International Journal of
DATA SCIENCE AND IOT MANAGEMENT SYSTEM
Peer Reviewed, Referred & Indexed Journal
ISSN: 3068-272X www.ijdim.com Original Research Paper

Machine Learning For Earthquake Emergency Evacuation: Site Selection And Neighborhood Navigation

Ms.K.Sai Durga, MCA-Assistant Professor, Department of MCA, Bapatla Engineering College, Bapatla, Andhra Pradesh

Mr.Gumma Sairam (Reg No:Y25MC23025), Mr.Kondra Sai (Reg No:Y25MC23035)
Mr.Shaik Thayab (Reg No:Y25MC23081), Mr.Adusumalli Naga Chaitanya (Reg No:Y25MC23003)
Department of MCA, Bapatla Engineering College, Bapatla, Andhra Pradesh.

***Abstract*—Abstract— Many big cities are at risk of earthquakes. Need good plans to help people evacuate quickly and safely. Cities with a lot of people often don't have emergency centers making it hard for some areas to get help. This study aims to create a plan for emergency evacuations during earthquakes. It uses a computer model to find the locations for emergency centers and help people navigate to them.**

The city of Tehran with 8.7 million people and several active fault lines is used as an example. Many neighborhoods in Tehran lack evacuation facilities. The computer model uses data about the city, its people and earthquake risks to find locations for emergency centers.

Tehrans data was used to train the model along with data from cities with similar risks and characteristics. The results show that this approach makes it much easier for people to evacuate. It reduces the distance people need to travel to reach an emergency center and increases the number of centers per person in each neighborhood.

A special app was also developed to help guide people to the emergency center during an emergency. This app uses maps. Routing algorithms to find the best route.

Combining computer-based site selection with navigation makes emergency evacuation planning more efficient, accessible and reliable. This framework can be used in cities, with similar characteristics and can be updated with local data to support disaster preparedness and urban planning.

Keywords: Earthquake Emergency Evacuation, Machine Learning, Evacuation Center Site Selection, Disaster Management, Urban Safety and Resilience, Evacuation Navigation Systems

I. INTRODUCTION

Earthquakes are bad natural disasters that can cause a lot of damage to buildings and roads and many people can get hurt or killed. In cities with a lot of people earthquakes can be even worse because it is hard for people to get out of the city quickly. So it is very important to have a plan for getting people to safety during an earthquake. One of the

...

things we need to do is find good places for people to go to be safe and make sure people can get to these places quickly.

The usual way of choosing where to put these places or earthquake evacuation centers is to use old methods that do not take into account how people move around the city how many people live in each area and how to get to these places. This means that many cities do not have enough of these places and they are often too far away from where people live. We need to find a way to plan for earthquakes and make sure people are safe.

New computer programs, like machine learning can help us plan for earthquakes. Make cities safer. These programs can look at a lot of information about the city like where people live and how they get around and use this information to make decisions. For example we can use machine learning to find the places to put earthquake evacuation centers so people can get to them quickly and easily. This can make a difference in keeping people safe during an earthquake.

In addition to finding places for earthquake evacuation centers we also need to make sure people can find their way to these places during an emergency. We can use maps and computer programs to help people find the shortest and safest way to get to the nearest earthquake evacuation center. By using machine learning to find locations for these centers and maps to help people get to them we can make a plan that helps keep people safe during an earthquake.

This study is trying to solve these problems by using machine learning to find the places for earthquake evacuation centers and to help people get to these places. We are using information about the city like where people live and how they get around to find locations, for these centers. We are also making a map to help people find the nearest earthquake evacuation center. By using machine learning and maps we hope to make cities safer and help people get to safety during an earthquake.

International Journal of
DATA SCIENCE AND IOT MANAGEMENT SYSTEM
Peer Reviewed, Referred & Indexed Journal
ISSN: 3068-272X www.ijdim.com Original Research Paper

II. ALGORITHM

The proposed algorithm uses machine learning techniques to identify optimal evacuation center locations and guide residents to the nearest safe center using navigation systems. The system analyzes urban, demographic, and seismic data to determine suitable evacuation sites and dynamically routes users during emergencies.

A. Algorithm: ML-Based Emergency Evacuation Site Selection and Navigation

Input: Urban dataset D containing population density, road network, building distribution, open spaces, seismic risk zones, and geographic coordinates.

Output: Optimal evacuation center locations and navigation route to the nearest evacuation center.

Step 1: Data Collection:

- Collect spatial and demographic data from urban planning databases.
- Gather seismic risk information and infrastructure data.
- Obtain road network and geographic coordinates from mapping platforms.

Step 2: Data Preprocessing:

- Remove incomplete or duplicate data records.
- Normalize spatial and demographic attributes.
- Convert geographic data into structured feature format.

Normalization is defined as:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

Step 3: Feature Extraction: Extract relevant features such as population density, distance to open spaces, road accessibility, and seismic risk level.

$$F = \{f_1, f_2, f_3, \ldots, f_n\} \quad (2)$$

where f_i represents urban or environmental features.

Step 4: Model Training: Train a Machine Learning model (Artificial Neural Network) using historical evacuation and spatial data to predict suitable evacuation center locations.

$$Y = f(F) \quad (3)$$

where Y represents the suitability score of a potential evacuation site.

Step 5: Optimal Site Selection: Rank candidate locations based on predicted suitability scores and select locations with the highest scores as evacuation centers.

The distance between residential parcels and evacuation centers is calculated as:

$$d = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \quad (4)$$

Step 6: Neighborhood Coverage Analysis: Evaluate evacuation center capacity relative to neighborhood population and ensure that each neighborhood meets minimum per capita evacuation requirements.

Step 7: Navigation Route Generation: Integrate OpenStreetMap data for road networks and compute the optimal evacuation path using routing algorithms.

$$Route = \min \sum_{i=1} w_i \quad (5)$$

where w_i represents the distance or travel time weight of each road segment.

Step 8: Real-Time Evacuation Guidance: Identify the nearest evacuation center for each user and provide navigation instructions using the routing algorithm.

Step 9: System Update: Continuously update urban and population data and retrain the machine learning model to adapt to changing city conditions.

III. METHODOLOGY

The proposed methodology aims to develop an intelligent framework for earthquake emergency evacuation planning using machine learning techniques. The framework focuses on two main components: optimal evacuation center site selection and dynamic neighborhood-level evacuation navigation. The system utilizes spatial, demographic, and infrastructural data to identify suitable evacuation center locations and guide residents to the nearest safe locations during emergencies.

A. Data Collection:

The first stage involves collecting relevant datasets required for evacuation planning. The dataset includes urban spatial data, population distribution, road networks, building density, land use information, and seismic risk data. Geographic information is obtained from open-source platforms such as OpenStreetMap, while demographic and urban planning data are collected from municipal or governmental databases. These datasets provide the necessary information to evaluate evacuation accessibility and neighborhood coverage.

B. Data Preprocessing: The collected data often contains missing values, redundant entries, and inconsistent formats.

International Journal of
DATA SCIENCE AND IOT MANAGEMENT SYSTEM
Peer Reviewed, Referred & Indexed Journal
ISSN: 3068-272X www.ijdim.com Original Research Paper

Therefore, preprocessing steps are applied to improve data quality and model performance. These steps include removing duplicate records, handling missing values, normalizing numerical attributes, and converting geographic coordinates into structured spatial features. The normalization process ensures that all features are scaled within a consistent range for machine learning processing.

C. Feature Extraction and Selection:

After preprocessing, relevant features are extracted to represent important urban and environmental characteristics affecting evacuation planning. These features include population density, distance to open spaces, road connectivity, accessibility to transportation routes, building distribution, and seismic vulnerability levels. Feature selection techniques such as correlation analysis and importance ranking are applied to identify the most significant variables influencing evacuation center suitability.

D. Machine Learning Model Development:

A machine learning model based on an Artificial Neural Network (ANN) is developed to identify optimal locations for evacuation centers. The model learns relationships between urban features and suitable evacuation site locations by analyzing spatial and demographic data. The ANN processes the input features and generates a suitability score for each potential evacuation site, indicating its effectiveness in serving nearby populations during emergencies.

E. Evacuation Center Site Selection:

Based on the predicted suitability scores generated by the machine learning model, candidate locations are ranked to determine the most appropriate evacuation centers. Spatial distance calculations are performed to evaluate accessibility between residential parcels and evacuation centers. The selected sites are distributed across neighborhoods to ensure balanced coverage and improved evacuation capacity for the population.

F. Neighborhood Coverage Analysis:

The system evaluates whether each neighborhood has adequate access to evacuation centers based on distance thresholds and population capacity. This analysis ensures that evacuation facilities are evenly distributed and that the per capita availability of safe spaces meets emergency planning standards. If coverage gaps are identified, additional candidate locations are recommended.

G. Evacuation Navigation System:

To support real-time evacuation during disasters, a navigation module is integrated into the system. Using OpenStreetMap data and routing algorithms, the system calculates the shortest or safest path from a user's location to the nearest evacuation center. The navigation system dynamically guides residents through accessible road networks, helping reduce congestion and evacuation delays during emergencies.

H. System Adaptability and Model Updating The proposed framework is designed to be adaptable to different cities. The machine learning model can be retrained with local urban and demographic data to improve prediction accuracy for new locations. Continuous updates to spatial and population datasets allow the system to adapt to urban changes and maintain effective evacuation planning.

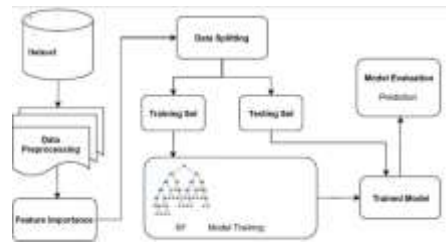

Fig. 1. Architecture Overview

IV. RESULT ANALYSIS

V. Results and Analysis

This section presents the results obtained from the proposed **Machine Learning-based Earthquake Emergency Evacuation framework** for optimal evacuation center site selection and neighborhood navigation. The evaluation focuses on improving evacuation accessibility, reducing travel distance to evacuation centers, and ensuring adequate evacuation capacity for residents across different neighborhoods.

A. Experimental Setup

The model was trained using spatial, demographic, and urban infrastructure data including population density, building distribution, road networks, land use patterns, and seismic risk zones. The dataset was divided into training and testing sets using an 80:20 ratio to evaluate the performance of the machine learning model.

An Artificial Neural Network (ANN) was used to analyze the relationships between urban features and suitable evacuation center locations. Additionally, geographic routing algorithms were integrated with OpenStreetMap data to compute optimal evacuation routes from residential areas to the nearest evacuation centers.

B. Accessibility Improvement Analysis

The machine learning model significantly improved evacuation accessibility by identifying optimal locations for evacuation centers. The analysis showed a reduction in the average minimum distance between residential parcels and evacuation centers, allowing residents to reach safe locations

International Journal of
DATA SCIENCE AND IOT MANAGEMENT SYSTEM
Peer Reviewed, Referred & Indexed Journal
ISSN: 3068-272X www.ijdim.com Original Research Paper

more quickly during emergencies.

The distance between a residential parcel and an evacuation center is calculated as:

$$d = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \tag{6}$$

where x_1, y_1 represent the coordinates of the residential reduces travel distances, and improves neighborhood-level coverage of evacuation facilities.

Overall, the proposed framework provides a data-driven and scalable solution for disaster preparedness, enabling urban planners to optimize evacuation infrastructure and improve public safety during earthquakes.location and x_2, y_2 represent the coordinates of the evacuation center.

By optimizing site selection, the system ensures that evacuation centers are more evenly distributed across neighborhoods.

C. Coverage and Capacity Analysis

The proposed framework also improved the per capita evacuation capacity across neighborhoods. The model evaluated whether each neighborhood had sufficient evacuation space based on population size and available evacuation facilities.

The per capita evacuation capacity is represented as:

Visualization and Output:

Fig. 2. wed page

$$C = \frac{A_e}{P_n} \tag{7}$$

where C represents per capita evacuation capacity, A_e represents the total evacuation area available, and P_n represents the population of the neighborhood.

The results showed that the optimized evacuation center locations significantly increased the coverage and accessibility of safe spaces for residents.

D. Navigation System Performance

The integrated navigation module used routing algorithms to guide residents to the nearest evacuation center through the shortest available path in the road network.

The optimal evacuation route was determined by minimizing the total travel distance across connected road segments:

$$Route = \min \sum_{i=1}^{n} w_i \tag{8}$$

where w_i represents the distance or travel cost associated with each road segment.

This routing approach ensures efficient evacuation guidance while minimizing travel time and reducing congestion during emergencies.

E. Discussion:

The experimental results demonstrate that the proposed machine learning framework effectively improves emergency evacuation planning in earthquake-prone cities. By combining machine learning-based site selection with real-time navigation, the system enhances evacuation accessibility,

Fig. 3. login page

Fig. 4. Prediced value

Fig. 5. Prediced value

VI. CONCLUSION

This research was conducted with two main objectives. The first was to develop an AI-based method to enhance the site selection of Emergency Evacuation Centers (EECs) in Tehran. The second aimed to address the existing gap in the emergency evacuation process by creating a web-based application for dynamic navigation, utilizing a neighborhood- based approach to guide users from their location to the nearest EEC. Employing AI-based models eliminates the conventional errors associated with traditional questionnaire- based approaches. These errors include limitations in respondent sample size,

International Journal of
DATA SCIENCE AND IOT MANAGEMENT SYSTEM
Peer Reviewed, Referred & Indexed Journal
ISSN: 3068-272X www.ijdim.com Original Research Paper

spatial constraints in questionnaire results, omission of key criteria, and the static nature of questionnaire outcomes. In this research, due to the similarities between Tehran and San Francisco in terms of seismic risk, urban fabric, building types, and population density—key factors influencing the selection of Emergency Evacuation Centers (EECs)—the AI model was applied to Tehran using data from San Francisco. It is worth noting that San Francisco has extensive experience in earthquake disaster management, making it a suitable reference for developing the model for Tehra sample size, spatial constraints in questionnaire results, omission of key criteria, and the static nature of questionnaire outcomes. In this research, due to the similarities between Tehran and San Francisco in terms of seismic risk, urban fabric, building types, and population density—key factors influencing the selection of Emergency Evacuation Centers (EECs)—the AI model was applied to Tehran using data from San Francisco. It is worth noting that San Francisco has extensive experience in earthquake disaster management, making it a suitable reference for developing the model for Tehran. To achieve this, various algorithms, such as Gaussian Processes Classifier, K-Nearest Neighbors, Support Vector Machines, and Artificial Neural Networks (ANN), were tested. Ultimately, the ANN method was selected as it yielded the most favorable results, achieving an F1 score of over 95%. The ANN model was developed using information layers such as land use, land area, land slope, population density, minimum distance to emergency water supplies, minimum distance to medical centers, minimum distance to fire stations, and minimum distance to public security centers. These layers underwent necessary pre-processing before being input into the model to generate a map of the estimated EECs. The results showed.

VII. FUTURE SCOPE:

The scope of this research can be extended in several directions to further enhance its applicability and impact: 1. Integration of real-time data from wearable devices and Internet of Medical Things (IoMT) sensors for continuous health monitoring. 2. Expansion of the diagnostic framework to include additional diseases and multi-class disease prediction. 3. Implementation of federated learning combined with blockchain to enable privacy-preserving collaborative model training across healthcare institutions. 4. Adoption of explainable AI (XAI) techniques to improve the transparency and interpretability of diagnostic decisions. 5. Deployment of the proposed system in real-world clinical settings and evaluation using large-scale, diverse patient datasets.

REFERENCES

[1] G. Pallis, D. Zeinalipour-Yazti and M. D. Dikaiakos, ”Online social networks: Status and trends” in New Directions in Web Data Management 1, Berlin, Germany:Springer, pp. 213-234, 2011. Show in Context CrossRef Google Scholar

[2] J. Heidemann, M. Klier and F. Probst, ”Online social networks: A survey of a global phenomenon”, Comput. Netw., vol. 56, no. 18, pp. 3866-3878, Dec. 2012. Show in Context CrossRef Google Scholar

[3] L. C. Freeman, ”Centrality in social networks conceptual clarification”, Social Netw., vol. 1, no. 3, pp. 215-239, Jan. 1978. Show in Context CrossRef Google Scholar 4. U. Brandes, ”A faster algorithm for betweenness centrality”, J. Math. Sociol., vol. 25, no. 2, pp. 163-177, 2001. Show in Context CrossRef Google Scholar

[4] K. Okamoto, W. Chen and X.-Y. Li, ”Ranking of closeness centrality for large-scale social networks”, Proc. Int. Workshop Frontiers Algorithmics, pp. 186-195, 2008. Show in Context CrossRef Google Scholar

[5] P. Bonacich, ”Some unique properties of eigenvector centrality”, Social Netw., vol. 29, no. 4, pp. 555-564, Oct. 2007. Show in Context CrossRef Google Scholar

[6] P. Bonacich, ”Factoring and weighting approaches to status scores and clique identification”, J. Math. Sociol., vol. 2, no. 1, pp. 113-120, Jan. 1972. Show in Context CrossRef Google Scholar

[7] M. Kitsak, L. K. Gallos, S. Havlin, F. Liljeros, L. Muchnik, H. E. Stanley, et al., ”Identification of influential spreaders in complex networks”, Nature Phys., vol. 6, no. 11, pp. 888-893, Nov. 2010. Show in Context CrossRef Google Scholar

[8] S. X. Zhao, R. Rousseau and F. Y. Ye, ”H-degree as a basic measure in weighted networks”, J. Informetrics, vol. 5, no. 4, pp. 668-677, Oct. 2011. Show in Context CrossRef Google Scholar