



EARTHQUAKE DEPTH PREDICTION IN THE HIMALAYAS USING ENSEMBLE MACHINE LEARNING

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ABSTRACT

This study assesses the potential of ensemble ML methods for earthquake focal depth prediction in the Central Himalaya. The basic catalog parameters (time, location, magnitude) are used from 1964-2024. Four regression models - Decision Tree, Bagging, Random Forest, and Tuned Random Forest were evaluated using a train-test split. Using ensemble methods, tree over fitting was substantially reduced compared to a single Decision Tree (test R^2 improved from 0.112 to 0.425). However, all R^2 values remained low that indicating limited overall predictive capability. Specifically, the tuned Random Forest achieved the highest test R^2 of 0.425. Despite this improvement, all models had a systematic bias of predicting depths shallower than the actual depths and under predicting the events below 80 km reflecting the bimodal seismicity of the region and the different tectonics processes governing crustal and lithospheric earthquakes. The results of the study indicate that catalog parameters alone are not sufficient for reliable depth prediction in this tectonically complex setting. To achieve any meaningful improvement, geophysical variables including crustal thickness, fault geometry and heat flow must be incorporated. Moreover, crustal and mantle seismicity should be modelled separately using a stratified approach.

Keywords: Central Himalaya, Depth prediction, Machine learning, Random Forest, Seismotectonic

INTRODUCTION

The Himalayan Arc resulting from the collision between the Indian and Eurasian plates, which is one of the most tectonically active regions in the world (Molnar & Tapponnier, 1975; Ni, 1989). Frequent and destructive earthquakes impact regions across India, Nepal, Bhutan, Pakistan, and the southern Tibetan (Avouac, 2003; Bilham, 2004; Bollinger et al., 2014). Historical events such as the 1934 Nepal-Bihar earthquake (Kumar et al., 2006) and the 2015 Gorkha earthquake (Tiwari & Paudyal, 2021; Subedi et al., 2025; Tiwari et al., 2025a) highlight the severe seismic hazard in this region (Stevens & Avouac, 2015). Earthquake magnitude is the most commonly used measure of released seismic energy (Richter, 1935; Kanamori, 1977). However, focal depth is equally important as it strongly influences ground shaking intensity and the resulting damage distribution (Lay & Wallace, 1995; Allen et al., 2012). Shallow earthquakes are characterized by very strong shaking at the surface. Intermediate and deep earthquakes influence regional stress transfer. In turn, these stresses contribute to long term seismic hazards (Lay & Wallace, 1995; Houston, 2015).

Earthquake depth distribution in Himalayas is controlled largely by Main Himalayan Thrust (MHT), Main

Boundary Thrust (MBT) and Main Frontal Thrust (MFT) and associated fault system (Pandey et al., 1999; Avouac, 2003). The distribution of the depths of the hypo-centers of earthquakes is influenced by how these structures are built (Cattin & Avouac, 2000; Ader et al., 2012) and the mechanical behavior of those structures. The prediction of the depth of an earthquake is a non-linear problem and depth is controlled by the interaction between a number of different tectonic and geophysical processes (Kanamori & Brodsky, 2004; Shearer, 2019).

So far, the studies conducted in the Himalaya region have been mostly focused on estimating either the earthquake magnitudes, estimating recurrence intervals or probabilistic seismic hazard assessment (Bilham, 2004; Bollinger et al., 2014). Historically, depth was a target variable not predicted but rather measured (Lay & Wallace, 1995; Shearer, 2019). Typical statistical models, like those in earthquake studies, assume normal distributions and linearity, which may limit their ability to represent the earthquakes' non-linear depths (Kanamori & Brodsky, 2004). Münchmeyer et al. (2024) further advanced this by creating a deep-learning-based depth-picking approach for estimating the depth of an earthquake using seismic waveforms. Their approach provides much greater accuracy than

available catalog-based methods in well-instrumented areas. However, seismic waveforms must be recorded with dense seismic networks and have high-quality phase data which are absent for large portions of the Himalayan Arc, especially for older events before modern broadband networks were created. Thus, our study aims to determine if ensemble machine learning using catalog parameters alone will be able to produce meaningful estimates of earthquake depths in areas with limited data.

The latest advancements in machine learning offer new opportunities to model complex geophysical distributions. Ensemble learning methods like Random Forest, especially tree-based methods, work well with nonlinear interactions, heterogeneous datasets and multicollinearity. Highly robust models capable of extracting meaningful patterns from large datasets have demonstrated excellent predictive performance by

researchers in geosciences (Hastie et al., 2009; Belgiu & Drăgu, 2016; Mousavi et al., 2020) Recent studies have begun applying such methods to seismological problems in the Himalayan region specifically. Aryal et al. (2024) and Tiwari et al. (2025b) have shown that both ensemble and supervised learning can be used effectively to predict earthquakes' magnitudes based on the parameters sourced from catalogs in the Central Himalaya, achieving good predictive performance. As with magnitude, however, there has been little formal analysis of focal depth, even though it too is a critical variable affecting the intensity of ground shaking and how damage is distributed. While magnitude is more directly linked to measurable catalog parameters, depth is influenced by the interplay between tectonic structure, fault geometry and crustal rheology and is therefore a far more difficult target for prediction than magnitude based on catalog parameters alone. This study aims to fill this gap.

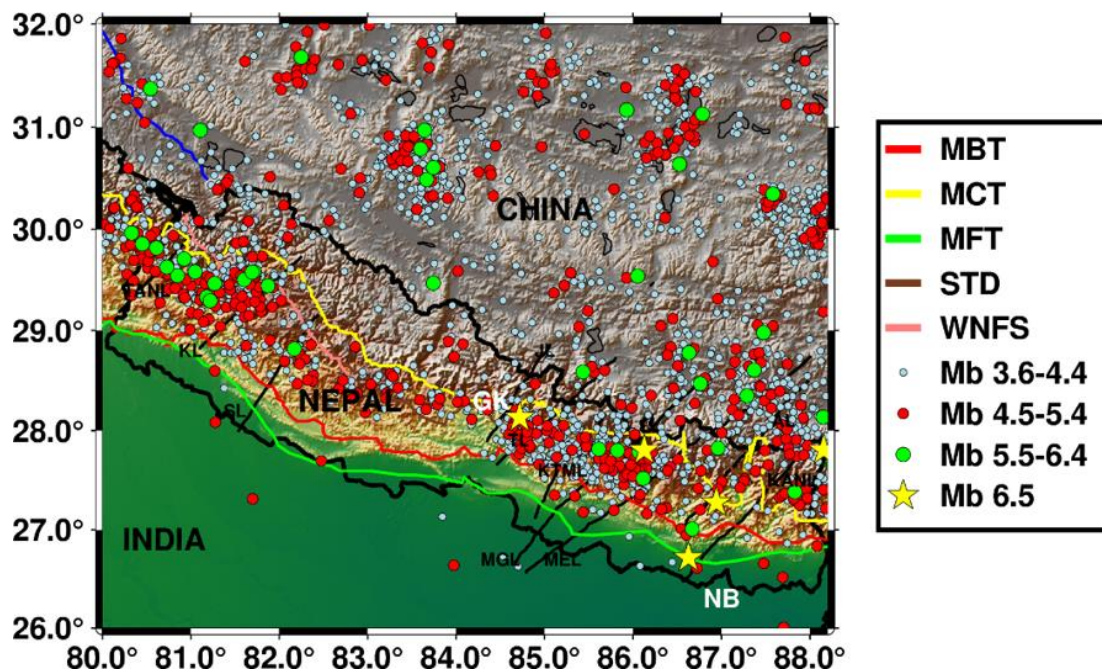


Figure 1. A tectonic map of the study area in the Himalayas showing distribution of earthquakes and interpreted source regions. Past earthquakes are marked by yellow stars and encircled with different colors to denote their source zones, with each circle centered on the epicenter. The MCT, MBT and MFT are the major Himalayan thrust systems indicated. The regional structural lineaments are also marked Tanakpur (TL), Karnali (KL), Samea (SL), Judi (JL), Thaple (TL), Kathmandu (KTML), Motihari-GauriShanker (MGL), Motihari-Everest (MEL), Arun (AL), Kanchenjunga (KANL). Yellow stars indicate the location of great earthquakes ($M_b > 6.5$) and other historical events while red rectangular boxes show the subdivided regions that were used for the analysis in parts of Nepal

In this study, earthquake focal depth in the Central Himalayan (Fig. 1) is modeled using four regression approaches: Decision Tree, Bagging, Random Forest, and Tuned Random Forest. The objectives are to (i) assess the ability of ensemble learning techniques for the

prediction of earthquake depth, (ii) evaluate and compare the predictive ability of these various models through standard regression metrics, and (iii) determine the most significant controlling variables of depth variability in this tectonically complex area. The region

chosen for the study is the Central Himalayas (80°E–88°E), which is one of the most seismically active segments in the Himalaya Arc. In the selected area, earthquake events of various magnitudes are spread over a vast geographical area.

MATERIALS AND METHODS

Data collection

Earthquake data were obtained from the ISC catalog (Willemann & Storchak, 2001; Woessner & Wiemer,

2005) for the period 1964–2024. Events below the magnitude of completeness ($M_c = 3.6$) were removed, and declustering was performed using the Reasenberg (1985) algorithm to retain independent mainshock events (Fig. 2). A total of 2117 events were used. Focal depth uncertainties, particularly for early 20th-century events, are recognized as a source of noise in the dataset (Bai et al., 2017); this inherent uncertainty contributes to the upper bound of achievable predictive accuracy.

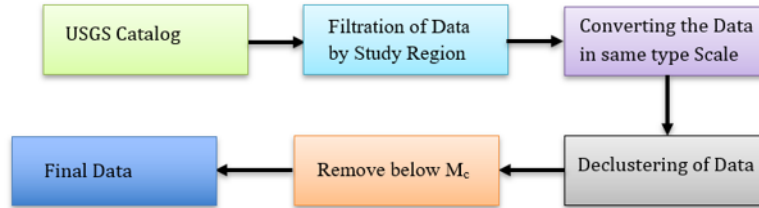


Figure 2. Earthquake data preprocessing steps from USGS catalog to final cleaned dataset

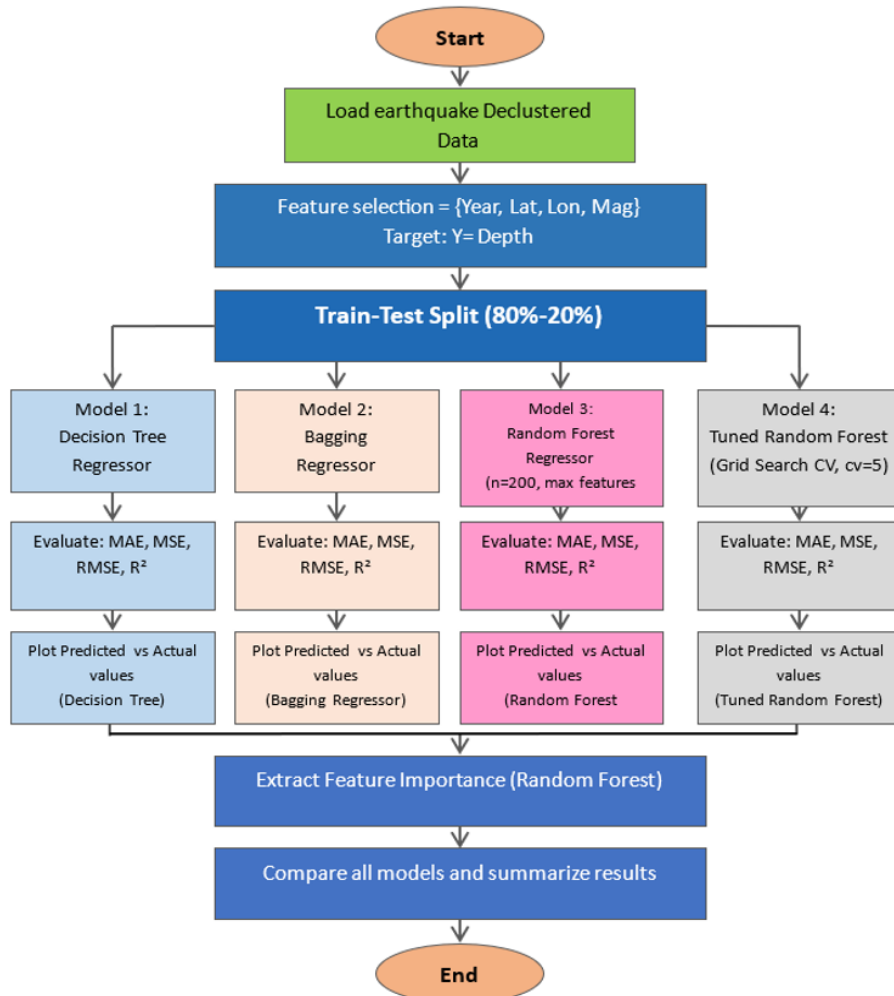


Figure 3. Machine learning workflow for earthquake depth prediction, showing data loading, feature selection, train–test split, model comparison (Decision Tree, Bagging, Random Forest, Tuned Random Forest), evaluation, and feature importance analysis

The data were split into a training set to build our models (n = 1692) and a held-out test set (n = 424). We deliberately did not split the data randomly, as this would allow the model to train on events temporally separated from the test events, thereby distorting generalization estimates. The final predictor set consisted of four variables: year, magnitude, latitude, and longitude. Focal depth was used as the response variable. No feature scaling was applied, as tree-based methods are invariant to monotonic transformations of the input features. Figure 3 illustrates the complete preprocessing and modeling pipeline.

Following data preparation, four regression models were developed to predict earthquake depth: Decision Tree, Bagging, Random Forest and Tuned Random Forest. A simple Decision Tree was taken as a baseline, to which ensemble components were consecutively added for better stability and predictability. The performance of the model is evaluated using Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Coefficient of Determination (R^2).

Decision tree regressor

The Decision Tree model keeps splitting the dataset into subsets based on the values of the predictor variables. The selection of each split aims to minimize the target variable's variance in its daughter nodes. While decision trees are easy to interpret, they tend to overfit when the data is complex (Breiman et al., 1984).

Bagging regressor

Bagging or Bootstrap Aggregating is used to stabilize the predictions by fitting multiple decision trees on the bootstrapped samples of the training dataset. Each tree produces a depth prediction, and the final output is the average of those predictions. Due to averaging the results of multiple classifiers, it has less variance and better generalization error than a single decision tree (Breiman, 1996).

Random forest regressor

Random Forest extends bagging by introducing additional randomness during model construction. Alongside bootstrapped sampling, the selection of a random subset of predictor variables occurs at each split. Greater tree diversity further reduces overfitting.

The predicted depth for a regression is calculated as:

$$\widehat{D}(x) = \frac{1}{T} \sum_{t=1}^T f_t(x) \quad (1)$$

where T is the total number of trees and $f_t(x)$ is the prediction from the t^{th} tree, Random Forest was chosen due to its ability to model non-linear relationships, cope with multicollinearity and its robustness to outliers; seismic data typically have these properties (Breiman, 2001).

Tuned random forest

To enhance predictive performance, the Random Forest model was optimized using GridSearchCV with 5-fold cross-validation applied strictly to the training set. The hyperparameter search space covered four parameters: n_estimators (number of trees: 50, 100, 200), max_features (features considered at each split: 1, 2), max_depth (maximum tree depth: None, 5, 10), and min_samples_leaf (minimum samples per leaf node: 1, 2, 4). This yielded 54 candidate combinations ($3 \times 2 \times 3 \times 3$), each evaluated by minimizing negative mean squared error across the five cross-validation folds. The hyperparameter combination producing the lowest cross-validated MSE was selected as the final model configuration and subsequently evaluated on the held-out test set (Bergstra & Bengio, 2012).

Model evaluation

The model's efficacy was assessed through established regression metrics, specifically:

Mean Squared Error (MSE) by the formula

$$MSE = \frac{1}{n} \sum_{i=1}^n (D_i - \widehat{D}_i)^2 \quad (2)$$

Root Mean Squared Error (RMSE) by the formula

$$RMSE = \sqrt{MSE} \quad (3)$$

And, Coefficient of Determination (R^2) by the formula

$$R^2 = 1 - \frac{\sum (D_i - \widehat{D}_i)^2}{\sum (D_i - \bar{D})^2} \quad (4)$$

where D_i represents observed depth and \widehat{D}_i represents predicted depth (James et al., 2021).

In addition to predictive accuracy, feature importance derived from the Random Forest model was analyzed to identify the most influential factors controlling earthquake depth distribution (Breiman, 2001).

RESULTS AND DISCUSSION

Results are presented in order of model complexity, progressing from the baseline Decision Tree through to the Tuned Random Forest, followed by an integrated comparison and feature importance analysis (Fig. 4).

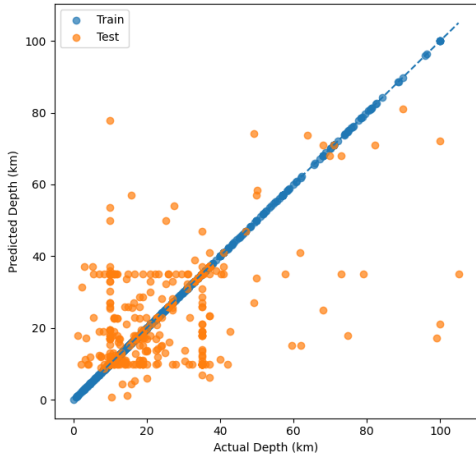


Figure 4. Decision Tree regression results showing predicted vs. actual earthquake depth for training and testing datasets

The Decision Tree regressor performed extremely well on train data as it achieved a MAE of 0.0 km, RMSE of 0.0 km, and R^2 value of 1.00 on test data. Despite this, its performance on the test data was weak, with a test R^2 of 0.112 (Fig. 4). The model shows extreme overfitting whereby it remembers the noise instead of learning the actual pattern (Hastie et al., 2009). There is a striking drop in performance from train to test. This implies that a single decision tree is not enough for seismic depth prediction to show any generalization (Fig. 5).

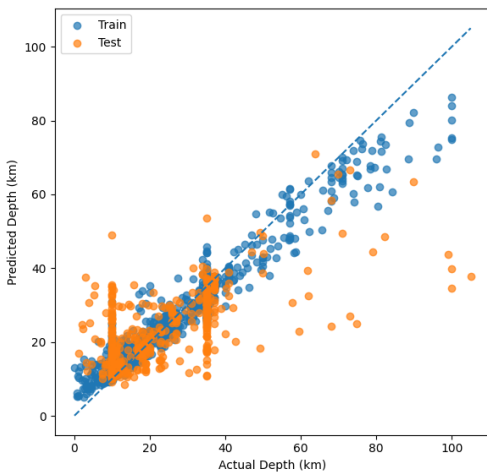


Figure 5. Random Forest regression results show predicted vs. actual earthquake depth for training and testing datasets

The Bagging regressor achieved a substantially improved test score ($R^2 = 0.399$) alongside a high training score ($R^2 = 0.923$), as shown in Figure 5. This improvement is consistent with bootstrap aggregating theory, which reduces variance by averaging predictions across multiple models trained on different bootstrap samples (Breiman, 1996). Ensemble methods seem to be better suited for capturing the nonlinear relationship present in seismological data as evident from the noticeable gap between training error and testing error.

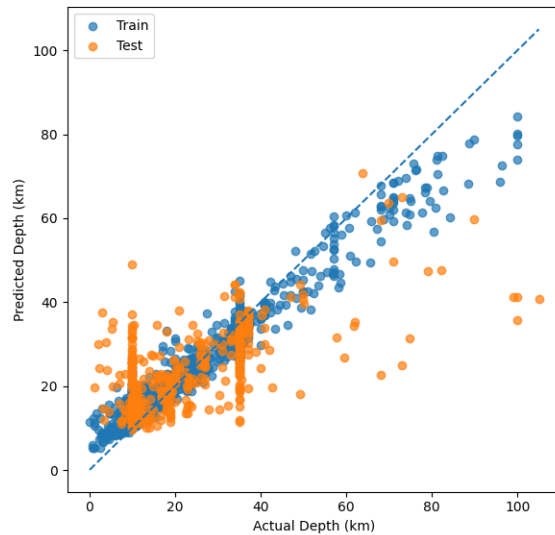


Figure 6. Random Forest regression results show predicted vs. actual earthquake depth for training and testing datasets

Random Forest extended Bagging by introducing additional randomness at each split (Fig. 6), yielding a more robust model with comparable training performance (MAE = 2.80 km, RMSE = 4.28 km, $R^2 = 0.922$) and a marginally better generalization to the test set (MAE = 8.06 km, RMSE = 12.56 km, $R^2 = 0.416$) model. Yet the predicted vs. actual depth scatter plot shows clear systematic pattern in that shallow earthquakes are generally over-predicted and deep earthquakes are under-predicted capturing extreme depth values remains problematic.

The Tuned Random Forest achieved the best balance between bias and variance (Fig. 7), with a test R^2 of 0.425 and RMSE of 12.29 km. Despite these improvements, all models showed reduced accuracy for extreme depth values.

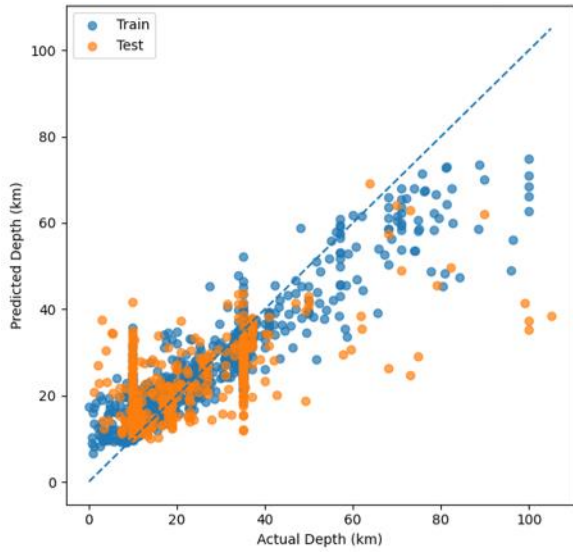


Figure 7. Tuned Random Forest regression results show predicted vs actual earthquake depth for training and testing datasets

Tuned ensembles showed better performance and less overfit than Decision Trees. Increasing model complexity improved generalization performances and reduced overfitting. The accuracy of the training of the Decision Tree is 100%. But the accuracy on the test set is worse thereby proving the classical bias variance failure of unconstrained trees on complex data. The

Bagging model improved test performance and reduced variance by averaging ensemble predictions. Random Forest achieved more success because of more diverse trees. The Tuned Random Forest demonstrates a reasonable bias-variance trade-off, attaining the highest test R^2 (0.425) and lowest RMSE (12.29 km) (Table 1). Although there was some improvement in the models, a significant amount of prediction error remained for earthquakes recorded at shallow <30 km and deep >130 km depth. It shows that their capability to capture extreme behavior is limited.

The residual (Fig. 8) diagnostics reveal systematic weaknesses in the model. The plots of residuals versus predicted depth as well as residuals versus actual depth are evidently not random, meaning they display a non-random structure. The residuals appear to decrease as predicted depth increases and residuals appear to increase as actual depth increases. There is a systematic bias, whereby shallow earthquakes are overestimated and deeper earthquakes are underestimated. Such behavior shows the model’s incapability of capturing the bimodal and non-linear behavior of the seismic depth distribution of the Himalaya.

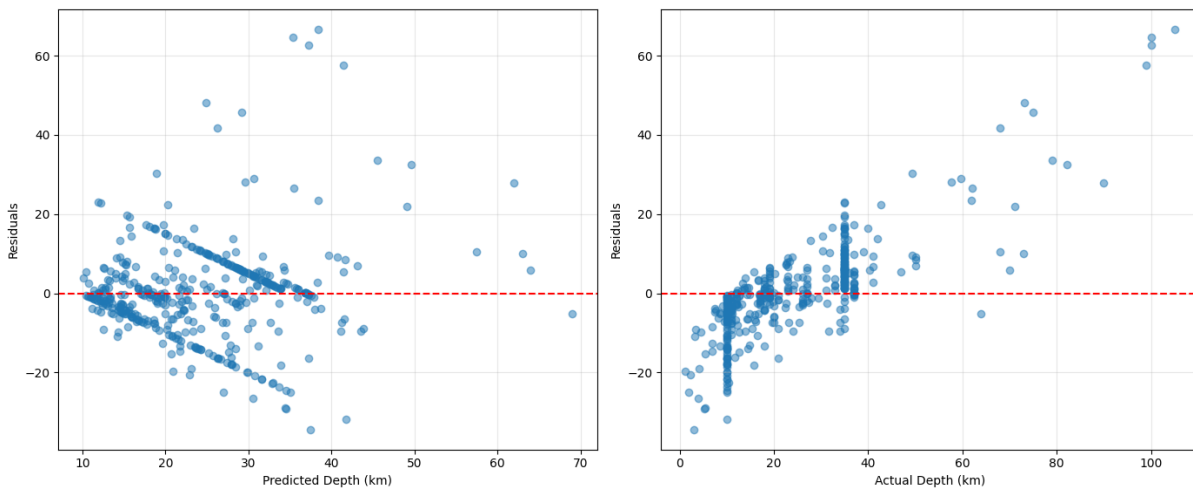


Figure 8. Residuals vs Predicted Depth (left) and Residuals vs Actual Depth (right) for the Tuned Random Forest model

Table 1. Performance comparison of tree-based models using MAE, RMSE, and R^2 on training and test datasets. Ensemble methods (Bagging and Random Forest) improve generalization over a single Decision Tree, while the tuned Random Forest achieves the best overall test performance

Model	MAE (train)	MAE (test)	RMSE (train)	RMSE (test)	R^2 (train)	R^2 (test)
Decision Tree	0.00	8.99	0.00	15.27	1.000	0.112
Bagging (Decision Trees)	2.73	8.06	4.24	12.56	0.923	0.399
Random Forest	2.80	8.06	4.28	12.38	0.922	0.416
Tuned Random Forest	4.09	8.02	6.32	12.29	0.829	0.425

In particular, poor performance at depths greater than 80 km has a clear geophysical cause. The seismotectonic assessment of the eastern Himalaya by Kayal & Hazarika (2025) states bimodal seismicity with shallow (0–20 km) as well as deeper (40–80 km) events and that deeper events occur due to strike-slip faulting on transverse structures at mantle depth. Bai et al. (2017) reported on the Earthquake Focal Depths in the Himalayan Tibetan Region. The authors found that depth uncertainties exceeding 20 km are most common for earthquakes deeper than 20 km. The authors report that nearly 15% of earthquakes have depth estimate discrepancies exceeding 20 km.

Research has indicated that deeper Himalayan earthquakes engage fundamentally different tectonic mechanisms (mantle faulting, stress transfer along transverse structures, or lower crustal deformation) which surface/near-surface predictors cannot account for (Jackson et al., 2008; Molnar & Wang-ping, 1983). The bimodal pattern of the depth distribution noticed by Kayal & Hazarika (2025) indicate that modelling for

crustal and mantle earthquakes could be done with different predictive equations or additional geophysical parameters (crustal thickness, heat flow, fault geometry) must be included in the model to capture this feature.

Table 2 shows the model's calculated values and the observed focal depths for the earthquakes. The single Decision Tree model shows the most significant differences. This suggests a limited ability to generalize and a high sensitivity to changes in the data. Employing ensemble methods leads to more trustworthy predictions. Bagging and random forest do not produce overly large over- or under-predictions. The Tuned Random Forest exhibits the closest alignment with observed depths for both shallow and deeper events, indicating that hyperparameter tuning enhances the stability of predictions as well as reduces variance. When compared to a single decision tree, tuned ensemble methods enable more reliable estimation of focal depth. However, we are limited in accuracy in absolute terms because of the predictors at our disposal.

Table 2. Comparison of observed earthquake focal depths with predictions from four machine-learning models (Decision Tree, Bagging Decision Tree, Random Forest, and Tuned Random Forest)

Event	Actual Depth (km)	Predicted Depth (km)			
		Decision Tree Model	Bagging Decision Tree Model	Random Forest Model	Tuned Random Forest Model
Mb 3.9 (2014)	37	10	17.851	19.6095	19.75
Mb 5.6 (2015)	20.1	13.8	17.0735	16.3645	15.16
Mb 3.8 (2015)	19	28.7	19.977	19.557	19.89
Mb 3.6 (2015)	12	12	11.782	12.8405	11.93
Mb 4.0 (2019)	21	35	22.8465	21.9845	21.62
Mb 3.8(2020)	4.1	10	25.196	23.9225	23.12
Mb 4.0 (2021)	13.8	10.4	11.949	12.3555	12.70

Mb 3.8 (2021)	68	25.1	24.3705	22.802	26.28
Mb 4.3 (2022)	7	12.4	19.6515	20.5435	19.63
Mb 3.9 (2022)	8.5	10	14.002	13.037	13.45
Mb 5.3 (2023)	11	22.8	17.357	17.588	17.46
Mb 4.4 (2024)	100	72.1	39.954	41.194	37.30

The moderate importance of these variables validates that the spatial location significantly dictates earthquake depth aligned to tectonic segmentation of Himalayan Arc (Tiwari & Paudyal, 2024). The Central Himalaya (80°E–88°E) has variations along-arc in crustal thickness, ramp geometry on the MHT and foreland basin structure (Pandey et al., 1999; Cattin & Avouac, 2000). All this influences where earthquakes initiate. The results of our analysis provide quantitative evidence of the model’s capturing of these spatial controls. Earthquake depth is not a strong function of event size in the Himalayan Arc as shallow and deep events cover the entire magnitude range. This finding agrees with global data which show that, in subduction and collision zones, depth and magnitude are weakly associated Shearer (2019), validating the interpretation that depth is governed by tectonic setting rather than rupture characteristics.

CONCLUSION

In this study, the feasibility of ensemble machine learning models was investigated for forecasting earthquake focal depth in the Central Himalaya based on basic catalog parameters. The results showed that ensemble methods (Bagging, Random Forest) have significantly reduced the over fitting of a single Decision Tree, while Tuned Random Forest has given the best generalization with the test R^2 equal to 0.425 and RMSE 12.29 km. Despite the modest performance of the predictions, these findings themselves are of importance. The basic parameters, year, magnitude, latitude, and longitude, are insufficient for reliable depth prediction. Each model indicated systematic overestimation of shallow events and underestimation of deeper earthquakes (>80 km). This had occurred as various surface predictors failed to capture events that involved distinct tectonic processes for instance, mantle faulting or deformation on other transverse structures fundamentally limited by data relevance. Future research should incorporate geophysical parameters such as (crustal thickness, heat flow, and distance to major thrusts) as well as a stratified approach dealing

with the crustal and lithospheric earthquakes separately for a meaningful predictive improvement.

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AUTHOR CONTRIBUTIONS

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CONFLICT OF INTEREST

The authors declare that there are no conflicts of interest regarding the publication of this article.

ETHICAL STATEMENT

We declare that it is our original work and has not been previously published or submitted for publication elsewhere.

DATA AVAILABILITY STATEMENT

Data are freely available from the websites of the International Seismological Center. Supporting information decluster Data and code are available at a reasonable request from the corresponding author.

SUPPLEMENTARY INFORMATION

None.

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