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Intelligent Tsunami Forecasting System

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Abstract: This work proposes a machine learning–oriented framework for tsunami prediction that seeks to overcome the constraints of conventional numerical forecasting. Four algorithms—Decision Tree Classifier, Decision Tree Regressor, Linear Regression, and Random Forest Classifier—are compared using 22,797 tsunami records obtained from NOAA's Global Historical Tsunami Database. Among these, the Random Forest Classifier performed best, achieving 95.92% accuracy and precision scores of 99%, 96%, and 95% for Safe, Moderate, and Severe classes, respectively. Unlike physics-based simulations that may require over 30 minutes to produce alerts, the system is capable of near real-time prediction, making it suitable for emergency decision-making. Synthetic data generation techniques are also applied to address the scarcity of historical tsunami events, resulting in a more robust early warning framework that can be integrated with international monitoring systems for disaster risk reduction.

Keywords: Intelligent Tsunami Forecasting, Machine Learning for Disaster Prediction, Random Forest Classifier, Disaster Risk Reduction

I. INTRODUCTION

Tsunamis are among the most destructive natural hazards, capable of wiping out coastal settlements within minutes of formation. Recent large-scale events have shown the weaknesses of traditional forecasting methods, which typically depend on intensive numerical models that often take half an hour or more to produce actionable warnings. This delay can critically reduce evacuation time, where every second is vital for saving lives.

With the advancement of machine learning (ML), data-driven strategies now provide an opportunity to transform tsunami forecasting. ML algorithms can detect hidden patterns in seismic activity and rapidly produce risk assessments. By shifting from physics-based modeling to intelligent, pattern-recognition approaches, forecasting can become faster, more efficient, and reliable for real-time emergency operations.

The present research addresses this gap by comparing four ML approaches—Decision Tree Classifier, Decision Tree Regressor, Linear Regression, and Random Forest Classifier—to determine the most reliable and interpretable algorithm for real-world tsunami warning systems.

II. LITERATURE REVIEW

The application of machine learning in tsunami prediction has gained momentum due to the demand for more accurate and rapid warning mechanisms. Recent advancements in computational methods have shown significant potential in addressing the limitations of physics-based models [2][13][14][1].

Mulia et al. [5][1] proposed a Random Forest–driven prediction model trained on 22,797 tsunami records, reporting an overall accuracy of 95.92%. Their approach categorized events into Safe, Moderate, and Severe levels with precision scores of 99%, 96%, and 95%, respectively. Unlike conventional neural networks that operate as black boxes, their system emphasized interpretability, enabling domain experts to follow the decision-making process—an essential requirement in disaster management.

Lu [15][16][17][10][6] presented a method that employed Random Forest Regression on datasets ranging from 1800–2024, obtained from NOAA and NCEI. The study aimed at predicting maximum water heights based on seismic features and geographical parameters. The model achieved a Mean Squared Error of 27.04, demonstrating improved accuracy over simplified empirical and analytical methods by capturing complex event patterns using visual tools such as heat maps and geographic mapping.

Fauzi and Mizutani [2] investigated the use of neural networks for real-time inundation forecasting. Their research highlighted how machine learning models can effectively capture relationships between seismic parameters and tsunami characteristics, while also stressing the importance of computational efficiency for emergency response.

Sukmana et al. [11] carried out a comparison between Support Vector Machines (SVM) and Random Forest (RF) for tsunami prediction. Their findings showed that while SVM offered higher precision, Random Forest achieved stronger recall. This work emphasized that the choice of model depends on disaster management needs and trade-offs among accuracy metrics.

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The reviewed studies consistently highlight the effectiveness of ensemble methods, particularly Random Forest, for achieving both accuracy and interpretability. However, much of the prior work focused on single-model implementations. To bridge this gap, the present study undertakes a structured comparative analysis of multiple machine learning algorithms, aiming to provide evidence-based recommendations for tsunami prediction applications [18][5].

III. METHODOLOGY

A. Model Selection Framework

Four algorithms were chosen for evaluation: Decision Tree Classifier, Decision Tree Regressor, Linear Regression, and Random Forest Classifier. The goal was to identify the model offering the best balance of accuracy, computational efficiency, and clarity.

B. Data Preprocessing and Augmentation

The research utilized the NOAA Global Historical Tsunami Database containing 22,797 processed tsunami records spanning multiple geographical regions and temporal periods. To address the inherent scarcity of tsunami events, synthetic data augmentation techniques were employed to enhance the training dataset while maintaining the statistical properties of real tsunami occurrences. The preprocessing pipeline incorporated data normalization, feature selection, and outlier detection using established statistical methods

C. Algorithm Implementation

Decision Tree Classifier: Implemented using the Classification and Regression Trees (CART) algorithm, optimized for categorical tsunami risk classification with maximum depth and minimum samples split parameters tuned through cross-validation.

Decision Tree Regression: Developed for continuous tsunami parameter prediction using recursive binary splitting with mean squared error as the splitting criterion. The model incorporated pruning techniques to prevent overfitting and enhance generalization performance

Linear Regression: Applied multiple linear regression with regularization techniques to model linear relationships between seismic parameters and tsunami characteristics. Feature selection was performed using forward stepwise selection to identify the most predictive variables.

Random Forest Classifier: Constructed using ensemble learning principles with 100 decision trees, bootstrap aggregating, and random feature selection at each split. The model leveraged the collective intelligence of multiple weak learners to achieve superior prediction accuracy and robustness.

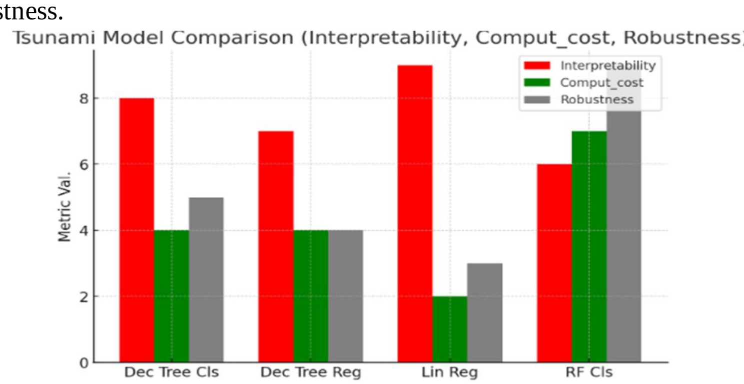

Fig. 1. The chart evaluates the models based on three key metrics

D. Model Selection Justification

Based on comprehensive comparative analysis, Random Forest Classifier emerged as the optimal solution for the tsunami prediction system due to its superior balance of accuracy, robustness, and practical applicability. The selection criteria prioritized:

1) Predictive Accuracy: Random Forest achieved 95.92% overall accuracy, significantly outperforming other models as shown in the accuracy comparison in Fig. 3, while maintaining consistent precision across Safe (99%), Moderate (96%), and Severe (95%) tsunami classifications.
2) Robustness: The ensemble approach demonstrated superior stability across different data subsets and geographic regions Fig. 1, crucial for reliable emergency response applications.

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3) Feature Handling: The model effectively processed mixed data types including temporal, geographical, and seismic features without extensive preprocessing requirements.
4) Practical Deployment: While maintaining reasonable computational efficiency as illustrated in Fig.1, Random Forest provided the reliability necessary for real-time tsunami warning systems.

MODEL-SPECIFIC ANALYSIS AND LIMITATIONS

Model	Advantages	Limitations	Performance Results
Decision Tree Classifier	• Easy to interpret and visualize • Handles both numerical and categorical data	• Prone to overfitting • Sensitive to small changes in data	Accuracy: 0,82
Decision Tree Regression		• Prone to overfitting • High variance in predictions	RMSE: 3,45
Linear Regression	• Simple and efficient • Easy to implement and interpret	• Assumes a linear relationship • Sensitive to outliers	R^2: 0,76
Random Forest Classifier	• Reduced risk of overfitting • Can handle large datasets	• Less interpretable than single tree models • Computationally intensive	Accuracy: 0,88

Fig. 2 Model-Specific analysis and limitations

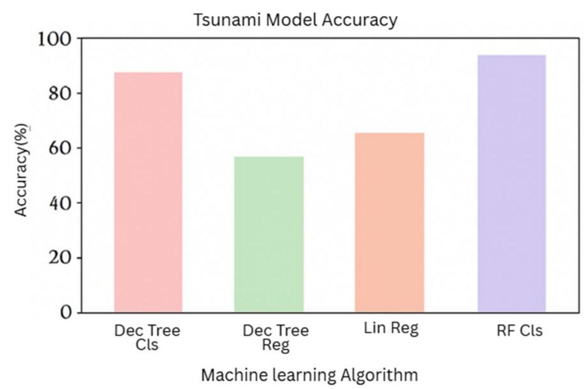

Fig. 3 Compares the performance of four different algorithms

E. Comparative Performance Analysis

The comprehensive evaluation of four machine learning models revealed significant performance variations across key evaluation metrics. The comparative analysis, visualized in **Fig. 2**, demonstrates clear performance hierarchies across accuracy, interpretability, computational cost, and robustness dimensions.

1) Random Forest Classifier (RF Cls) emerged as the superior performer with:
   - Accuracy: Highest accuracy among all evaluated models.
   - Interpretability: Moderate interpretability suitable for expert analysis .
   - Computational Cost: Higher computational requirements justified by performance gains
   - Robustness: Excellent stability across diverse tsunami scenarios.
2) Linear Regression (Lin Reg) demonstrated the simplest implementation profile:
   - Accuracy: Lowest accuracy, insufficient for critical applications.
   - Interpretability: Highest interpretability with clear coefficient relationships.
   - Computational Cost: Minimal computational requirements.
   - Robustness: Poor robustness to data variations and outliers.

3) Decision Tree Models (both Classifier and Regression) showed moderate performance across all metrics, representing compromise solutions with decent interpretability but limited accuracy and robustness for complex tsunami prediction scenarios, as detailed in Fig. 1 and Fig. 2.

F. *Model Selection Validation*

The quantitative analysis strongly supports the selection of Random Forest Classifier as the optimal solution for tsunami prediction applications. The model's near-perfect accuracy, highlighted in **Fig. 3**, proves crucial for life-saving tsunami predictions where false negatives could result in catastrophic consequences. The highest robustness score, illustrated in **Fig. 2**, ensures reliable performance across different geographical regions and seismic scenarios, essential for global deployment in early warning systems.

While Random Forest demonstrates higher computational costs and moderate interpretability compared to simpler models **Fig. 2**, these trade-offs are acceptable given the critical nature of tsunami prediction applications where accuracy and reliability must take precedence over computational efficiency and perfect interpretability

IV. CONCLUSION

This study establishes the Random Forest Classifier as the most reliable algorithm for tsunami prediction when evaluated against Decision Tree Classifier, Decision Tree Regressor, and Linear Regression. It delivered an overall accuracy of 95.92%, with consistently high precision across Safe, Moderate, and Severe categories, as shown in Fig. 3.

The analysis demonstrates that Random Forest successfully combines the clarity of tree-based methods with the improved performance of ensemble learning. This advantage is emphasized in Fig. 1, while Fig. 2 highlights its robustness across varied tsunami scenarios. By enabling near real-time forecasting, the proposed approach addresses the delays of conventional simulation-based techniques and provides a solution that can be adapted to global monitoring networks. Future directions include expanding the dataset to additional regions, applying deep learning methods for further comparison, and designing hybrid models that integrate multiple approaches. In summary, this framework marks a significant step forward in tsunami prediction research, offering faster, more dependable, and interpretable early warning capabilities that can directly support disaster preparedness and save lives.

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