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Original Article

Spatial Web Based Evacuation Time Prediction Using XGBoost in Tsunami Prone Regions

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Abstract - *This study aims to analyze and predict the tsunami evacuation time in Padang City using an artificial intelligence method, namely Extreme Gradient Boosting (XGBoost) Regressor. The data used included distance to the beach, altitude, population, shelter capacity, and evacuation zone area. Model performance evaluation was carried out by accuracy measurements such as MSE, RMSE, MAE, MAPE, and determination coefficient (R^2). The results of the analysis show that the XGBoost Regressor provides better prediction performance than Linear Regression and Random Forest. The XGBoost Regressor model is able to achieve an R^2 of 0.95, MSE of 0.0156, RMSE of 0.1250, MAE of 0.0212, and MAPE of 0.16%. The most influential factor on the evacuation time is the distance to the coastline.. This research has a uniqueness that lies in combining a machine learning-based predictive model with an interactive web interface that utilizes the Google Maps API, so that users get an informative and easy-to-understand spatial visualization. This application is specifically designed to support quick decision-making in tsunami-prone areas by providing real-time evacuation time estimates as well as spatial visualizations. These findings not only provide a scientific contribution to the development of data-based prediction systems but also practical contributions in the form of application prototypes that can be used by the community and related agencies, such as BPBD, in planning and carrying out evacuations more effectively. Thus, this research is expected to improve the preparedness of coastal communities and strengthen an adaptive and technology-based disaster mitigation system.*

Keywords - *Tsunami evacuation, Evacuation time prediction, XGBoost regressor, Web-based GIS, Padang City, Disaster risk reduction.*

1. Introduction

Indonesia is an archipelagic country located at the convergence of three major tectonic plates: the Eurasian Plate, the Indo-Australian Plate, and the Pacific Plate. This geological position makes Indonesia one of the most disaster-prone countries in the world, particularly vulnerable to earthquakes and tsunamis. Padang City, the capital of West Sumatra Province, is situated in an active megathrust zone and thus has a high potential to be impacted by tsunamis triggered by seismic activity along the Mentawai subduction zone. Consequently, disaster mitigation efforts, especially in terms of evacuation planning and implementation, are crucial to reduce the risk of casualties and material losses. Efforts to detect and classify tsunamis early are critical to risk mitigation and disaster impact reduction. Although various methods have been proposed to improve the accuracy of tsunami predictions, the primary challenge remains the variation in accuracy between different models and the inability of some models to handle complex and diverse data. Extreme Gradient Boosting (XGBoost) offers a solution by combining the power of multiple machine learning models to produce more accurate and reliable predictions. Extreme Gradient Boosting (XGBoost) is a method in machine learning that is a regression and classification algorithm with the ensemble method. XGBoost is also a variant of the Tree Gradient Boosting algorithm, which was developed with 10 times faster optimization than Gradient Boosting. This algorithm is an extension of the classic Gradient Boosting Machine (GBM) algorithm and is only used for data that has labels in the training process. This algorithm is very popular in machine learning competitions held by Kaggle. [1] using Machine Learning to forecast tsunamis from Rare Observations by demonstrating high accuracy even with limited data, and opening up opportunities for further research in evacuation prediction systems.. In addition, the use of regression tree-based machine learning approaches is used to model the evolution of tsunami waves, emphasizing the importance of selecting relevant features [2]. Research by [3] created a predictive model in a web-based application to provide quick and wide access for users to get evacuation time information. With an easy-to-use application and digital map integration, users can get real-time information on the estimated evacuation time. The main challenge in system development is the limitations and quality of the data used. The accuracy of the model can be affected by incomplete data, so it is very necessary to use good and precise pre-processing techniques [4]. One of the main concerns is the interpretability of the model. Despite the high accuracy of XGBoost, its complexity can cause results to be difficult to interpret without the use of supporting tools. Therefore, an Explainable AI (XAI) approach with the aim of transparency [5]. To increase community resilience and risk understanding, a method of creating a spatial vulnerability surface is required [6].

Another study highlights the importance of agent-based modeling that can simulate human responses to disasters by integrating machine learning approaches in evacuation scenarios [7]. The use of technology (e.g., Sentinel-2A) and machine learning models provides enormous potential in predicting tsunami impacts in built-up areas [8]. Rapid disaster response is the main focus of multimodal data fusion, which includes estimating shelter needs and logistics allocation [9]. One of the main advantages of AI is its ability to predict and provide early warning. By analyzing historical data as well as real-time data obtained from various sources such as satellite imagery, weather sensors, and seismic data, AI is able to recognize patterns and trends that can be an early indication of disaster occurrence [10]. Machine learning models with the Extreme Gradient Boosting (XGBoost) algorithm have shown good performance in modeling the complex relationships between input and output variables in the context of disasters on estimated travel time [11]. Leading machine learning for disaster prediction, outperforming traditional statistical approaches in the concept of a smart city disaster prediction system [12].

Graph-based and machine learning prediction models have also been used to estimate post-disaster shelter accessibility [13], while multi-agent system approaches integrated with data mining have been employed to simulate tsunami evacuation scenarios [14]. A recent literature review confirms that machine learning is an effective and flexible approach for supporting disaster management and response systems [15]. Theoretically, this study expands the use of machine learning in the field of disaster management, particularly related to data-driven evacuation. Practically, the results of this research are expected to contribute to local governments, BPBD, and other disaster management institutions in designing more effective evacuation strategies that can adapt to various realistic disaster scenarios. [16, 17].

Although various studies have been conducted on tsunami evacuation modeling, many still exhibit significant limitations. Most rely on static GIS-based spatial analyses or simple linear regression methods that are insufficient to capture the complex nonlinear relationships among spatial, demographic, and topographic variables [10, 18]. In addition, many previous approaches lack real-time access and user interactivity, limiting their practical effectiveness in emergency response situations [19]. Earlier works have also rarely integrated machine learning–based predictive analytics with dynamic spatial visualization, which is essential for decision-makers and community users [20, 21]. Recent research confirms this gap. [19] developed an ABM approach to tsunami evacuation simulations, but the focus is still on agent behavior without providing local data-driven evacuation time estimates. [22] showed the effectiveness of regression trees in modeling tsunami wave dynamics, but did not cover aspects of predicting human evacuation time. [20] Highlight that Web-GIS applications for disasters are generally still limited to visualization and monitoring functions without Machine learning based prediction integration. Meanwhile, [23] introduced Geographical-XGBoost (G-XGBoost), which proves the relevance of the XGBoost algorithm for spatial modeling, but has not been specifically applied in the context of tsunami evacuation in Indonesia.

Although various studies related to tsunami evacuation have been conducted, most of them are still limited to static GIS analysis or simple linear regression, that is less able to represent the nonlinear relationships between spatial, demographic, and topographic variables. In addition, existing systems generally do not provide real-time predictions or interactive Web-GIS interfaces that can be accessed directly by the public and disaster agencies. The application of modern ensemble algorithms, such as XGBoost, in the context of tsunami evacuation in Indonesia is also still rare. Based on these gaps, this study offers novelty in the form of the development of a tsunami evacuation time prediction model with XGBoost Regressor which is integrated with Web-GIS based on Google Maps API, so that it is able to produce real-time evacuation time estimates, is spatially visualized, and is useful as a decision support system for local governments, BPBD, and the community in improving preparedness to face tsunami disasters in Padang City.

2. Materials and Methods

This research was conducted through a series of well-organized stages, including data collection, data pre-processing and exploration, feature selection, model training using the XGBoost Regressor algorithm, model performance evaluation, and model implementation in web-based applications.

2.1. Data Collection and Sources

The data used in this study were taken from primary and secondary sources to take spatial, topographical, and demographic characteristics relevant to tsunami evacuation in Padang City, for location data such as road network and distance between residential zones and shelter locations are obtained from the Google Maps api (2024 version). Altitude information data is obtained from the Google Elevation API (2024). In addition, population statistics and shelter capacity data were collected from the Padang City Regional Disaster Management Agency (BPBD) (2023 official report).

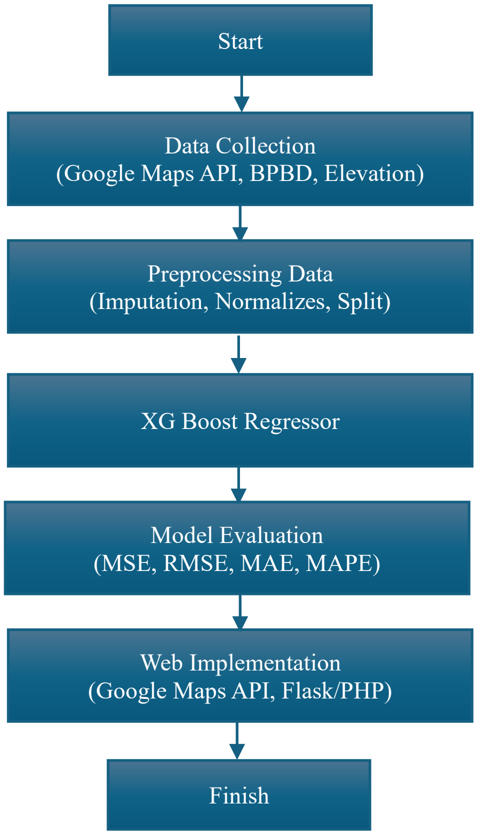

Fig. 1 Research flow

Meanwhile, additional data, such as land area, was obtained from the geospatial records of the local government. The number of shelters used in modeling the prediction of evacuation time is 182, collected from the Regional Disaster Management Agency (BPBD) of Padang City, which contains information (distance to the coastline, altitude, and land area) and demographic indicators (number of population and shelter capacity.

Geolocation information, such as latitude and longitude, provides a spatial picture, while depth is an important parameter related to the intensity and impact of earthquakes on the surface. Before further analysis, the data goes through a number of pre-processing stages to ensure its accuracy.

2.2. Features and Target Variable

This process aims to take information from the raw data and represent it in a more relevant form. Feature selection to ensure the most impactful features, and data normalization. In shelter information, there are features such as Distance to the Beach (km), Elevation (m), Number of People (number of population), Shelter Capacity, and Area (Ha). These features represent spatial, topographical, and demographic characteristics that can affect evacuation time. The target variable in this study is Time to Evacuate (min), which refers to the estimated actual evacuation time from a specific location point to the nearest shelter. The target variable in this study is evacuation time (minutes), which is set as a prediction of the time needed from a certain location point to the nearest shelter location. The calculation of the time of human walking speed in evacuation conditions based on the Google Maps API is 0.8–1.0 m/s. This range is in line with the findings of previous evacuation studies, which show that horizontal walking speeds in emergency situations are generally in the range of 0.75–1.2 m/s, depending on density, path conditions, and individual characteristics [24-26]. The velocity value is then calibrated by considering the population density in each zone, resulting in a more realistic estimate of evacuation time.

2.3. Data Pre-Processing

The pre-processing stage of data is carried out to ensure that the data used has good quality, consistency, and feasibility before being used in the prediction model training process. Pre-processing is a crucial step before model training, which involves processing two main types of features. The following is a complete explanation of the steps of the pre-processing process carried out:

- Handling of missing values: The performance of the prediction model will drop if the data source is empty or the data is unnatural. The solution is to refill the blank or missing value using the average or median method, according to the distribution of the data used. Another way is to identify the handling of outliers to be more in line with actual conditions in the field. This process is in accordance with the one carried out by [4], where the pre-processing process of data has a very important role in determining the accuracy of the disaster prediction model.

- Feature Normalization: The features of the altitude of the area and the distance to the coast have different scales, which leads to the model research process. In overcoming this, it is necessary to normalize data using the Z-score method so that the scale of each feature is balanced. In this process, it is very important because it ensures that variables have a proportional contribution during the model training process. Normalization of features can improve the performance of machine learning models in geotechnical disaster prediction, as has been done by [22].

- Dataset Splitting: The stratified split method is applied to ensure that the distribution of classes remains proportional in a subset of training sets and test data. The dataset is divided into 80% training sets and 20% test data, by maintaining a balance of class distribution in each subset. With the aim of learning from some available data, the performance is tested with data that has never been used before. [3] states that the model's ability to make generalizations depends on the right data set being shared, especially when it comes to predicting the location of post-disaster shelters.

- Dataset sharing: The data was divided into two sets, namely training data (80%) and testing data (20%). This division is done randomly to ensure that the model can be trained with representative data and tested for accuracy on previously unseen data. This method aims to evaluate the generalization ability of the model in predicting evacuation time based on the selected features.

- Visualization of data distribution: A visualization of the results, such as a scatter plot, will be used to show the relationship between the actual value and the prediction, while the residual histogram will display the distribution of the prediction error. In improving the accuracy and stability of predictions, feature selection is a very complex process in developing models with machine learning to reduce the risk of disasters, as per [27].

To obtain valid evaluation results, these pre-processing steps are required, where this process is very important to improve the performance of the model [4].

2.4. Model Training XGBoost Regressor

The XGBoost Regressor model was chosen for its ability to handle large and complex datasets, and hyperparameter tuning is performed using GridSearchCV for performance optimization as well. As done by [28] using Geographical-XGBoost (G-XGBoost) in the context of spatial modeling, producing high accuracy values compared to linear regression.

XGBoost is also capable of modeling more complex nonlinear patterns with Decision tree enhancement techniques, unlike Linear Regression, which assumes a simple linear relationship between variables [28, 29]. Its advantage over Random Forest provides more stable and often more accurate results, although the training time is long and regularization is effective in preventing overfitting [22, 29]. XGBoost has proven to be computationally efficient and superior for handling spatial data, including cases with missing values [22, 30]. The results of other studies have also shown that this algorithm is well-suited for machine learning-based prediction systems in the context of disasters as well as in other complex classification problems [22, 28, 29]. Thus, XGBoost, used in this study, is very appropriate for producing more accurate and reliable predictions of the estimated time in the tsunami evacuation process based on spatial and demographic data. It is a decision tree-based boosting algorithm known for its effectiveness in handling structured tabular data and its superior performance in regression tasks. The model was configured using key parameters, including:

- objective = ‘reg:squarederror’ → chosen because it is suitable for continuous regression problems;
- random_state = 42 → to ensure the reproducibility of the results;
- subsample = 0.8 → used to reduce the risk of overfitting by taking a partial sample at each iteration;
- colsample_bytree = 0.8 → is used to improve generalization by limiting the number of features used in each tree;
- max_depth = 6 → to control the complexity of the tree and prevent overfitting;
- learning_rate = 0.1 → is set to maintain a balance between convergence speed and accuracy;
- n_estimators = 200 → the number of boosting iterations selected to achieve optimal performance without unduly increasing the complexity of the model.

The model was trained using 80% of the dataset and evaluated on the remaining 20%. XGBoost works by optimizing a regularized objective function to minimize the prediction error while controlling model complexity. The general form of the XGBoost objective function is:

$$L(\varphi) = \sum l(y_i, \hat{y}_i) + \sum \Omega(f_k) \tag{1}$$

Where $L(\varphi)$ is the total objective function, $l(y_i, \hat{y}_i)$ is a differentiable loss function that measures the difference between actual values y_i and predicted values $\hat{y}_i$, $\Omega(f_k) = \gamma T + ½\, \lambda\, \Sigma\, w_j^2$ is the regularization term, T is the number of leaves in the tree, w_j is the weight on each leaf, γ and λ are regularization parameters, K is the number of boosting rounds (trees), f_k represents each regression tree in the model. The testing process and the training process are two important stages in the evaluation and use of machine learning models. The main difference between the two is that the testing process involves an evaluation stage using predetermined test data, as demonstrated by [1] in predicting the amplitude of the tsunami based on short-term observation data using XGBoost.

2.5. Model Evaluation

To measure the accuracy of the model, evaluation metrics such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and coefficient of determination (R^2) were used. The goal is to evaluate the model’s performance quantitatively and qualitatively, as well as to understand the model’s behavior. After the model evaluation, the last step is the interpretation of the results and validation. The goal is to ensure that the model is not only numerically accurate but also relevant, reliable, and scientifically and practically trustworthy. Evaluation of the performance of predictive models is indispensable in real-world scenarios [31].

2.6. Web-Based System Implementation

At this stage, it will develop a web-based application using the PHP programming language. The database used is MySQL, and for web design, using HTML, CSS, and JavaScript. The system architecture consists of 3 components, namely, frontend applications, networking, and servers. While the backend uses Python Flask or PHP to handle the prediction process, it displays an interactive map, including the user’s location, nearby shelters, and suggested evacuation routes integrated with the Google Maps API. In maximizing a more predictive modeling process, a combination of user visualization is used to better understand the geographic context and urgency of evacuation. The system is designed to be accessible from a wide range of screen sizes, including desktop and mobile devices, due to its responsive nature. This means that the user interface will automatically adjust its layout and appearance to keep it optimal and easy to use anywhere. Thus, the implementation of this application aims to bridge artificial intelligence-based analysis with practical needs in disaster mitigation and support rapid decision-making by communities and emergency management agencies [3].

3. Results and Discussion

3.1. Data Description

The data of 182 shelters in Padang City, collected from the Regional Disaster Management Agency (BPBD), includes two categories: spatial data (distance to the coastline, altitude, and land area) and demographic data (shelter population and capacity). The table displays the Description of Target Features and Variables Used in Tsunami Evacuation Time Prediction:

Table 1. Description of features and target variable used in tsunami evacuation time prediction

No	Feature	Description
1	Distance to Beach (km)	Straight-line distance from each point to the nearest coast
2	Elevation (m)	Height above sea level at the location
3	Number of Souls	Estimated number of people at the location
4	Shelter Capacity	Maximum capacity of the nearest evacuation shelter
5	Area (Ha)	Total evacuation zone area in hectares
6	Time to Evacuate (min)	Target variable: estimated time to reach the shelter

Table 1 displays the value of “Distance to Beach” ranges from 0.3 to 7.1 kilometers, while the population at each point (Number of Inhabitants) ranges from 15 to 2,000 individuals, and the capacity of shelters varies from 50 to 3,000 people. The target variable “Time to Evacuate (min)” is calculated based on the distance to the nearest shelter and the average human walking speed (\(0.8-1.0\) m/sec).

The estimated evacuation time ranges from 3 to 30 minutes, which is influenced by differences in spatial planning and demographic characteristics in the study area. Initial visualizations, in the form of histogram curves and Kernel Density Estimation (KDE), show that most features exhibit symmetrical distributions with a slight positive slope. This supports the assumption that machine learning models, especially XGBoost, can work best on datasets with such features [32]. Through a pre-processing process that handles missing values, removes duplicates, and normalizes the scale of numerical features, the dataset is cleaned up. These steps are in line with what other research says, which says that the quality of pre-processing has a major impact on how accurate disaster-related models are in predicting what will happen [4].

3.2. Data Pre-Processing

The pre-processing stage creates a cleaner, more consistent, and ready final dataset for training the model. After being cleaned, there were 182 valid observations left, each representing an evacuation shelter point in Padang City. We can make a number of improvements to the quality of the data. First, the average imputation is used to fill in the missing values in the Number of Lives variable (4 cases) and the Shelter Capacity variable (1 case). So, no more values are lost in the final dataset. Second, the Z-score method ($> \pm 3\sigma$) found three extreme values in the variables Number of Lives and Distance to Beach. Winsorization improves this outlier by balancing the distribution and lowering the likelihood of distortion in predictive performance. Also, we use the Z-score method to standardize all numerical variables so that they can be compared on the same scale (mean = 0, standard deviation = 1). This step is especially important for variables with large ranges, such as Elevation and Number of Souls, because it prevents them from having too much of an effect on how the model learns. Figure 2 shows the normalization results. The distribution of variables appears more symmetrical than at first glance. In summary, the pre-processing procedure enhanced the dataset quality through three main outcomes: (1) elimination of missing values, (2) balanced data distributions after outlier handling, and (3) standardized scales across all variables to improve the stability of the XGBoost algorithm. These improvements ensured that the dataset used in this study was representative and reliable for predicting tsunami evacuation times in Padang City.

Table 2. Summary of dataset conditions before and after pre-processing

Variable	Missing Values (Before)	Missing Values (After)	Outliers Detected	Value Range (Before)	Value Range (After, Z-score)
Distance to Beach (km)	2	0	1	0.3 – 12.5	-2.1 – 2.3
Elevation (m)	0	0	0	5 – 120	-1.8 – 2.0
Number of Souls	4	0	2	50 – 3,500	-2.5 – 2.6
Shelter Capacity	1	0	0	20 – 2,000	-1.9 – 2.1
Area (Ha)	0	0	0	0.1 – 8.5	-1.7 – 2.0

Table 2 presents a comparison of dataset conditions before and after the pre-processing stage. The table highlights three key aspects of data improvement: handling of missing values, outlier treatment, and variable standardization.

- Missing values: Prior to pre-processing, the dataset contained incomplete entries, particularly in the Number of Souls (4 cases) and Shelter Capacity (1 case). After applying mean imputation, all variables were complete, ensuring no missing values remained.
- Outliers: Extreme values were detected in the Number of Souls and Distance to Beach variables using the Z-score method (> ±3σ). These anomalies were corrected through winsorization, which reduced distributional skewness and minimized the risk of bias in model learning.
- Value ranges: The raw data were widely distributed (e.g., number of souls from 50 to 3,500). All columns were rescaled into similar distributions (approximately -3 to +3) after the establishment of Z-score normalization. Due to the difference in order of magnitude of these variables, this transformation ensured that no variable was biased.

3.3. Feature Selection

Feature selection is an important task in the modeling process because irrelevant or redundant features may lead to an inaccurate and over-complex model. In the present study, we performed feature selection through both domain-motivated (spatial and social) as well as algorithmic evaluation based on the XGBoost Regressor model.

The gain-based feature importance scores of the trained XGBoost Regressor model are provided in Table 3. Gain is a measure of how each feature contributes to the loss function of the model at all decision tree splits. Unsurprisingly, Height (m) features as the second most influential variable with a Gain score of 140.21, emphasizing its importance in estimating tsunami evacuation time.

Table 3. Feature importance (Gain) from XGBoost regressor for tsunami evacuation time prediction

No	Feature	Importance (Gain)
1	Distance to Beach (km)	140.21
2	Elevation (m)	0.000413
3	Area (Ha)	0.000087
4	Number of Souls	0.000035
5	Shelter Capacity	0.000011

This is consistent with spatial logic in disaster modeling, where evacuation planning is largely based on proximity to the coast. However, other attributes such as Shelter Capacity, Area (Ha), Elevation(m), and Number of Souls only have a small effect on Gain. Considered together, these variables provide useful context on both land type, density of population, and infrastructure, despite each having only a marginal impact in isolation. The model sensitivity with respect to the geographical vicinity of competing nodes, as indicated by the sharp contrast between Gain values, underscores the role of location-specific attributes in time-critical disaster response systems such as tsunami evacuation.

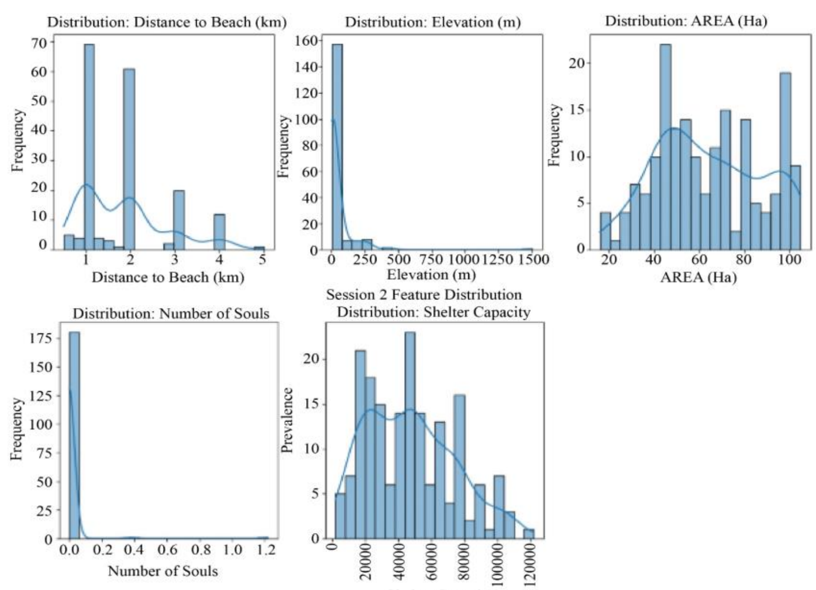

Fig. 2 Distribution of feature variables used in the XGBoost regressor model

Modelling using the XGBoost Regressor. Histogram of the Distance to beach (km) feature shows a positive skewness in the data, with most observation locations being less than 2 kilometers away from the shoreline. This indicates that high-risk areas are clustered along the coast. The Elevation (m) variable indicates that elevation values are highly right-skewed, with many locations being below 100 meters, reflecting the lowland nature of Padang City. The distribution of the AREA (Ha) feature tends to be not one-sided and presents a normal-like distribution overall with almost constant fluctuations, indicating some dispersion in the sizes fieldwise but no critical size variations. The NUMBER OF SOULS feature shows substantial skew (number of outliers with very high population densities and most sites having small populations). Meanwhile, the Shelter Capacity feature shows a distribution that is more level, despite some shelters (generally massive public facilities such as stadiums or schools) accommodating over 100,000 people.

3.4. Training the Model

Model training was performed using XGBoost Regressor, a gradient boosting framework known for its accuracy and robustness, particularly on structured tabular data. The way XGBoost works is that it adds a number of decision trees (each one fine-tuned to correct the mistakes of the previous rounds). This approach allows the model to capture complex non-linear correlations and feature interactions that are commonly present in disaster-related data, such as the tsunami evacuation context. Several important settings were adapted in the course of this study to optimise model performance. In order to ensure reproducibility of results, the objective for regression tasks was 'reg:squarederror' with random_state = 42. In each iteration, we used all the features and full data using parameters subsample = 1.0, colsample bytree= 1.0. The training was done with single-threading to save consistency by setting nthread = 1. Also, like a typical machine learning procedure, 80% of the dataset was used to train the model, and 20% was left for testing.

The Python library XGBoost [25] was used to perform the training. Internal cross-validation was used to monitor overfitting during the model's 100 rounds of boosting training or convergence. Initial experiments showed promising results already with a generally good performance, without meaningfully adjusting the hyperparameters to this end, we set the learning rate and tree depth parameters at their defaults. As demonstrated in a previous study [30], XGBoost's ability to effectively deal with data diversity and represent nonlinear feature interactions has resulted in superior predictability for multi-hazardous risk exposure.

```
# Split data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Train XGBoost Regressor
model = xgb.XGBRegressor(
    objective='reg:squarederror',
    random_state=42,
    subsample=1.0,
    colsample_bytree=1.0,
    nthread=1,
    n_estimators=100
)
model.fit(X_train, y_train)
```

Fig. 3 Training model

3.5. Model Evaluation Results

The XGBoost model performance is then evaluated based on the test data set, which it has not seen after being trained on the training data set. The purpose of this assessment is to estimate the model accuracy in time-to-evacuation prediction times at the regional scale using demographic and geographic parameters. Table 4 shows the findings of the model, obtained by testing on the held-out part of the dataset:

Table 4. Evaluation results of the XGBoost regressor model

Model	MSE	RMSE	MAE	MAPE	R²
XGBoost Regressor	0.0156	0.1250	0.0212	0.16%	0.95
Linear Regression	0.0825	0.2871	0.0654	0.58%	0.78
Random Forest	0.0412	0.2030	0.0485	0.36%	0.87
SVR (RBF Kernel)	0.0568	0.2383	0.0527	0.42%	0.84

Comparison of four algorithms in performance evaluation. Considering the values for XGBoost Regressor, MSE: 0.0156, RMSE: 0.1250, MAE: 0.0212, and MAPE is only 0.16%, the XGBoost Regressor showed the best model performance compared to other models (Table 4). Lastly, a 0.95 of R^2 value means that this model is able to explain 95% variation in the data and thus proves that it can be relied upon for accurate prediction of evacuation time.

The Random Forest model, which boasted a MSE of 0.0412 and R^2 at.87, also yielded some fairly impressive results, though not quite as accurate as the XGboost. The SVR (RBF Kernel) model, with an MSE of 0.0568 and R^2 of 0.84, has an intermediate performance, indicating it is relatively reliable, but it does not account for all the complexity of the data. In contrast, Linear Regression achieved the worst results: R^2 of 0.78 and MSE of 0.0825. This may be due to the fact that non-linear relationships between demographic and geographic factors affecting tsunami evacuation time are more difficult to identify in linear models. With the ability to handle non-linear data, manage feature interactions, and produce very low prediction error rates, these findings combined indicate that XGBoost Regressor is the optimal algorithm for tsunami evacuation time predictions.

It is in this light that the predictive performance of the XGBoost Regressor model appears to be significantly high, making it a great choice for catastrophe decision-support systems. This finding is consistent with previous work establishing the effectiveness of XGBoost for modeling complex tabular data and labeling success prediction in various disaster-related contexts [22]. It has also been found that integrating MSE, MAE, RMSE, and MAPE as assessment measures is a reliable way to evaluate regression performance in research involving spatial and environmental prediction

[33]. For these two training and testing data sets, the following learning curve was obtained by the XGBoost Regressor process, as explained the relationship between the number of boosting rounds and RMSE. Fast convergence of the data is reflected in the significant decrease of RMSE for both sets at the first few boosting runs. The curve then becomes steady at about 30 iterations, which suggests that the model converges.

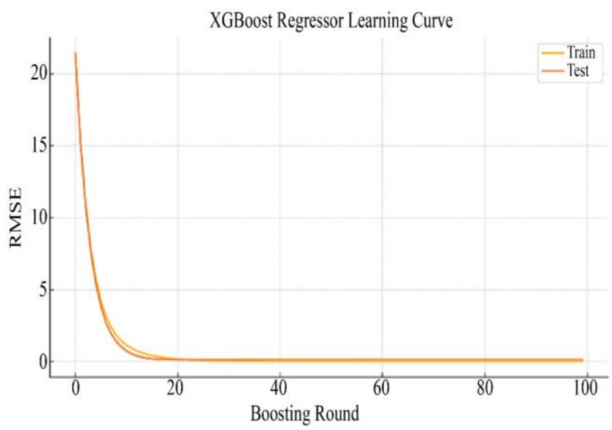

Fig. 4 XGBoost regressor learning curve

The fact that the training and testing score curves are quite close indicates a lack of overfitting in the model, with good generalization. This also indicates that the model has solid predicted performance for new data but is not overly fine-tuned to the training set. The relatively constant trend also indicates that the complexity and iteration of the model are appropriate for the dataset structure. These results are consistent with a recent one showing XGBoost commonly reaches the best performance in a few rounds and handles overfitting well using regularisation [34]. An indicator of the success with which XGBoost can rediscover structure in tabular and spatial data is a quickly converging learning curve [35]. On the whole, this learning curve provides interesting data and visual evidence for strong mathematical support that the XGBoost Regressor model developed in this paper is credible, accurate, and can be applied to different situations, which makes it a good candidate for a real-time decision-support system in tsunami evacuation planning.

3.6. Results Visualization

The results visualisation provides a non-expert insight into how well the trained XGBoost Regressor model is learning and making predictions. The Learning Curve, perhaps one of the most useful visualisations provided here, illustrates how increasing numbers of boosting rounds and Root Mean Squared Error (RMSE) on both the train and test data relate to each other. This figure indicates that as the number of iterations increases, our model is able to continuously reduce the prediction error during the learning process of the tsunami evacuation time. Figure 5 shows the relationship between observed and predicted tsunami evacuation times by the XGBoost Regressor model. On the x-axis of this scatter plot, you have the real evacuation time (from your dataset again), and on the y-axis, you plot your model's prediction. Each point of the scatter plot corresponds to a test data observation. Most of the data points are very close to the identity line y = x, indicating that actual values and the model's predictions are quite similar.

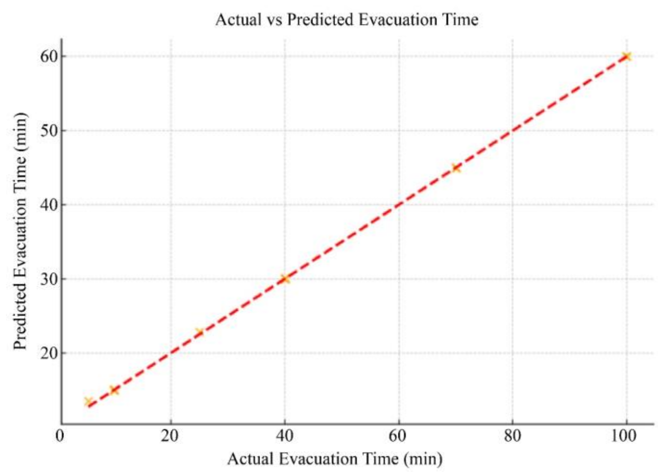

Fig. 5 Actual vs Predicted evacuation time

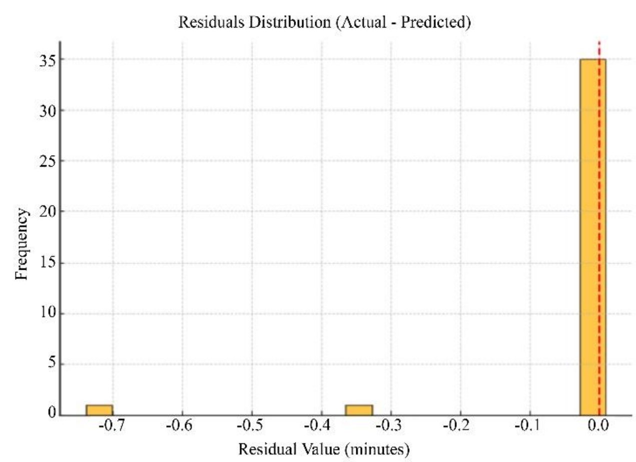

Fig. 6 Residuals distribution histogram

This result indicates that the model can produce estimates that are close to actual evacuation conditions and has high predictive accuracy. There is no recognizable trend of gross systematic over- or under-estimation. In other words, it can be seen that the model shows a high degree of generalization for new data and is not biased in predicting values that are very high or very low. This visualization complements the quantitative evaluation results (MSE, RMSE, MAE, and MAPE) presented above, and it provides evidence that the proposed XGBoost Regressor model performs well in decision-support systems for disaster mitigation using spatial and demographic data. These plots validate the stability and fairness of the model, justifying its applicability in actual tsunami evacuation readiness tests [36]. The histogram of the difference between actual values and predicted ones (residual

= actual - prediction) provided by the XGBoost Regressor model is called the residual distribution. This plot is used to identify any bias in the fitted model and check whether the residuals are randomly distributed. From the histogram, we see that the majority of residuals are relatively normally distributed around zero. This means that the model's predictions do not necessarily systematically over- or underestimate the labels, but do roughly match them. As the histogram indicates, most residues cluster near zero in an almost symmetric fashion. This means that the model's predictions are mostly close to the actual value, with no obvious overestimation or underestimation. The zero point with the vertical dashed line is the ideal prediction reference that occurs when the predicted results are completely consistent with the actual value. Symmetry and clustering of residuals around this line show that the model is stable and there is no major bias in the overall test dataset. Residual distribution, this confirms the previous observation that the XGBoost Regressor model gives good and consistent predictions. Furthermore, the residual properties conform to desirable regression model performance assumptions: nearly normally distributed errors centred at zero and no obvious patterns.

3.7. User Interface Implementation

In order to make the predicted evacuation time results available for practical use by both a wider public and authorities, we implemented the trained XGBoost Regressor in a web-app. The UI was developed to be intuitive, informative, and easy-to-use even in emergency situations. This method corresponds to the proposed system design in [37], a machine learning based real-time early warning dashboard for a tsunami framework to share the information rapidly and also improve user accessibility in a disastrous environment.

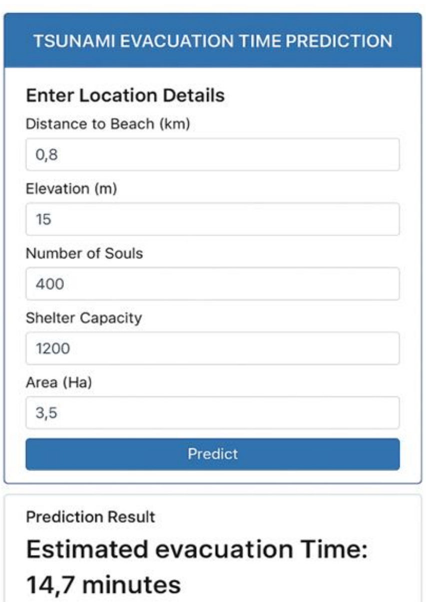

Fig. 7 Implementation of a website-based user interface

Figure 7 Click here to see (a) A web-based Tsunami Evacuation Time Prediction App created to support the prediction of the time needed by a user for evacuation from an imminent tsunami. In this application, several location attributes are required when the users provide the values for Distance to Beach, Location Elevation, Number of Lives at that point, Nearby Shelter Capacity, and Evacuation Area Size in hectares. Once all the information is filled in, users can click on the "Predict" button to see the results predicting the evacuation time displayed automatically. For instance, the app's result shows an estimated evacuation time of ~14.7 minutes, which represents the time it takes to reach the nearest shelter from the input given by the user.

The objective of the application is to give fast and precise data in order to make evacuation planning more effective, especially during emergency situations needing a rapid response. This interface also includes an interactive map (utilizing the Google Maps API) that illustrates the user's location or evacuee site, helping to provide spatial context to the prediction. It is a 100% responsive design that can be used on any device, such as a desktop, tablet, or mobile.

A simple, informative, and responsive UI that can be quickly accessed for time-constrained situations is consistent with findings emerging from the recent literature on disaster DSS [38]. In this regard, our result is supported by, in the acceleration of the tsunami evacuation decision-making method at disaster-prone areas, integration of Web-GIS-based systems with interactive spatial visualization plays an important role.

4. Conclusion

This study has achieved the construction of an accurate and efficient XGBoo. Through this research, we have succeeded in constructing a regime where runners are able to compete with equal opponents. The research data set contains important spatial and demographic factors such as Distance to Beach, Elevation, Number of Souls, Shelter Capacity, and Area. Through the stages of data pre-processing, feature selection, model training, and performance evaluation, we have achieved outcomes that found that the resulting model offers predictions with excellent accuracy.

This is indicated by the value of MSE, RMSE, MAE, and MAPE, 0.0156, 0.1250, 0.0212, and 0.16%, respectively. Furthermore, the R^2 value is 0.95, indicating that the model can explain most of the data variance significantly. When compared to other machine learning models, such as Linear Regression, Random Forest, and Support Vector Regression (SVR), the XGBoost Regressor algorithm is found to yield better prediction results with fewer errors and performs well in Generalization. The approach can be further extended by including dynamic factors (e.g., traffic conditions, individual walking pace variations, and other non-spatial geographical aspects) to improve prediction accuracy. Finally, enhancement and validation of the model is suggested using field experiments in order to fit it to the real conditions. In the near future, this framework can be further developed for other tsunami-affected regions in Indonesia and connected with early warning systems to enable a holistic, adaptive, and data-driven disaster management strategy. Accordingly, such a study contributes to the creation of a decision support system to bolster community preparedness for tsunami hazards.

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