further analysis and interpretation of the seismic activity under investigation.

## 3 Methodology

The earthquake dataset prepared here is divided into 5 different datasets based on the seismic zones present in the NW part of Indian subcontinent (**Figure 1**). The number of earthquakes in each dataset can be seen in **Table 1**.

**Table 1.** Earthquake Distribution Zone Wise

| Seismic Zone | Number of Earthquakes |
|---|---|
| Zone 1 | 525 Earthquakes |
| Zone 2 | 645 Earthquakes |
| Zone 3 | 5283 Earthquakes |
| Zone 4 | 512 Earthquakes |
| Zone 5 | 543 Earthquakes |

### 3.1 Random Forest Regressor

The Random Forest Regressor is a Machine Learning (ML) algorithm useful for predicting continuous values i.e earthquake magnitude. It operates by creating an ensemble of decision trees, where each tree is trained on a different subset of the data (Segal et al 2004). Additionally, at each split in the decision tree, only a random subset of features is considered. These two sources of randomness inject diversity into the model, enabling it to capture a wide range of patterns and relationships within the data. Given a random forest model with $K$ decision trees, the prediction $y$ for a given input sample $x$ can be computed as the aggregation of the predictions from each individual tree, typically using voting or averaging. For regression tasks like the forecasting of earthquake magnitude, the individual tree predictions are averaged as shown in equation $I$.

$$y = \frac{1}{K}\sum_{k=1}^{K} y_k \tag{1}$$

Above equation is the Random Forest Regressor Equation where $y_k$ represents the prediction of the $k$-th decision tree, $K$ represents the number of decision trees in a random forest model. By introducing randomness and diversity, the Random Forest Regressor mitigates the risk of overfitting, a phenomenon where a model becomes too finetuned to the data that it was trained on, but fails to do so on new examples it has not seen before. The combination of multiple decision trees helps to smooth out individual biases and noise, resulting in more reliable forecasts. Additionally, the algorithm provides a measure of feature importance based on how much the trees rely on each feature, offering insights into which factors play a significant role in determining earthquake magnitudes. For each selected seismic zone, a separate Random Forest Regressor is constructed. During the training phase, each decision tree in the model learns from a random subset of features and samples from the corresponding zone's dataset. This enables the model to capture the zone-specific patterns and relationships that affect earthquake magnitudes. For each model, the input features given to the model are described in **Table 2**.

These parameters are used by the random forest regressor to predict the magnitude of an earthquake. For each zonal model, an 80-20 split is utilized, where 80% of the dataset is allocated for training and fitting the random forest regressor, while the remaining 20% is set aside for validation. This partitioning allows for an effective evaluation of the random forest's performance on unseen data. During the training phase, the zonal random forest models iteratively learn from the training dataset, leveraging an ensemble of decision trees to capture the complex relationships between features and earthquake magnitudes. The hyperparameters of the random forest, such as the number of trees in the ensemble and the maximum depth of the trees, are fine-tuned during the training process using techniques like grid search. This optimization process aims to maximize the model's performance and generalization ability.

**Table 2.** Random Forest Model Features

| Parameter Name | Definition | Parameter Type |
|---|---|---|
| Zone | Zone in which the earthquake occurred, as defined in section 3. | Discrete |
| Latitude | Latitude at which the earthquake was detected | Continuous |
| Longitude | Longitude at which the earthquake was detected | Continuous |
| Depth | Depth at which the earthquake was detected | Continuous |

Following the training phase, the validation dataset is employed to assess the predictive performance of the trained zonal random forest regressor. By evaluating the model's forecasts on this separate dataset, we are able to estimate how well the model generalizes to new, unseen earthquake data. This validation process helps to identify any potential issues related to overfitting or underfitting, allowing for adjustments to be made to improve the model's accuracy and reliability. By utilizing an 80-20 split for training and validation, the zonal random forest regressor models benefit from being trained on a substantial portion of the dataset. This allows them to effectively capture the complex relationships between features and earthquake magnitudes within each zone. The validation process ensures that the trained models can accurately predict earthquake magnitudes in scenarios where they encounter previously unseen data.

### 3.2 Hyperparameter Optimization of Random Forest Regressors

Hyperparameter tuning holds immense importance in optimizing the performance of the earthquake forecasting models proposed. The accurate forecasting of earthquake magnitudes is a complex task, and hyperparameter tuning is used to increase the accuracy of each model. We tune the following parameters for each model:

- 'n_estimators': The number of decision trees.
- ‘max_depth’: The maximum depth allowed for each decision tree.
- 'min_samples_leaf': The minimum number of samples required to be present in a leaf node.
- 'min_samples_split': The minimum number of samples required to split an internal node.

For each hyperparameter, the following values are tried:

- 'n_estimators': [10, 20, 40, 50, 75, 100, 125, 150, 200, 225, 250]
- ‘max_depth’: [None, 5, 10, 15]
- 'min_samples_split': [5, 10, 15]
- 'min_samples_leaf': [1, 2, 4, 8]

### 3.3 Support Vector Regressors

Support Vector Regression (SVR) is a ML model that has recently gained significant popularity in the field of regression analysis. It is an extension of Support Vector Machines (SVM) and has proven to be highly effective in solving complex regression problems. Support Vector Regressor provides a robust and flexible framework for predicting continuous target variables i.e the magnitude of an earthquake. The foundation of Support Vector Regression lies in the concept of margin maximization. It aims to find an optimal hyperplane that separates the predicted values from the actual target values while allowing a certain degree of tolerance for errors. The Support Vector Regressor differs from conventional regression methods by focusing on capturing the data points that lie within a specified margin around the hyperplane, known as support vectors. By utilizing these support vectors, a Support Vector Regressor can effectively model complex non-linear relationships between features and the target variable. To handle non-linear regression tasks, the Support Vector Regressor employs the kernel trick, which allows the transformation of the original feature space into a higher-dimensional space. This enables the model to capture intricate patterns and dependencies that may not be apparent in the original feature representation. The choice of kernel function, such as linear, polynomial, RBF, or sigmoid, plays a crucial role in determining the model's ability to capture different types of relationships. The equation for SVR can be given as follow:

$$f(x) = \langle w, x \rangle + b \tag{2}$$

Above equation shows the SVR model given a training dataset with $N$ samples, where each sample has $D$ features where $w$ represents the weight vector, $x$ denotes the input feature vector, and $b$ is the bias term.

SVR optimizes a cost function that consists of an epsilon-insensitive loss and a regularization term, as shown in equation 3.

$$L\big(y, f(x)\big) = \max(0, |y - f(x)| - \epsilon) \tag{3}$$

In Equation 3, the first term is the regularization term which controls the model complexity, and the second term is the sum of the loss values over all training samples. The parameter $C$ is a hyperparameter that determines the trade-off between minimizing the error and controlling the complexity of the model. Equation 4 shows the prediction equation of the SVR model, as used in our methodology.

$$f(x) = \sum_{i=1}^{N} (\alpha_i - \alpha_i^*) \langle x_i, x \rangle + b \tag{4}$$

Here sample $x$ is obtained using the learned weight vector $w$, bias term $b$, and the inner product of the new sample with the training samples as shown. $\alpha_i$ and $\alpha_i^*$ are the Lagrange multipliers obtained through solving the dual form of the optimization problem. The Earthquake dataset is partitioned into five distinct datasets, corresponding to the proposed zones outlined by Chingtham et al (2017). For each zone, a Support Vector Regression (the Support Vector Regressor) model is constructed. Throughout the training phase, each Support Vector Regressor model learns from a specific subset of features and samples derived from the respective zone's dataset. By adopting this approach, the model can effectively capture the unique patterns and relationships specific to each zone, which directly impact earthquake magnitudes. For each model, the input features given to the model are described in **Table 2**. These parameters are used by the Support Vector Regressor to predict the magnitude of an earthquake.

For each zonal model, 80-20 split is used, where 80% of the earthquake data is utilized to train and fit the model, while the remaining 20% is used to validate the random forest regressor. By utilizing an 80-20 split for training and validation, the zonal Support Vector Regressor models are trained on a significant portion of the dataset, enabling them to capture the complex relationships between features and earthquake magnitudes. The validation process helps evaluate the models' generalization abilities, ensuring that the trained models can accurately predict the magnitudes of earthquakes in unseen data scenarios. Once the zonal models are constructed using Support Vector Regression (SVR), specific parameters are utilized to enable the forecasting of earthquake magnitudes. These parameters, such as the regularization parameter (C), the kernel type, and the kernel-specific hyperparameters (e.g., gamma for the Radial Basis Function kernel), play a crucial role in determining the SVR's performance and its ability to capture the underlying patterns in the data.

During the training phase, the zonal SVR models iteratively learn from the training dataset, adjusting their internal parameters to minimize the forecasting errors and optimize the fit to the training data. Following the training phase, the validation dataset is used to evaluate the performance and predictions of the trained zonal SVR model. By evaluating the model's forecasts on this separate dataset, we are able to estimate how well the model generalizes to unseen earthquake data. This validation process helps to identify any overfitting or underfitting issues, enabling adjustments to be made to improve the model's accuracy and reliability.

## 3.4 Hyperparameter Optimization of Support Vector Regressors

Hyperparameter tuning holds immense importance in optimizing the performance of the earthquake forecasting models proposed. The model's hyperparameters, such as the kernel type and its associated hyperparameters, are fine-tuned using the technique of grid search to optimize the model's performance and generalization ability. The accurate forecasting of earthquake magnitudes is a complex task, and hyperparameter tuning is used to increase the accuracy of each model. We tune the following parameters for each model:

- ‘C’: The C hyperparameter controls the trade-off between achieving a small margin and allowing more errors. It determines the penalty for misclassifying data points.
- ‘kernel’: The kernel hyperparameter specifies the type of kernel function to be used in Support Vector Regressor. Different kernel functions can be chosen based on the characteristics of the data and the desired modeling flexibility. Each kernel function provides a different way of mapping the data to a higher-dimensional feature space.
- ‘gamma’: Gamma is a hyperparameter specific to certain kernel functions (RBF and polynomial). It determines the influence of individual training samples on the overall decision boundary.

For each hyperparameter, the following values are tried:

- 'C': [0.1, 1, 10]
- 'kernel': ['linear', 'rbf']
- 'gamma': [0.1, 1, 'scale']

These hyperparameters control different aspects of the Support Vector Regressor model and can significantly impact its performance. Proper tuning of these hyperparameters is crucial to achieving optimal results and generalization ability for earthquake magnitude forecasting. The proposed methodology and model are summarized in **Figure 4** in form of a flowchart.

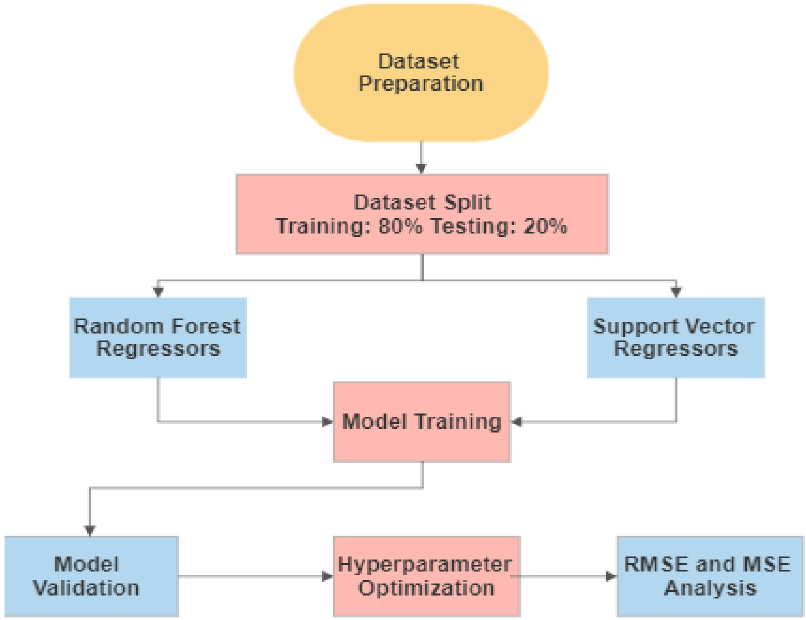
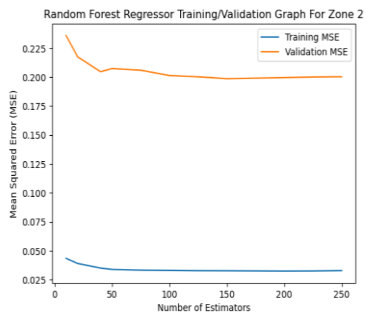
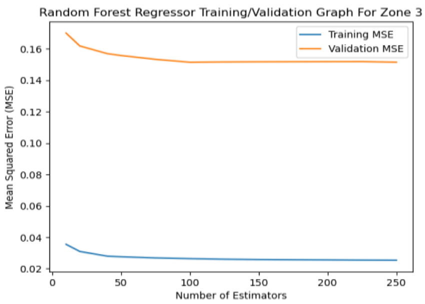



**Fig. 4.** Flowchart to demonstrate the proposed Methodology and Model used in the present study.

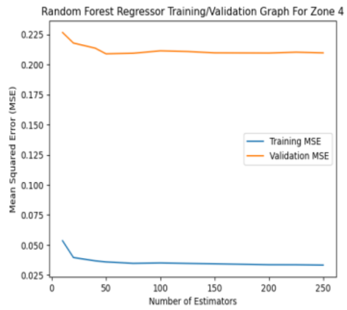
# 4 Results and Discussion

a) 


b) 



c)



d)

e)

**Fig. 5 (a-e).** Training/Validation Graphs of Random Forest Models

The training and validation graphs for the 5 zonal Random Forest Regressor models are shown in **Figure 5**. Each model was tuned on its hyperparameters for optimal accuracy. The best hyperparameters for each of the 5 zones for the Random Forest Regressor model are given in **Table 3**.

**Table 3.** Optimal Hyperparameters for Random Forest Regressor Models

| Earthquake Zone | 'n_estimators' | 'min_samples_leaf' | 'min_samples_split' | 'max_depth' |
|---|---|---|---|---|
| Zone 1 | 20 | 8 | 5 | 5 |
| Zone 2 | 100 | 8 | 5 | 5 |
| Zone 3 | 250 | 1 | 5 | 10 |
| Zone 4 | 225 | 2 | 15 | 5 |
| Zone 5 | 50 | 8 | 5 | 5 |

Based on the best hyperparameters in each zone, we are able to determine the Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) of each random forest zonal model, providing a sense of the accuracy of the model, as can be seen in **Table 4** and **Figure 6**. The results were statistically significant. The model has a cumulative - weighted average across all zones - RMSE of 0.407. These results suggest a significant improvement over the results (Jain et al, 2021).

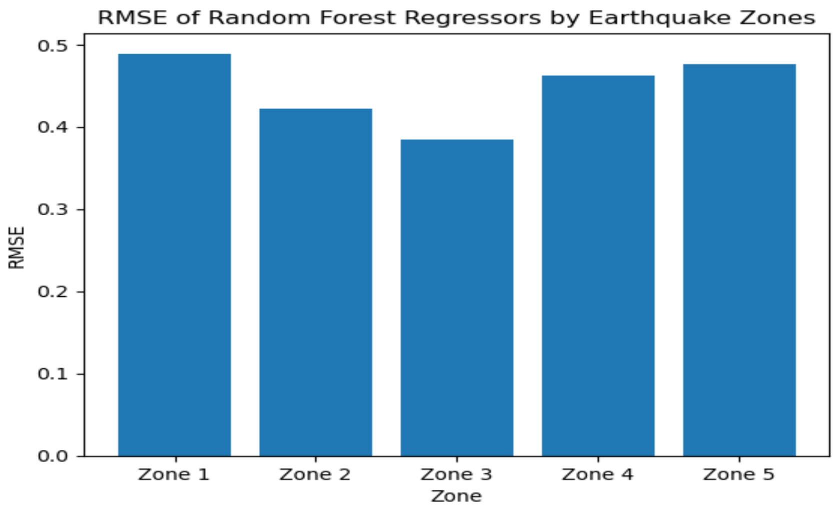



**Fig. 6:** RMSE of Random Forest Regressors by Earthquake Zones

**Table 4:** Evaluation Metrics of Random Forest Regressor Models

| Earthquake Zone | MSE | RMSE |
|---|---|---|
| Zone 1 | 0.239 | 0.489 |
| Zone 2 | 0.178 | 0.422 |
| Zone 3 | 0.148 | 0.385 |
| Zone 4 | 0.213 | 0.462 |
| Zone 5 | .227 | .476 |
| Cumulative (Weighted Average Across all Zones) | .166 | .407 |

A possible reason for this may be that creating individual models trained on each of the 5 major earthquake zones in the Indian sub-continent allows for the model to better fit the earthquake data. Several reasons can be attributed to why this approach may lead to improved data fitting and more accurate earthquake magnitude forecasts. The Indian sub-continent is geographically diverse, comprising various tectonic features and fault lines. Each earthquake zone within this region exhibits distinct geological characteristics, seismic activity patterns, and earthquake magnitudes. By creating individual models for each zone, the proposed models can account for the unique geological variations, allowing the models to capture the specific dynamics and complexities of seismic events within each zone more effectively.

Training models with data specific to each earthquake zone enables the models to learn zone-specific patterns and relationships. The seismic data collected in form of catalog from different zones may have variations in terms of frequency content, amplitude, and temporal behavior. By training individual models for each zone, the models can focus on learning the specific patterns relevant to that zone, leading to a better fit to the data and improved forecasting accuracy. Seismic activity within the Indian sub-continent is not uniformly distributed across all earthquake zones. Some zones may experience frequent and significant seismic events, while others may have relatively lower activity. By creating individual models for each zone, researchers can concentrate their analysis and modeling efforts on the seismicity patterns that are relevant to a particular zone. This localized approach allows for a more targeted and accurate representation of the seismic behavior within each zone.

Each earthquake zone in the Indian sub-continent exhibits unique features and characteristics, such as fault types, focal depths, and crustal structures. These zone-specific factors can significantly influence the generation and propagation of seismic waves, ultimately impacting earthquake magnitudes. By training individual models for each zone, researchers can incorporate and prioritize the relevant zone-specific features in the modeling process, leading to improved understanding and forecasting of earthquake magnitudes within each zone. Next, the Support Vector Regression model results are discussed. The best hyperparameters for each of the 5 zones for the Support Vector Regressor models are given in **Table 5**.

**Table 5**: Optimal Hyperparameters for Support Vector Regressor Models

| Earthquake Zone | ‘kernel’’ | 'C' | 'gamma' |
|---|---|---|---|
| Zone 1 | rbf | 0.1 | 1 |
| Zone 2 | rbf | 0.1 | 1 |
| Zone 3 | rbf | 0.1 | 1 |
| Zone 4 | rbf | 0.1 | 0.1 |
| Zone 5 | rbf | 1 | 1 |

Based on the best hyperparameters in each zone, we are able to determine the MSE and RMSE of each zonal model, providing a sense of the accuracy of the model. The results were statistically significant. The model has a cumulative - weighted average across all zones - RMSE of 0.42 as can be seen in **Table 5**. The complete results of the support vector regressors can be seen in figure 8. These results suggest a significant improvement over the results reached in Jain et al (2021). The reasons for such an improvement in results are most likely similar to the reasons discussed earlier for the performance of the random forest regressors.

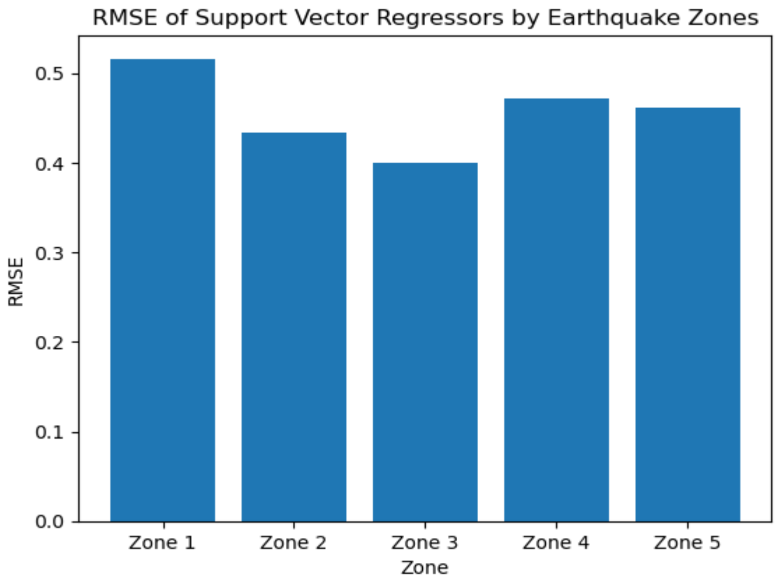


**Fig. 7:** RMSE Of Support Vector Regressors by Earthquake Zones

**Table 6**: Evaluation Metrics of Support Vector Regressor Models

| Earthquake Zone | MSE | RMSE |
|---|---|---|
| Zone 1 | 0.266 | 0.516 |
| Zone 2 | 0.188 | 0.434 |
| Zone 3 | 0.160 | 0.400 |
| Zone 4 | 0.222 | 0.471 |
| Zone 5 | 0.213 | 0.462 |
| Cumulative (Weighted Average Across all Zones) | 0.177 | 0.420 |

The random forest regressors show a slight improvement in RMSE over the support vector regressor model. This may be due to several reasons. Random forests can effectively capture nonlinear relationships between input features and earthquake magnitudes. They consist of an ensemble of decision trees, where each tree can model complex interactions and nonlinearity. In contrast, the Support Vector Regressor assumes a linear relationship between features and targets unless a nonlinear kernel is explicitly used. Random forests inherently have the ability to learn and represent nonlinear patterns, making them more suitable for capturing the intricate relationships often found in seismic data.

Seismic data can be prone to outliers and noise, which can affect the performance of forecasting models. Random forests are robust to outliers and noise due to their ensemble nature. Individual decision trees within the random forest can independently make forecasts, and the final forecasting is based on the aggregated results of all trees. This ensemble approach helps to mitigate the influence of outliers and noise, leading to more accurate and robust forecasts compared to the Support Vector Regressor, which may be more sensitive to outliers. Thus, it reasonably holds that the proposed random forest regressor models provide a better accuracy than the Support Vector Regressor models.

In the evaluation of both proposed models, it was found that the depth feature played a more significant role in earthquake magnitude forecasting compared to the location features. One potential explanation for this observation is the contribution of the zonal models in reducing the model's reliance on location information. Since each zonal model focused solely on earthquakes within a specific zone, the effect of location variability within that zone was minimized.

By training zonal models that are specific to each earthquake zone, the models could capture zone-specific patterns and relationships. This localized approach allowed the models to learn and understand the seismic behavior within each zone more effectively. As a result, the models could better discern the influence of depth, which is a critical factor affecting earthquake magnitudes, regardless of the specific location within the zone. Furthermore, the zonal models' ability to capture zone-specific patterns and relationships may have contributed to a better fit of the data. By considering the specific geological characteristics and seismic activity patterns of each zone, the models could more accurately capture the nuances of earthquake magnitudes within their respective zones. This improved data fitting might have also highlighted the significance of depth as a key predictor of earthquake magnitudes. This study demonstrates the potential of machine learning techniques in earthquake magnitude forecasting which may be utilized for proactive measures in mitigating the impact of seismic events especially for the NW region of Indian Subcontinent.

## 5 Conclusion

In this paper, we proposed a machine learning-based approach for earthquake magnitude forecasting in space and time in the NW part of Indian subcontinent. For this purpose, homogenized earthquake catalog for the period from 1975 to 2010 has been used. With the emergence of machine learning techniques, the ability to analyze large datasets and uncover hidden patterns has greatly been improved. To address the forecasting task, we developed two models: The Random Forest Regressor and the Support Vector Regression. We trained separate models for five identified zones to capture zone-specific patterns and relationships that affect earthquake magnitudes. Through our experiments and validation on unseen data, we demonstrated the effectiveness of our models in predicting earthquake magnitudes in the NW Indian subcontinent region. Our models obtain a cumulative weighted average (Root Mean Square Error) RMSE of 0.407 for the Random Forest Regressors and a cumulative weighted average RMSE of

0.420 for the Support Vector Regressors. The results obtained showed promising accuracy and reliability, surpassing traditional approaches in earthquake magnitude forecasting. This study demonstrates the potential of machine learning techniques in earthquake magnitude forecasting and emphasizes the importance of proactive measures in mitigating the impact of seismic events.

**Acknowledgements**
The homogenized catalog divided in 5 zones published by Chingtham et al, 2017 has been used for the present research work. All code was created in the Python language, with use of the Scikit-learn library (Pedregosa et al., 2011).

**Author's Contributions**
Aditya Gupta wrote the main manuscript text and prepared all figures and tables. Aditya Gupta created all python code and models. Babita Sharma and Prasanta Chingtham obtained original data. All authors reviewed and edited the manuscript.

**Data Availability**
The data that support the findings of this study are available from the corresponding author, A.G., upon reasonable request.

**Funding**
No funding was obtained for this study.

**Competing interests**
The authors have no competing interests as defined by Springer, or other interests that might be perceived to influence the results and/or discussion reported in this paper.

## 6 References

1. Adeli, Hojjat, and Ashif Panakkat. "A probabilistic neural network for earthquake magnitude prediction." Neural networks 22.7 (2009): 1018-1024. DOI: 10.1016/j.neunet.2009.05.003

2. Asim, K. M., et al. "Earthquake magnitude prediction in Hindukush region using machine learning techniques." Natural Hazards 85 (2017): 471-486. DOI: 10.1007/s11069-016-2579-3
3. Asim, Khawaja M., et al. "Earthquake prediction model using support vector regressor and hybrid neural networks." PloS one 13.7 (2018): e0199004. DOI: 10.1371/journal.pone.0199004
4. Bao, Zhenyu, et al. "A deep learning-based electromagnetic signal for earthquake magnitude prediction." Sensors 21.13 (2021): 4434. DOI: 10.3390/s21134434
5. Billington, Selena, Bryan L. Isacks, and Mauwia Barazangi. "Spatial distribution and focal mechanisms of mantle earthquakes in the Hindu Kush–Pamir region: A contorted Benioff zone." Geology 5.11 (1977): 699-704.
6. Cardona, O. D. (2019). United Nations atlas maps risks from earthquakes worldwide. Nature, 566(7743), 182-182 DOI:10.1038/d41586-019-00552-9
7. Chingtham P, Chopra S, Baskoutas I, Bansal BK. 2014. An assessment of seismicity parameters in northwest Himalaya and adjoining regions. Nat Hazards. 71:1599–1616. DOI:10.1007/s11069-013-0967-5.
8. Chingtham, P., et al. "Time-dependent seismicity analysis in the Northwest Himalaya and its adjoining regions." Natural Hazards 80 (2016): 1783-1800.
9. Chingtham, Prasanta, et al. "Forecasting seismicity rate in the north-west Himalaya using rate and state dependent friction law." Geomatics, Natural Hazards and Risk 8.2 (2017): 1643-1661. DOI: 10.1080/19475705.2017.1369168
10. Chingtham, Prasanta, and Babita Sharma. "Detection of seismic quiescences before 1991 Uttarkashi (M w 6.8) and 1999 Chamoli M w (6.6) earthquakes and its implications for stress change sensor." Acta Geophysica 70.2 (2022): 509-523.
11. Coward, M. P., et al. "The tectonic history of Kohistan and its implications for Himalayan structure." Journal of the Geological Society 144.3 (1987): 377-391.
12. D. D. Jackson, “Hypothesis testing and earthquake prediction,” Proc. Natl. Aca. Sci. USA, vol. 93, pp. 3772–3775, 1996. DOI: 10.1073/pnas.93.9.3772
13. Galkina, Alyona, and Natalia Grafeeva. "Machine learning methods for earthquake prediction: A survey." Proceedings of the Fourth

Conference on Software Engineering and Information Management (SEIM-2019), Saint Petersburg, Russia. Vol. 13. 2019.

14. Gupta, Aditya, and Vijay Kumar Tayal. "Analysis of Twitter Sentiment to Predict Financial Trends." 2023 International Conference on Artificial Intelligence and Smart Communication (AISC). IEEE, 2023. DOI: 10.1109/AISC56616.2023.10085195
15. Gupta, Aditya, and Vijay K. Tayal. "Using Monte Carlo Methods for Retirement Simulations." arXiv preprint arXiv:2306.16563 (2023).
16. Gupta, Aditya, Christopher Grattoni, and Arnav Gupta. "Determining Chess Piece Values Using Machine Learning." Journal of Student Research 12.1 (2023). DOI: 10.47611/jsrhs.v12i1.4356
17. Gupta, Harsh, and V. K. Gahalaut. "Seismotectonics and large earthquake generation in the Himalayan region." Gondwana research 25.1 (2014): 204-213.
18. Gusiakov, V.K. Relationship of Tsunami Intensity to Source Earthquake Magnitude as Retrieved from Historical Data. Pure Appl. Geophys. 168, 2033–2041 (2011). DOI: /10.1007/s00024-011-0286-2
19. Jain, Rachna, et al. "A comprehensive analysis and prediction of earthquake magnitude based on position and depth parameters using machine and deep learning models." Multimedia Tools and Applications 80.18 (2021): 28419-28438. DOI: 10.1007/s11042-021-11001-z
20. Mishra, O. P. "Intricacies of the Himalayan seismotectonics and seismogenesis: need for integrated research." Current Science (2014): 176-187. DOI:
21. Mogi, Kiyoo. "Earthquake prediction." (1985).
22. Narayanakumar, S., and K. Raja. "A BP artificial neural network model for earthquake magnitude prediction in Himalayas, India." Circuits and Systems 7.11 (2016): 3456-3468. DOI: 10.4236/cs.2016.711294
23. Ni, James, and Muawia Barazangi. "Seismotectonics of the Himalayan collision zone: Geometry of the underthrusting Indian plate beneath the Himalaya." Journal of Geophysical Research: Solid Earth 89.B2 (1984): 1147-1163.
24. Pedregosa, Fabian, et al. "Scikit-learn: Machine learning in Python." the Journal of machine Learning research 12 (2011): 2825-2830.
25. Rikitake, Tsuneji. "Earthquake prediction." Earth-Science Reviews 4 (1968): 245-282. DOI: 10.1016/0012-8252(68)90154-2

26. Segal, M. R. (2004). Machine Learning Benchmarks and Random Forest Regression. UCSF: Center for Bioinformatics and Molecular Biostatistics. Retrieved from https://escholarship.org/uc/item/35x3v9t4
27. Yadav RBS, Bayrak Y, Tripathi JN, Chopra S, Singh AP, Bayrak E. 2011. A probabilistic assessment of earthquake hazard parameters in NW Himalaya and the adjoining region. Pure Appl Geophy. 169(9):1619–1639. DOI:10.1007/s00024-011-0434-8.
28. Zhou, Zheng, et al. "Earthquake detection in 1D time-series data with feature selection and dictionary learning." Seismological Research Letters 90.2A (2019): 563-572. DOI: 10.1785/0220180315