Interactive Flood Inundation Probability Mapping: A Web-Based Application with Machine Learning Models

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***Abstract*— Flooding is the most common and destructive natural disaster globally, affecting millions of lives annually and causing significant economic losses. Flood forecasting is a critical aspect of disaster risk reduction and management. This study explores the application of machine learning techniques, particularly classification-based models like logistic regression and gradient boosting algorithms (XGBoost, CatBoost), to predict flood likelihood. The research emphasizes the potential of machine learning methods to enhance flood hazard assessment and proposes the use of web applications for real-time flood risk evaluation, leveraging geological data from APIs to provide actionable insights for disaster preparedness and community resilience.**

Keywords*— Classification based, Regression based, Gradient Boosting models, XGBoost model, CatBoost Model, Logistic Regression, flood hazard, APIs, ANN, Categorical factors, encoding, standardized, sklearn, confusion matrix, Precison, Recall, F1-score, MSE , R^2 score, web application, Normalization, Scaling, learning rate, estimators, Hyperparameters, DEM records, Hydrological modelling, Predicted values, dataset-1 , dataset-2, Accuracy, multilayer perceptron, Susceptibility maps, Synthetic Aperture Radar, one-hot encoding, Label encoding, n_estimators, max_depth, loss function, RMSE, CatBoostRegressor, XGBoostRegressor.

I. Introduction

Floods are the most widespread and destructive natural disasters globally, affecting millions of lives and causing significant economic losses annually. Each year, floods result in 6,000 to 20,000 fatalities, with countless others facing displacement, infrastructure damage, and disruptions to their livelihoods. The increasing frequency and severity of floods are closely tied to climate change, urbanization, and deforestation, which heighten vulnerability in both urban and rural areas. As a consequence, predicting and mitigating flood impacts has become a critical priority for governments, communities, and disaster management agencies. Traditional flood forecasting methods rely on hydrological and meteorological data but often prove inadequate due to the complex and dynamic nature of flooding and the growing complexity of environmental variables. Machine learning (ML), with its ability to analyze vast datasets and identify hidden patterns, presents a groundbreaking approach to flood prediction. ML models can combine diverse inputs, such as rainfall, terrain data, land use patterns, and infrastructure conditions, to generate accurate and timely forecasts. This study focuses on employing machine learning models like logistic regression and gradient boosting. By utilizing two datasets that include features such as monsoon intensity, drainage quality, and urbanization levels, this research aims to effectively assess flood probabilities. Furthermore, a user-friendly web application is proposed to empower real-time flood chance evaluation based on geological information fetched from APIs. By giving noteworthy bits of knowledge, this work points to back disaster readiness, minimize misfortunes and improve community versatility to flood dangers.

Overall, this research presents a novel approach to predict flood occurrence with utilizing web applications that can significantly improve the efficiency and accuracy of the disaster management.

II. Related Work

In a study by Amir Mosavi, Pinar Ozturk & Kwok-wing chau [2018] [1], the authors proposed a paper that introduces the most promising prediction methods for both long-term and short-term floods, emphasizing the role of machine learning models in flood prediction.

A study by Zaharaddeen Karami Lawal, Hayati Yassin & Rufai Zakari Yusuf [2021] [2]. This study aimed to create a machine learning model that can predict floods in Kebbi state based on historical rainfall dataset of thirty-three years (33), so that it can be used in other Nigerian states with high flood risk.

In a study by Nguyen, D.L., Chou, T. V. and chen, M. H. [3], the authors proposed a paper that aims to construct flood susceptibility maps in the Huong Khe district using three machine learning algorithms, namely the K - Nearest Neighbour (KNN), the Support Vector Machine (SVM) and Artificial Neural Network (ANN).

In a study by Sliman Hitouri, Meriame Mohajane, Meriam Lahsaini, Sk Ajim Ali, Tadesual Asamin Setargie, Gaurav Tripathi, Paola D'Antonio, Suraj Kumar Singh and Antonietta Varasano [4], the authors proposed a paper that a novel approach for flood susceptibility mapping by integrating Synthetic Aperture Radar (SAR) data with machine learning techniques.

In a study by Yogesh Bhattarai, Sunil Duwal, & Akitoshi Hanazawa[2024][5], authors proposed a paper that uses machine learning, including ANN, SVM, LSTM, and RF, for flood susceptibility mapping in Laos, highlighting the potential of open-source data in flood risk assessment.

In a study by Adel Rajab, Hira Farman, Norman Islam, Darakhshan Syed, M.A. Elmagzoub, Asadullah Shaikh, Muhammad Akram & Mesfer Alrizq[2023][6], This research focuses on leveraging historical meteorological data to find trends using machine learning and deep learning approaches to estimate rainfall.

In a study by Rahma Khalid & Usman T. Khan [2024][7], this paper explores the influence of model development and validation in FSM using Artificial Neural Networks (ANNs).

In a study by Mohammad Ahmadlou, A'kif Al-Fugara, Abdel Rahman Al-Shabeeb, Aman Arora, Rida Al-Adamat, Quoc Bao Pham, Nadir Al-Ansari, Ngyuen Thi Thuy Linh & Hedieh Sajedi[8], they proposed a novel hybrid model combining the multilayer perceptron (MLP) and autoencoder models to produce susceptibility maps for two study areas, enhancing flood risk assessment.

In a study by Md Hasanuzzaman, Aznarul Islam, Biswajit Bera, Pravat Kumar Shit [2022][9], they proposed a paper about a comparison of performance measures of three machine learning algorithms for flood susceptibility mapping of river Silabati (tropical river, India).

III. Methodology

The idea proposed for this research paper is to make a user-friendly web application where user can chose a location and get the flood probability. The probability are calculated using Machine Learning models.Here are the modules for the proposed approach:

1-Data collection and Preprocessing: The essential objective was to accumulate significant information that seem impact flood probabilities. This included topographical, climatic, and socio-economic factors. Two datasets were utilized. Missing values were dealt with utilizing imputation strategies or by dropping incomplete records. Categorical factors were encoded utilizing one-hot encoding or label encoding. Numerical features were standardized to guarantee uniform scaling. The datasets were part into preparing (80%) and testing (20%) sets to assess demonstrate execution. Confusion metrices were utilized of both dataset.

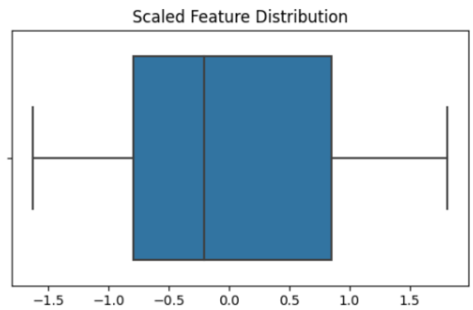

Figure 1: Feature Scaling Effectiveness (Dataset1):

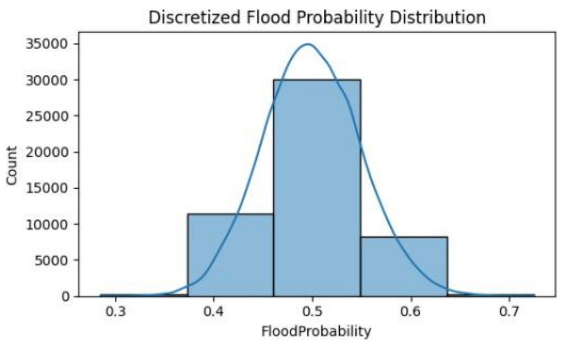

Figure 2: Discretization of Target Variable (Dataset2)

2- Machine Learning Models (Training phase):

(i)-Logistic Regression Model:

A Logistic Regression model was utilized for binary classification of flood chance. It permitted for understanding the relationship between predictor factors and the probability of a flood occasion occurring. The Logistic Regression model from sklearn was designed with parameters like max_iter=200 to adjust training term and model convergence. The target variable was discretized into bins to encourage logistic regression. The model was trained utilizing the preprocessed training data. Performance metrics including precision, accuracy, review, F1 score, and AUC-ROC were utilized to assess the model. A confusion matrix provided a point by point breakdown of the models performance. A classification report was produced to summarize precision, recall, and F1 score for each course during the model learning process.

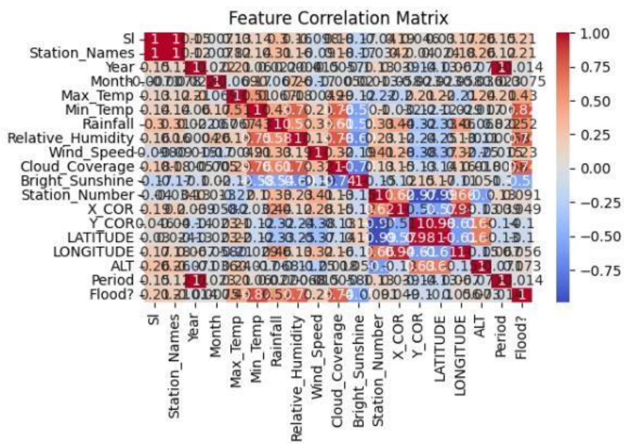

Figure 3: correlation matrix (dataset 1)

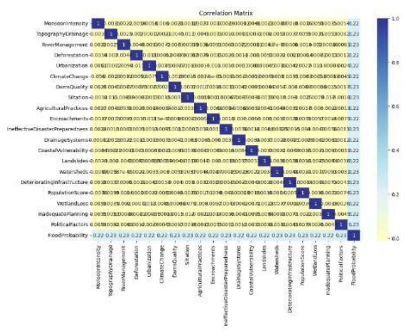

Figure 4: Correlation matrix (dataset - 2)

(ii)-XGBoost Model:

An XGBoost show was utilized for relapse assignments to anticipate ceaseless surge probabilities. This demonstrate is known for its effectiveness and tall expectation accuracy. The XGBRegressor from xgboost was arranged with n_estimators=100, learning_rate=0.1, and max_depth=6 to adjust demonstrate complexity and computational cost. Features were standardized to preserve consistency. The model was prepared on the training information to memorize complex connections between indicator factors and flood probabilities. Performance was evaluated utilizing Mean Squared Error (MSE) and R^2 Score, which gage the models expectation exactness and the variance explained by the model.

Factor	Score
MSE	0.00121
R^2	0.93209

Factor	Score
MSE	0.0002
R^2	0.9049

Figure 5: performance of dataset-1 and dataset-2 respectively

(iii)- CatBoost Model :

A CatBoost demonstrate was utilized for foreseeing persistent surge probabilities, A CatBoost model was utilized for foreseeing continuous flood probabilities, leveraging its strength and high efficiency. The CatBoostRegressor from the catboost library was arranged with iterations=100, learning_rate=0.1, depth=6, and loss_function='RMSE'. Standardization of features was performed to guarantee consistency over models. The model was prepared on the training information to capture connections between indicator factors and flood probabilities. Metrics such as Mean Squared Error (MSE) and R^2 Score were utilized to assess the models performance. During the training phase, Predicted values were compared with genuine values to survey the precision of the models expectations.

Factor	Score
MSE	0.0008906
R^2	0.9502992

Factor	Score
MSE	0.00017495
R^2	0.929756

Figure 6: performance of dataset-1 and dataset-2 respectively

3- Web Application Development :

To supply an interactive stage where clients can select a area of intrigued, and the trained models foresee the flood likelihood for that location. Clients can select a area by clicking on a map. The chosen locations coordinates are utilized to bring information pertinent to that range from the datasets. Based on the chosen area, the web application permits clients to choose a prepared machine learning model (logistic regression, XGBoost, or CatBoost) to get flood predictions. The application uses the chosen model to handle the location-specific information and produce flood likelihood outputs. The interface was designed to be user-friendly, directing the client through area choice, show choice, and showing forecasts clearly. The web application gets data related to the chosen area from different APIs, preprocesses it if essential, and applies the chosen model to create predictions. The result comes about are at that point displayed on the interface, giving a clear visualization of flood hazard for the chosen area.

4- Comparison Across Models :

The objective was to compare the performance of Logistic Regression, XGBoost, CatBoost, neural networks to decide the most viable model for flood prediction. Models were compared using metrics like accuracy, precision, recall, F1 score, MSE, and R^2 Score to provide a comprehensive understanding of their performance. Also we have compare the performance in terms of time and memory efficiency.

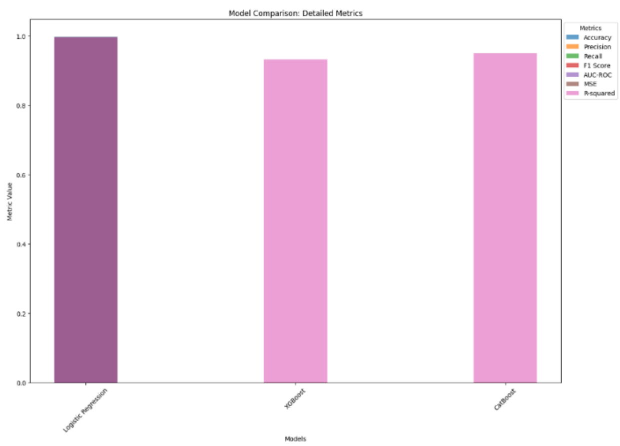

Figure 7: Models performance comparison (dataset 1)

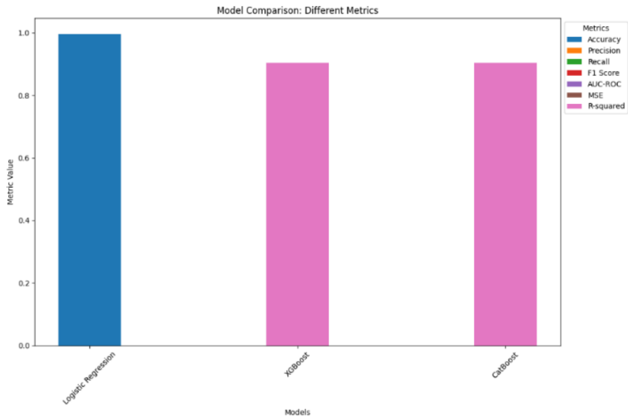

Figure 8 : Models performance comparison (dataset 2)

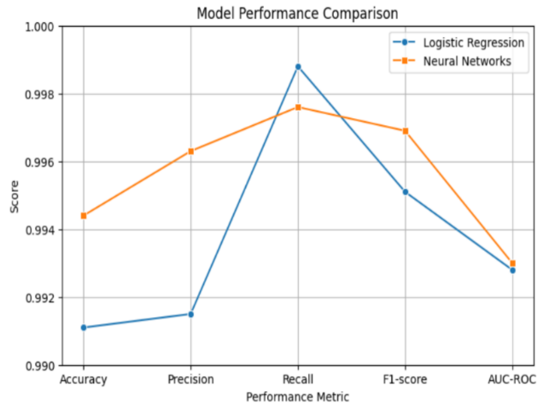

Figure 9 : Model comparison

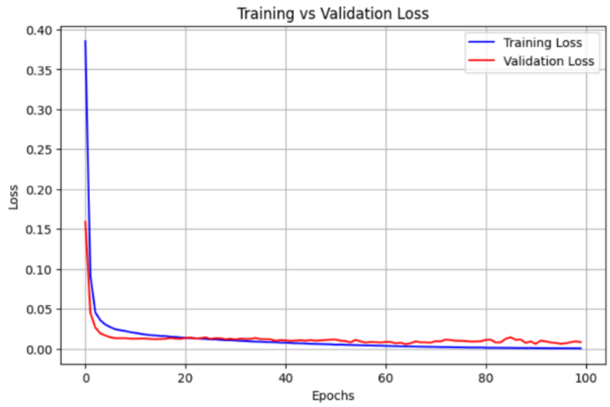

Figure 10: Training vs Validation Loss for neural networks

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Training Time: 0.02 seconds
Inference Time: 0.0009 seconds per batch
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Fifure 11: Time analysis for Logistic regression

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Training Time: 18.71 seconds
Inference Time: 0.1741 seconds per batch
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Figure 12: Time analysis for neural networks

IV. ALGORITHM

Here is a proposed algorithm for getting flood probabilities for a chosen location using web application and machine learning :

Step 1- Collect the relevant data for the flood prediction model using hydrological modelling , understanding of DEM records, collecting it from various different sources.

Step 2- Analyze the data and apply data preprocessing if required.

Step 3- Train your machine learning model using the dataset.

Step 4- Fine tune the model performance by using different methods like feature engineering, hyperparameters, Normalization, Scaling, categorical encoding (if required).

Step 5- After training the model as per your need, save the model.

Step 6- Make a web application where user can chose a location on map.

Step 7- For the chosen location, the geodata will be fetched from different authentic APIs. This data will be helpful in predicting the flood probabilities.

Step-8- User can also chose a model they want

to use (logistic regression, XGBoost, CatBoost)

Step-9- This Fetched data will be sent to previously trained machine learning model as a input.

Step-10- After this we will be able to get the predicted flood probabilities which will be shown to the user at the developed web application.

This algorithm could be further refined and optimized through machine learning techniques to improve its accuracy and efficiency.

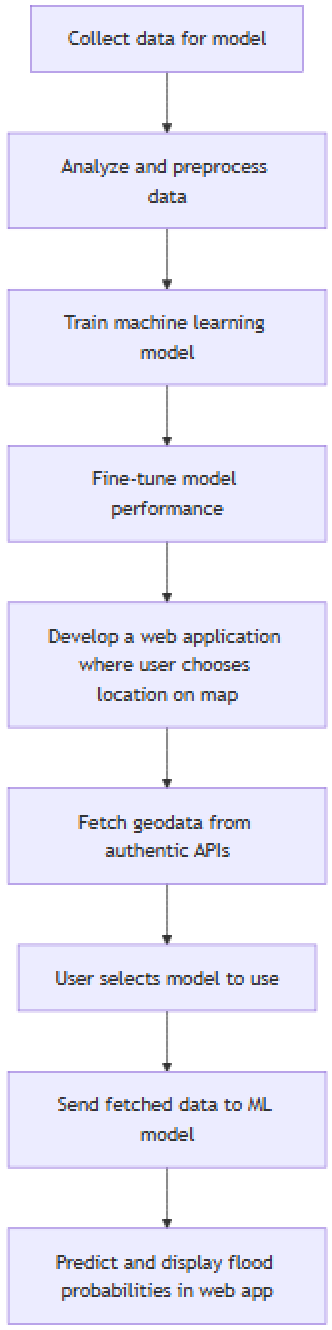

Figure 10 : Algorithm

CONCLUSION

In conclusion, This research presents a comprehensive system for flood prediction, joining machine learning algorithms with an interactive web application to improve usability and encourage informed decision-making. By utilizing logistic regression, XGBoost, and CatBoost models, the study illustrates the potential of machine learning to accurately and flexibly predict flood probabilities. The incorporation of a web-based interface empowers clients to choose particular geological areas and seamlessly access insights derived from the models, in this manner advancing timely decision-making and effective hazard management.

The proposed framework not only approves the viability of advanced machine learning methods within the domain of natural hazard appraisal but too underscores the significance of user-oriented plan in transforming complex algorithms into commonsense, noteworthy instruments. This technique viably bridges the partition between technical development and its application in real-world scenarios, giving fundamental support for calamity readiness, urban arranging, and climate adjustment strategies.

Future research endeavors may build upon this foundational work by joining real-time information streams, consolidating geospatial analytics, and growing the system's functionalities to figure other normal catastrophes. In advancing the integration of data science and calamity management, this study highlights the significant part of innovation in moderating natural dangers and cultivating versatile communities.

The system's capabilities can be significantly enhanced by expanding its geospatial coverage through training on global datasets, or we can train localized models for the locations with high flood chances and integrating high-resolution satellite imagery like Sentinel-1/2, while simultaneously improving prediction timeliness via real-time data streaming from IoT sensors such as river gauges and soil moisture probes; exploring advanced machine learning techniques including hybrid models (e.g., CNNLSTM) coupled with uncertainty quantification would further boost prediction accuracy and reliability; developing a Progressive Web App (PWA) would ensure mobile-first accessibility even in offline conditions in remote areas, and incorporating crowdsourcing features would allow community participation in reporting flood incidents to refine model accuracy; additionally, simulating flood risks under future climate scenarios using IPCC data would aid in climate change adaptation planning, and partnering with disaster management agencies to integrate the tool into earlywarning systems would maximize its policy impact and real-world-utility.

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