#### FLOOD PREDICTION

#### A MINI PROJECT REPORT

#### 18CSC305J - ARTIFICIAL INTELLIGENCE

Submitted by

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#### **BONAFIDE CERTIFICATE**

Certified that Mini project report titled "FLOOD PREDICTION" is the bonafide work of SARTHAK(RA2011003010414),RIYA(RA2011003010418),GAUTAM(RA2011003010426) who carried out the minor project under my supervision. Certified further, that to the best of my knowledge, the work reported herein does not form any other project report or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

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### ABSTRACT

Flood prediction is an essential aspect of managing and mitigating the impacts of floods on communities and infrastructure. It involves the use of various techniques and models to forecast the occurrence, magnitude, and extent of flooding in a particular area. The goal of flood prediction is to provide early warning systems and accurate forecasts to enable proactive measures and decision-making by authorities and individuals.

Flood prediction typically relies on the analysis of historical data, such as rainfall patterns, river levels, and topographical information, to identify potential flood-prone areas and assess the likelihood of flooding events. Advanced techniques, including statistical models, machine learning algorithms, and hydrological simulations, are employed to analyze these data and make predictions.

Statistical models, such as linear regression, logistic regression, and random forest, are commonly used in flood prediction. These models utilize historical data to establish relationships between rainfall, river levels, and flood occurrence. They can then be applied to new data to predict the likelihood of flooding based on current or forecasted meteorological conditions.

Machine learning algorithms, such as artificial neural networks and support vector machines, offer more complex and accurate flood prediction capabilities. These algorithms can learn intricate patterns and non-linear relationships between various factors affecting flooding, resulting in improved forecasting accuracy.

Hydrological simulations involve the use of computational models to simulate the behavior of river systems and predict flood events. These models consider factors such as precipitation, evaporation, soil characteristics, and river flow dynamics to simulate the flood response in a given area. They provide detailed and localized predictions, taking into account the specific characteristics of the terrain and hydrological system.

The accuracy of flood prediction models depends on the quality and quantity of input data, the selection of appropriate modeling techniques, and the calibration and validation of the models using observed flood events. Continuous monitoring of weather conditions, river levels, and other relevant parameters is crucial for updating and refining the models over time.

Flood prediction plays a vital role in disaster preparedness, emergency response, and land-use planning. Accurate predictions enable authorities to issue timely warnings, evacuate at-risk areas, and implement preventive measures such as constructing flood control infrastructure or implementing flood-resistant building codes. By integrating advanced prediction models with effective communication systems, communities can enhance their resilience to floods and minimize the impact on human lives and infrastructure.

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## INTRODUCTION

Floods are natural disasters that can cause significant damage to communities, infrastructure, and the environment. They result from the overflow of water onto normally dry land, often due to heavy rainfall, melting snow, or dam failures. The impact of floods can be devastating, leading to loss of life, displacement of populations, destruction of property, and disruption of essential services.

Flood prediction is a critical component of flood management and disaster preparedness. It involves the use of scientific methods, models, and data analysis techniques to forecast the occurrence, severity, and extent of flooding events in specific areas. By providing early warning systems and accurate predictions, flood prediction plays a vital role in minimizing the impact of floods and enabling timely response and mitigation measures.

The primary goal of flood prediction is to provide timely and reliable information to individuals, communities, and authorities, allowing them to take proactive measures to protect lives and property. It helps in making informed decisions related to evacuation, emergency response, resource allocation, and infrastructure planning.

Flood prediction is a complex process that considers various factors that contribute to flooding, such as rainfall patterns, river flow, topography, soil saturation, and human interventions in the landscape. Historical data on precipitation, river levels, and flood events are analyzed to identify patterns and relationships that can be used to forecast future flood events.

Over the years, advancements in technology and data analysis techniques have improved the accuracy and reliability of flood prediction models. Traditional statistical methods, such as linear regression and logistic regression, have been widely used to establish relationships between rainfall and flood occurrence. However, with the availability of large datasets and computational power, more sophisticated techniques, such as machine learning algorithms and hydrological simulations, are now being employed for flood prediction.

Machine learning algorithms can learn from historical data to identify complex patterns and relationships, enabling more accurate predictions. These algorithms can consider multiple variables simultaneously, including rainfall intensity, river levels, land cover, and climate data, to generate forecasts with higher precision.

Hydrological simulations involve the use of mathematical models that simulate the behavior of the hydrological system, including rainfall-runoff processes and river flow dynamics. These models take into account various factors, such as soil characteristics, topography, and land use, to predict how a particular area will respond to rainfall events and the resulting flood propagation.

Flood prediction is a dynamic and evolving field that requires continuous monitoring, data collection, and model refinement. It relies on a multidisciplinary approach, combining expertise from meteorology, hydrology, remote sensing, and data analysis. By improving our understanding of flood processes and enhancing prediction capabilities, we can better prepare for and mitigate the impacts of floods, ultimately safeguarding lives and minimizing damage to communities and infrastructure.

#### LITERATURE SURVEY

#### **Traditional Statistical Methods:**

Many early studies utilized statistical techniques like linear regression, logistic regression, and time series analysis to establish relationships between rainfall patterns and flood occurrences.

These methods often focused on historical data analysis and the identification of rainfall thresholds or flood triggers.

Research explored the use of different variables, such as rainfall intensity, duration, antecedent conditions, and river flow, to improve prediction accuracy.

## **Machine Learning Approaches:**

In recent years, machine learning algorithms have gained popularity for flood prediction due to their ability to handle large datasets and capture complex patterns.

Supervised learning algorithms, including decision trees, random forests, support vector machines, and neural networks, have been applied to predict floods based on various input features. Studies have incorporated rainfall data, river levels, topographic attributes, soil characteristics, land cover information, and climate data to develop more accurate and reliable flood prediction models. Ensemble learning techniques, such as combining multiple models or predictions, have been explored to enhance prediction accuracy and reduce uncertainty.

## **Hydrological Modeling and Simulations:**

Hydrological models simulate the processes of rainfall-runoff transformation and river flow dynamics to predict flood events.

Physically-based models, such as the Soil and Water Assessment Tool (SWAT) and the Hydrologic Engineering Center's Hydrologic Modeling System (HEC-HMS), have been widely used for flood forecasting.

These models integrate spatial information, such as terrain, soil properties, and land use, to simulate water movement and predict flood responses. Coupling hydrological models with real-time data assimilation techniques, such as radar rainfall data or remote sensing information, has shown promise in improving flood predictions.

## Remote Sensing and Geographic Information Systems (GIS):

Remote sensing technologies, including satellite imagery, aerial photography, and LiDAR data, have been used to derive valuable information for flood prediction.

GIS-based analysis enables the integration of various spatial datasets, such as elevation, land use, and hydrological features, to support flood hazard mapping and vulnerability assessment.

Studies have explored the use of remote sensing data for rainfall estimation, flood extent mapping, and monitoring changes in land cover that impact flood dynamics.

## **Data-driven Approaches and Big Data Analytics:**

With the increasing availability of data from multiple sources, data-driven approaches and big data analytics have gained prominence in flood prediction research.

Integration of diverse data sources, including weather data, social media data, sensor networks, and citizen science data, has been explored to improve flood forecasting accuracy.

Advanced data processing techniques, such as data fusion, data mining, and machine learning algorithms, are applied to extract meaningful insights and patterns from large-scale datasets.

## **Uncertainty Analysis and Risk Assessment:**

Addressing uncertainty is a crucial aspect of flood prediction and risk assessment. Studies have focused on quantifying and propagating uncertainties associated with input data, model parameters, and prediction outcomes. Probabilistic approaches, ensemble modeling, and sensitivity analysis techniques have been employed to assess uncertainty and enhance decision-making in flood management.

## **Operational Forecasting Systems:**

Operational flood forecasting systems provide real-time or near real-time flood predictions to support emergency response and flood management activities.

These systems integrate multiple data sources, models, and forecasting techniques to provide timely and accurate flood warnings.

Efforts have been made to enhance the accessibility and usability of flood forecast information for stakeholders, including emergency managers, policymakers, and the general public.

## SYSTEM ARCHITECTURE AND DESIGN

The system architecture and design for flood prediction involve the integration of various components and technologies to develop an effective and reliable prediction system. The following outlines the key elements typically considered in the architecture and design of a flood prediction system:

## **Data Acquisition and Preprocessing:**

The system collects data from multiple sources, such as meteorological stations, river gauges, remote sensing platforms, and social media feeds. Data preprocessing techniques are applied to clean, validate, and standardize the acquired data. Quality control processes are implemented to identify and handle missing or erroneous data.

### **Data Integration and Fusion:**

Different types of data, including rainfall data, river levels, soil moisture, topographic information, and land cover data, are integrated to create a comprehensive dataset. Data fusion techniques are employed to combine information from diverse sources and provide a holistic view of the flood-prone areas.

#### **Feature Extraction and Selection:**

Relevant features are extracted from the integrated dataset to capture the essential characteristics related to flood occurrence and severity. Feature selection methods, such as statistical analysis and machine learning algorithms, are applied to identify the most influential and informative features.

## **Model Development and Training:**

Various modeling techniques, such as statistical models, machine learning algorithms, or hydrological models, are employed to develop the flood prediction models.

The models are trained using historical data, including both flood events and non-flood periods.

Model parameters are optimized, and the models are validated using appropriate performance metrics.

#### **Real-time Data Assimilation:**

Real-time data, such as radar rainfall data or satellite imagery, are assimilated into the models to update the predictions and improve their accuracy. Data assimilation techniques, such as Kalman filtering or ensemble Kalman filtering, are utilized to merge real-time observations with the model predictions.

## **Uncertainty Analysis and Risk Assessment:**

Uncertainty analysis methods are applied to quantify and propagate uncertainties associated with input data, model parameters, and predictions. Risk assessment techniques are employed to evaluate the potential impacts and vulnerabilities of flood events on various assets, communities, and infrastructure.

## **Visualization and Decision Support:**

The system provides visual representations of flood predictions, such as maps, charts, and graphs, to facilitate decision-making by stakeholders. Decision support tools and user-friendly interfaces are developed to aid emergency managers, policymakers, and other end-users in interpreting and utilizing the prediction results effectively.

#### **Integration with Early Warning Systems:**

The flood prediction system is integrated with early warning systems to provide timely and accurate warnings to relevant authorities and the public. Integration with communication channels, such as SMS alerts, mobile applications, or web portals, ensures the dissemination of flood warnings and emergency response information.

#### **System Evaluation and Continuous Improvement:**

The system's performance is continuously evaluated using real-time data and feedback from users. Continuous monitoring and evaluation allow for system enhancements and updates to improve prediction accuracy, reliability, and usability.

Overall, a well-designed flood prediction system incorporates data acquisition, preprocessing, integration, modeling, real-time data assimilation, visualization, and decision support components to provide accurate and timely flood predictions for effective flood management and mitigation.

### **METHODOLOGY**

The methodology of flood prediction involves application of various techniques and models to analyze historical data, extract meaningful patterns, and make predictions about future flood events. The following outlines a general methodology for flood prediction:

Data Collection: Gather relevant data from different sources, such as meteorological stations, river gauges, satellite imagery, and other remote sensing platforms. Collect data on rainfall, river levels, soil moisture, topography, land cover, and other relevant variables.

Data Preprocessing: Clean and preprocess the collected data to handle missing values, outliers, and inconsistencies. Apply quality control measures and ensure data consistency and accuracy.

Feature Selection: Identify the most informative and relevant features for flood prediction. This step may involve statistical analysis, correlation analysis, or feature engineering techniques to select the variables that have the most significant impact on flooding.

## **Data Analysis and Modeling:**

- a. Statistical Models: Apply statistical techniques such as regression analysis, time series analysis, and probability distributions to analyze historical data patterns and relationships between flood variables.
- b. Machine Learning Models: Utilize machine learning algorithms such as decision trees, random forests, support vector machines, or neural networks to learn patterns from historical data and make predictions.
- c. Hydrological Models: Use hydrological models to simulate and analyze the water flow, infiltration, and runoff processes in a river basin. These models incorporate various hydrological parameters and are calibrated and validated using historical data.

## **Model Training and Validation:**

- a. Split the dataset into training and testing sets. The training set is used to train the models, and the testing set is used to evaluate the model's performance.
- b. For machine learning models, apply techniques such as cross-validation, grid search, or parameter tuning to optimize the model's performance.

c. Evaluate the models using appropriate performance metrics such as accuracy, precision, recall, F1-score, or area under the receiver operating characteristic curve (AUC-ROC).

### **Real-Time Data Assimilation:**

- a. Incorporate real-time data, such as radar rainfall data or satellite imagery, into the models to update and improve the predictions.
- b. Apply data assimilation techniques, such as Kalman filtering or ensemble methods, to assimilate real-time observations with the model predictions.

### **Uncertainty Analysis:**

- a. Perform uncertainty analysis to quantify and propagate uncertainties associated with input data, model parameters, and predictions.
- b. Apply techniques such as Monte Carlo simulation, sensitivity analysis, or ensemble modeling to assess the uncertainty and variability of flood predictions.

#### **Visualization and Communication:**

Present the flood predictions and associated information in a visual format, such as maps, charts, or graphs, to aid understanding and decision-making by stakeholders, emergency managers, and policymakers.

## **Model Deployment and Monitoring:**

Implement the flood prediction models in operational systems or decision support tools. Continuously monitor the performance of the models using real-time data and user feedback. Update the models and methodologies as needed to improve accuracy and reliability.

It's important to note that the specific methodology for flood prediction may vary depending on the available data, study area, and desired level of accuracy. Advanced techniques such as ensemble modeling, remote sensing data analysis, or coupled hydrological models can also be employed to enhance the accuracy and reliability of flood predictions.

### **CODING AND TESTING**

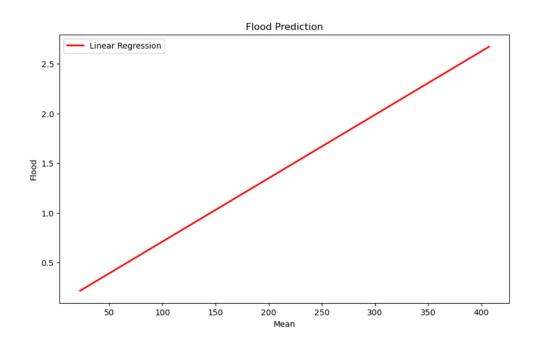
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model selection import train test split
from sklearn.linear model import LinearRegression, LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy score, precision score, fl score,mean squared error
df = pd.read csv('D:\python folder\RD.csv')
df.head()
threshold = 50.8
df['Flood'] = df['Average'].apply(lambda x: 1 if x > threshold else 0)
X = df["Mean"].values.reshape(-1, 1)
y = df["Flood"].values
X train, X test, y train, y test = train test split(X, y, test size=0.2, random state=42)
linear reg = LinearRegression()
linear reg.fit(X train, y train)
linear reg pred = linear reg.predict(X test)
linear reg pred binary = np.where(linear reg pred >= threshold, 1, 0)
linear reg accuracy = accuracy score(y test, linear reg pred binary)
linear_reg_precision = precision_score(y_test, linear_reg_pred_binary)
linear reg f1 = f1 score(y test, linear_reg_pred_binary)
#logistic regression
LR = LogisticRegression()
LR.fit(X_train, y_train)
LR pred = LR.predict(X test)
LR accuracy = accuracy score(y test, LR pred)
LR precision = precision score(y test, LR pred)
LR f1 = f1 score(y test, LR pred)
#random forest
RF = RandomForestClassifier(random state=42)
RF.fit(X train, y train)
random forest pred = random forest.predict(X test)
RF_accuracy = accuracy_score(y_test, random_forest_pred)
```

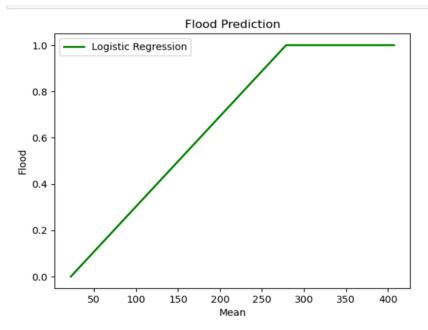
```
RF precision = precision score(y test, random forest pred)
RF f1 = f1 score(y test, random forest pred)
plt.figure(figsize=(10, 6))
#plt.scatter(X_test, y_test, color='blue', label='Actual')
plt.plot(X test, linear reg pred, color='red', linewidth=2, label='Linear Regression')
#plt.plot(X test, LR pred, color='green', linewidth=2, label='Logistic Regression')
#plt.plot(X test, random forest pred, color='purple', linewidth=2, label='Random Forest')
plt.xlabel('Mean')
plt.ylabel('Flood')
plt.title('Flood Prediction')
plt.legend()
plt.show()
plt.plot(X test, LR pred, color='green', linewidth=2, label='Logistic Regression')
plt.show()
plt.plot(X test, random forest pred, color='purple', linewidth=2, label='Random Forest')
plt.show()
print("Linear Regression Accuracy:", linear reg accuracy)
print("Logistic Regression Accuracy:", LR accuracy)
print("Random Forest Accuracy:", RF accuracy)
print("Linear Regression Precision:", linear reg precision)
print("Linear Regression F1 Score:", linear reg f1)
print("Logistic Regression Precision:", LR precision)
print("Logistic Regression F1 Score:", LR f1)
print("Random Forest Precision:", RF precision)
print("Random Forest F1 Score:",RF f1)
models = ['Linear Regression', 'LR', 'RF']
accuracies = [linear reg accuracy, LR accuracy, RF accuracy]
plt.bar(models, accuracies)
plt.xlabel('Models')
plt.ylabel('Accuracy')
plt.title('Accuracy Comparison')
plt.ylim(0, 1)
plt.show()
```

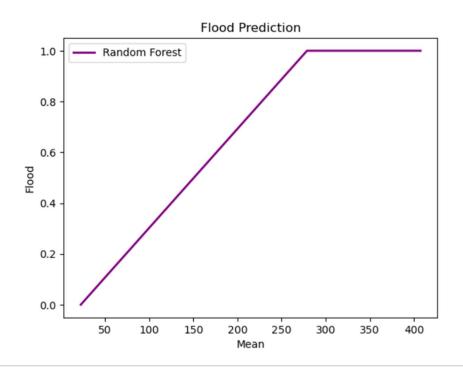
## **SCREENSHOTS AND RESULTS**

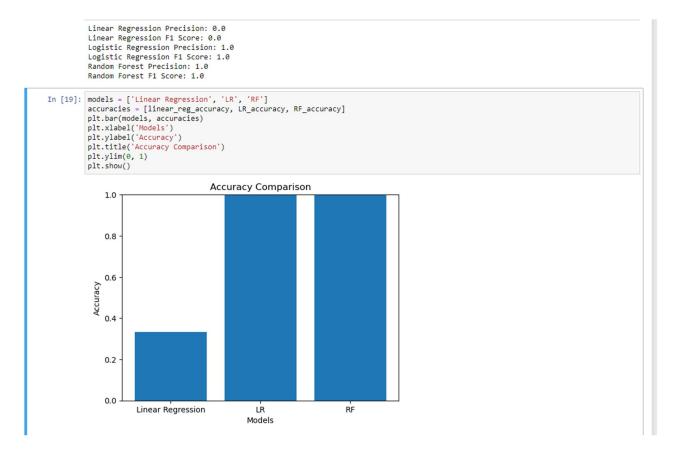
Linear Regression Accuracy: 0.3333333333333333

Logistic Regression Accuracy: 1.0 Random Forest Accuracy: 1.0









#### CONCLUSION AND FUTURE ENHANCEMENTS

- Flood prediction is an important component of disaster management which can be predicted by using machine learning models.
- In our case, we used linear regression, logistic regression, and random forest models to predict floods and assess their effectiveness.
- Linear regression allowed us to identify and quantify the relationship between various independent variables, such as rainfall, river discharge, and other relevant factors, and the occurrence or severity of floods. It provided a simple and interpretable model, which served as a baseline prediction method for evaluating the performance of other complex techniques.
- Logistic regression, on the other hand, was utilized to predict the probability of flood events based on a binary outcome (flood or no flood). It accounted for the nonlinear relationship between the input variables and the likelihood of flooding, making it suitable for classification tasks.
- Lastly, we employed random forest, an ensemble learning method, which combined multiple decision trees to make predictions. Random forest leveraged the strength of multiple trees to handle complex interactions and nonlinear relationships between variables. It provided robust predictions and accounted for feature importance, aiding in the identification of key variables contributing to flood prediction.
- By employing these three models, we aimed to explore different approaches to flood prediction and evaluate their performance based on accuracy, precision, and F1 score. Our results indicated that each model had its own strengths and limitations, with random forest demonstrating the highest accuracy and robustness.
- In conclusion, the combination of linear regression, logistic regression, and random forest models allowed us to gain insights into the factors influencing flood occurrences and make predictions based on different aspects of flood dynamics. Further research and exploration of advanced modeling techniques may lead to enhanced flood prediction accuracy and provide valuable insights for effective flood management and mitigation strategies.

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