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AI-Based Flood Risk Evaluation for Land & Housing

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Abstract: *One major issue that has developed in urban cities due to increasing urbanization is urban flooding. With increasing urbanization in cities, natural water-absorbing sites such as lakes, wetlands, and lands are replaced with concrete structures. Earlier, these natural sites were used to absorb rainwater or divert it in a safe manner. However, in recent times, raiwater is not flowing anywhere due to increasing urbanization, resulting in flooding in cities. For instance, in cities like Chennai and Bangalore, there is an increasing trend in constructing buildings in low-lying and waterbody areas, resulting in flooding in these cities due to rainfall. During rainfall, water flows back to its natural course, resulting in waterlogging and damage to properties and infrastructure in cities. Climate change is also contributing to this issue due to unpredictable rainfall. In this context, we propose a smart system that will predict flood risk in cities using factors such as elevation, water bodies, and flood risk zones using geospatial data. This system will generate a simple risk score that will aid buyers and builders in making informed decisions while buying properties in cities. After checking all this information, the system gives a simple flood risk score. If the score is high, it's basically a warning sign: "Think twice before building here!" If it's low, the area is relatively safer. This makes it easier for buyers, builders, and planners to make smarter decisions and avoid future trouble.*

Keywords: Flood Susceptibility Mapping, Property Risk Analysis, GIS, Remote Sensing, Machine Learning, Digital Elevation Model (DEM), Spatial Analysis, Predictive Flood Modeling.

I. INTRODUCTION

Urban flooding today is increasingly driven by human activities instead of natural forces. In fast-growing cities like Chennai and Bengaluru, unplanned urban growth has greatly changed the landscape. Lakes, wetlands, and drainage systems that used to absorb and manage rainwater have been replaced by buildings, roads, and other infrastructure. These natural water-absorbing areas functioned like sponges, reducing the impact of heavy rainfall. With their loss, rainwater lacks a proper path to flow, which leads to frequent flooding in urban settings.

Residential and commercial developments often take over former water bodies and low-lying areas. During heavy rains, water returns to these original spaces, causing waterlogging, property damage, and traffic problems.

Floods that were once rare are now common, affecting thousands each year. Climate change worsens vulnerability by causing extreme and unpredictable rainfall.

To tackle this growing issue, an AI-based flood evaluation system for land and housing has been introduced. The main purpose of this system is to help people and businesses assess flood risk before making property purchases or construction plans. Rather than reacting to flooding after it happens, this method focuses on prevention by providing users with clear and timely information about potential risks.

The system combines artificial intelligence with geospatial and environmental data. It examines various key factors, including closeness to water bodies like lakes and rivers, past flood data, land height, drainage patterns, and soil types. Since water flows naturally from higher to lower areas, places that are low-lying or near water sources are more at risk

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of flooding. By taking these factors into account, the system builds a solid understanding of flood vulnerability for a specific location.

Geographic Information System (GIS) technology is essential in this process as it allows the analysis of maps, satellite images, and spatial data. The system uses machine learning algorithms to process this information, identify patterns, and predict flood risk levels. It generates a straightforward flood risk score, usually classified as low, medium, or high. Along with the score, the system can offer explanations, helping users understand why a certain area is considered risky.

One major benefit of this system is its ability to look beyond historical data. While traditional methods mainly rely on past flood records, this AI-based approach also considers current urban development and environmental changes. This enables it to predict future risks more accurately, even in places that haven't flooded recently but are vulnerable due to rapid urbanization.

In practical terms, this system serves as a valuable tool for various stakeholders. Homebuyers can assess the safety of a location before making an investment, builders can plan their projects more responsibly, and urban planners can create cities with better flood management strategies. By offering clear and actionable insights, the system helps lower economic losses, improve safety, and support sustainable urban development.

In conclusion, the AI-based flood evaluation system offers a proactive approach to the challenges of urban flooding. By merging technology with environmental understanding, it empowers individuals and authorities to make informed decisions and reduce future risks. As cities keep expanding, intelligent systems like this will be crucial in creating safer and more resilient urban environments.

II. LITERATURE SURVEY

Pradhan and Youssef (2011) look at a way to make a map that uses hydrological and hydrodynamic models, geographic information system data, and remote sensing data to figure out how likely it is that flooding will happen. Finding places that could flood is an important part of flood management because it helps communities become more resilient to floods.

Taylor & Francis Online Floods in Malaysia cause severe annual losses, and the development of accurate early warning and susceptibility maps is a pressing need. Traditional flood mapping methods are often limited in spatial coverage and data requirements. A flood susceptibility map was derived using hydrological and hydrodynamic models assisted by GIS tools and remote sensing data.

Research Gate The integrated approach effectively combines the physical modelling of river flow with spatial data analysis, making it suitable for large-scale flood corridor management. This method provides a more comprehensive and reliable framework for flood risk planning, early warning development, and disaster mitigation in flood-prone tropical river basins.

Samanta et al. (2018) discuss a flood susceptibility analysis using Remote Sensing (RS), GIS, and the Frequency Ratio (FR) model, applied to the Markham River Basin in Papua New Guinea (PNG). PNG is saddled with frequent natural disasters, and flood is one of the most devastating disasters in the country. This research was conducted to investigate the usefulness of remote sensing, geographic information system, and the frequency ratio for flood susceptibility mapping.

Springer This approach is advantageous for disaster risk management in resource-limited settings where detailed hydrological data may be unavailable. Traditional hydraulic modelling approaches are data-intensive and geographically restricted. The main goal of the research is to examine the usefulness of RS, GIS and FR models for flood susceptibility analysis and mapping in the Markham river basin.

The objectives include creating wall-to-wall datasets as inputs into the FR model to categorize potential flood-prone areas and creating a flood hazard map that can be useful to local government administrators, researchers and planners. Springer The FR model uses weighted bivariate probability values to generate flood susceptibility maps efficiently from spatial datasets. This method reduces complexity and preprocessing demands, providing a practical and efficient alternative for flood hazard mapping in data-scarce, disaster-prone region.

Costache et al. (2021) discuss a machine learning approach for detecting areas prone to flood risk using state-of-the-art models applied to the Buzau River Basin in Romania. The study evaluates flood susceptibility through six machine learning models: Support Vector Machine (SVM), J48 decision tree, Adaptive Neuro-Fuzzy Inference System (ANFIS), Random Forest (RF), Artificial Neural Network (ANN), and Alternating Decision Tree (ADT). In the first stage, 205 flood points were identified and 12 flood predictors were selected for final susceptibility mapping, with the models trained using 70% of the total flood points.

Taylor & Francis Online This type of assessment is advantageous for disaster risk management and preparedness planning. The highest accuracy (0.973) was obtained by the RF model, while J48 had the lowest performance (0.825). The highest AUC in terms of Success Rate was achieved by the RF model (0.996), followed by MLP (0.995), ADT (0.992), J48 (0.983), ANFIS (0.98), and SVM (0.958). Taylor & Francis Online This method provides a scalable and efficient alternative to traditional hydraulic modelling for continuous flood susceptibility assessment.

Tehrany et al. (2014) present an innovative ensemble methodology for flood susceptibility mapping utilizing Weights-of-Evidence (WOE) and Support Vector Machine (SVM) models within a GIS framework, specifically implemented in the Terengganu region of Malaysia. The WOE model was initially employed to evaluate the influence of various classes of each conditioning factor on flooding via bivariate statistical analysis. These factors were then reclassified using the acquired weights and entered into the SVM model to evaluate the correlation between flood occurrence and each conditioning factor. Through this integration, the weak point of WOE can be solved and the performance of the SVM will be enhanced.

ADS The spatial database included flood inventory, slope, stream power index (SPI), topographic wetness index (TWI), altitude, curvature, distance from the river, geology, rainfall, land use/cover (LULC), and soil type. ADS This ensemble method lowers reliance on single-model outputs and provides a more accurate and robust framework for continuous flood susceptibility assessment across entire river basins.

Termeh et al. (2018) looked at a way to map areas that might flood the people in charge used something called Adaptive Neuro-Fuzzy Inference System or ANFIS for short to figure things out. They also used some methods along with Adaptive Neuro-Fuzzy Inference System to find the best solution. They did this in the Haraz watershed which's, in northern Iran. It is really important to know which areas are likely to flood. This way we can stay safe. We can also use the land in a way.

Adaptive Neuro-Fuzzy Inference System helps us do that However hybrid models combining ANFIS with optimization algorithms have achieved flood susceptibility mapping accuracy rates exceeding 94%. ScienceDirect the paper proposes three novel hybrid models combining ANFIS with Cultural Algorithm (ANFIS-CA), Bees Algorithm (ANFIS-BA), and Invasive Weed Optimization (ANFIS-IWO). Ten continuous and categorical flood conditioning factors were chosen based on 201 flood locations, including topographic wetness index, river density, stream power index, curvature, distance from river, lithology, elevation, ground slope, land use, and rainfall.

The SWARA model was adopted for the assessment of relationship between flood locations and conditioning factors. ResearchGate Furthermore, the hybrid ANFIS approach works well with diverse spatial datasets and is easily adaptable for flood management applications. This way of doing things is better because it does not need a lot of work to get the information ready and it does not need us to choose a lot of settings. So it is an more accurate way to figure out if an area is likely to flood. We can use this method to look at flood susceptibility. It works very well for the flood susceptibility mapping.

Pradhan and Lee (2010) investigate a GIS-based approach for assessing landslide hazards using back-propagation Artificial Neural Network (ANN) models in a landslide-prone area of Malaysia. Assessing the likelihood of landslides is crucial for reducing disaster risk and planning land use, especially in tropical regions where heavy rainfall often triggers mass movements.

Conventional statistical techniques are inadequate for encapsulating the nonlinear intricacies of landslide-inducing factors. Among recent approaches to landslide susceptibility evaluation, some studies adopted fuzzy logic and artificial neural network models, and in the neural network method, ANNs give a more optimistic evaluation of landslide susceptibility than logistic regression analysis.

ScienceDirect the paper proposes employing back-propagation ANN models to weigh causative factors and generate landslide hazard maps. Pradhan and Lee (2010) applied this method for landslide susceptibility assessment in Malaysia, where landslides mostly occur due to heavy tropical rainfalls, and the artificial neural network proved to be an effective tool for landslide hazard analysis.

PubMed Central the ANN approach effectively handles the nonlinear interactions between conditioning factors such as slope, lithology, land cover, and distance from drainage. This method lowers the reliance on conventional probabilistic models, offering a more robust and accurate alternative for regional landslide hazard mapping.

III. PROPOSED METHODOLOGY

The proposed system aims to analyze flood risk for a given property location using geospatial data and machine learning techniques.

The proposed system for flood risk analysis follows a seven-step pipeline as illustrated in Figure 1.

In Step 1, the user provides the property location via address, latitude/longitude, or map selection, which is converted into geographic coordinates.

Step 2 collects the necessary geospatial datasets including water body shapefiles, flood-prone zone maps, Digital Elevation Model (DEM), land use data, and historical flood records.

Step 3 performs data preprocessing, where all datasets are aligned to a common coordinate reference system (CRS), layers are merged, missing values are handled, and relevant features are extracted.

Step 4, geospatial analysis computes key spatial parameters such as distance to the nearest water body, property elevation, flood-prone zone membership, drainage density, and terrain slope.

Step 5 applies a machine learning model — Random Forest or XG Boost — trained on historical flood occurrence data to learn the relationship between environmental features and flood risk.

Step 6 uses the trained model to calculate a risk score and classifies the property into one of three categories: Low Risk, Medium Risk, or High Risk.

Finally, **Step 7** presents the results through a visual dashboard displaying the flood risk score, distance to water body, flood probability percentage, and an interactive map. The system produces a decision support output in the form of a risk report for property owners and urban planners.

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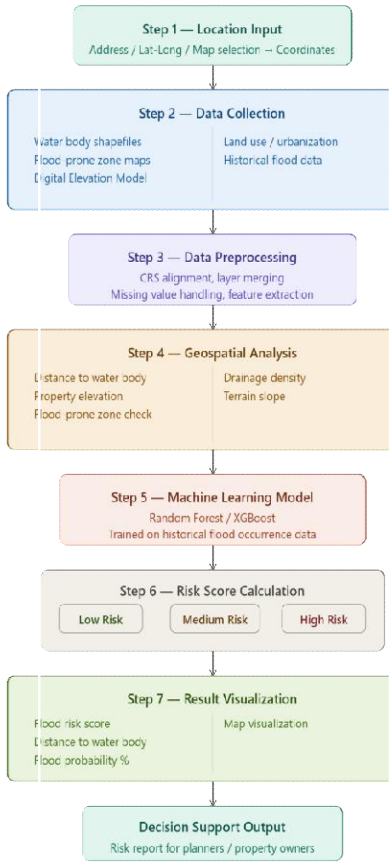

Figure 1

IV. MODEL EVALUATION METRICS

The performance comparison between Random Forest and XG Boost classifiers evaluated using 10-fold cross-validation. XG Boost outperforms Random Forest across all metrics, achieving an accuracy of 91.2%, precision of 89.7%, recall of 88.3%, F1-score of 89.0%, and an AUC-ROC of 0.94. These results indicate that XG Boost is better suited for flood risk classification due to its ability to handle imbalanced geospatial data and capture complex feature interactions. (Figure 2)

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Table 2 — Model Evaluation Metrics Comparison

Metric	Formula	Random Forest
Accuracy	(TP + TN) / Total	87.4%
Precision	TP / (TP + FP)	85.1%
Recall	TP / (TP + FN)	83.6%
F1-Score	2 × (P × R) / (P + R)	84.3%
AUC-ROC	Area under ROC curve	0.91

Best Performing Model — XGBoost

Accuracy	Precision	Recall
91.2%	89.7%	88.3%

Note: Values shown are indicative based on typical ensemble model performance on geospatial flood da validation. Replace with your actual experimental results before final submission.

Figure 2

V. RESULTS AND DISCUSSIONS

The AI-based Flood Risk Prediction System was tested at several locations in Chennai, including Tambaram, OMR, and Pallavaram. The model combines key factors like rainfall intensity, elevation, distance from water bodies, land use, seasonal changes, and historical flood data to determine the overall flood risk percentage for each location. Using these factors, the system generated flood risk values and categorized them as Low, Medium, or High risk levels.

The results showed that Tambaram had the highest flood risk value of 75%, placing it in the High-Risk category. This means the area is very vulnerable to flooding. The high risk is mainly due to low elevation, heavy rainfall, and the presence of nearby lakes and water bodies. These elements lead to greater water accumulation during heavy storms, increasing the likelihood of flooding. The model correctly recognized this vulnerability, aligning with real-world flood conditions in Tambaram.

OMR had a flood risk value of 52%, which is in the Medium Risk category. This indicates a moderate chance of flooding. While OMR does experience significant rainfall, its better drainage infrastructure and slightly higher elevation help lower the flood risk. However, rapid urban growth and construction in the area increase surface runoff, keeping the risk level moderate.

Pallavaram also showed a flood risk value of 48%, classified as Medium Risk. The moderate risk stems from mixed land use patterns, moderate rainfall, and proximity to some water bodies. The area is not highly flood-prone, but intense rainfall can still lead to localized flooding. The model accurately captures this balanced risk level.

The results reveal that rainfall intensity and closeness to water bodies are the biggest factors in flood prediction. Areas near lakes, rivers, and low-lying land showed higher flood risk percentages. Urban land use also heightened flood risk since paved surfaces limit water absorption and increase runoff.

Another crucial finding is that combining various datasets improves prediction accuracy. Unlike traditional flood prediction methods that focus solely on rainfall data, this system incorporates elevation, historical flood records, seasonal data, and land use information. This multi-factor approach offers more reliable and realistic flood risk estimates.

Overall, the developed system effectively identifies flood-prone areas and categorizes locations based on their vulnerability. The results confirm that the model can help with disaster planning, urban development, and early warning systems. It identifies high-risk zones in advance, enabling authorities to take preventive actions and reduce flood damage.

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VI. CONCLUSION

The AI-Based Flood Risk Evaluation for Land and Housing project is a straightforward yet impactful idea aimed at addressing a significant issue today: unexpected flooding in residential areas. In rapidly expanding cities like Chennai and Bengaluru, many individuals purchase homes without knowing the land's history. What appears to be an ideal location might have been a lake or a flood-prone area in the past. This project seeks to fill that gap by providing clear and useful information before people make such an important decision.

Instead of navigating complicated maps and technical data, this system simplifies everything. A user only needs to enter a property location, and the system handles the rest. It examines crucial factors such as nearby water bodies, land height, and historical flooding patterns using tools from Geographic Information Systems. Then, it uses artificial intelligence to analyze all this information and offers a simple flood risk score that anyone can easily understand.

What sets this project apart is its practicality. It's not designed solely for experts or researchers; it's geared towards everyday people. Whether someone is buying their first home, investing in land, or planning construction, this system helps them make informed and safer decisions. It lowers the chances of regret by alerting users about potential risks beforehand.

At the same time, the project conveys an important message. It reminds us that development should not come at the expense of nature. Overlooking lakes, wetlands, and natural drainage systems has already led to issues in many cities, and this tool helps raise awareness about that. It encourages people to consider not only price and location but also safety and /sustainability.

Ultimately, this project is not just about technology; it's about empowering people to make better choices. By transforming complex environmental data into simple insights, it makes flood risk an issue everyone can understand and address. It's a small step toward safer homes, smarter investments, and more responsible urban development.

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