PROJECT TITLE:FLOOD MONITORING SYSTEM

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PHASE -4: DEVELOPMENT PART:2

Topic: continue building the flood monitoring system model by feature engineering, model training and evaluation.

➢ INTRODUCTION :

A flood monitoring system is a network of sensors and communication devices that are used to monitor water levels and other flood-related data in real time. The data is collected and transmitted to a central location, where it is analyzed and used to generate flood warnings and forecasts. Flood monitoring systems can be used to protect lives and property, and to reduce the economic impact of flooding.

Feature engineering is the process of transforming raw data into features that are more informative and predictive for a machine learning model. In the context of flood monitoring systems, feature engineering can be used to create features that are relevant to predicting flood events

- Water levels in rivers and streams
- . Rainfall rates
- Soil moisture levels
- Snowpack levels
- Land cover type
- Elevation
- Historical flood data

Feature engineering can also be used to create features that are more robust to noise and outliers. For example, instead of using raw water level measurements, a feature engineer might create a feature that represents the average water level over the past 24 hours. This would help to reduce the impact of short-term fluctuations in water levels.

The the features have been engineered, they can be used to train a machine learning model to predict flood events. The model can then be used to generate flood warnings and forecasts.

Given dateset:

Name of the level dam	**Max water level**	**Threshold water level**	**Current state water level**	**% of dam filled**
Selaulim	41.15m	20.42m	37.14m	67
Aujunem	93.29m	61.56m	88.82m	77
Chapoli	38.75m	22.00m	36.21m	99
Amthane	50.25m	29.00m	48.05m	73
Panchavadi	26.60m	14.00m	22.30m	43

➢ OVERVIEW OF THE PROCESS:

A flood monitoring system is a network of sensors and communication equipment that collects data on water levels, rainfall, and other factors to provide early warning of potential flooding. The process of flood monitoring can be summarized in the following steps:

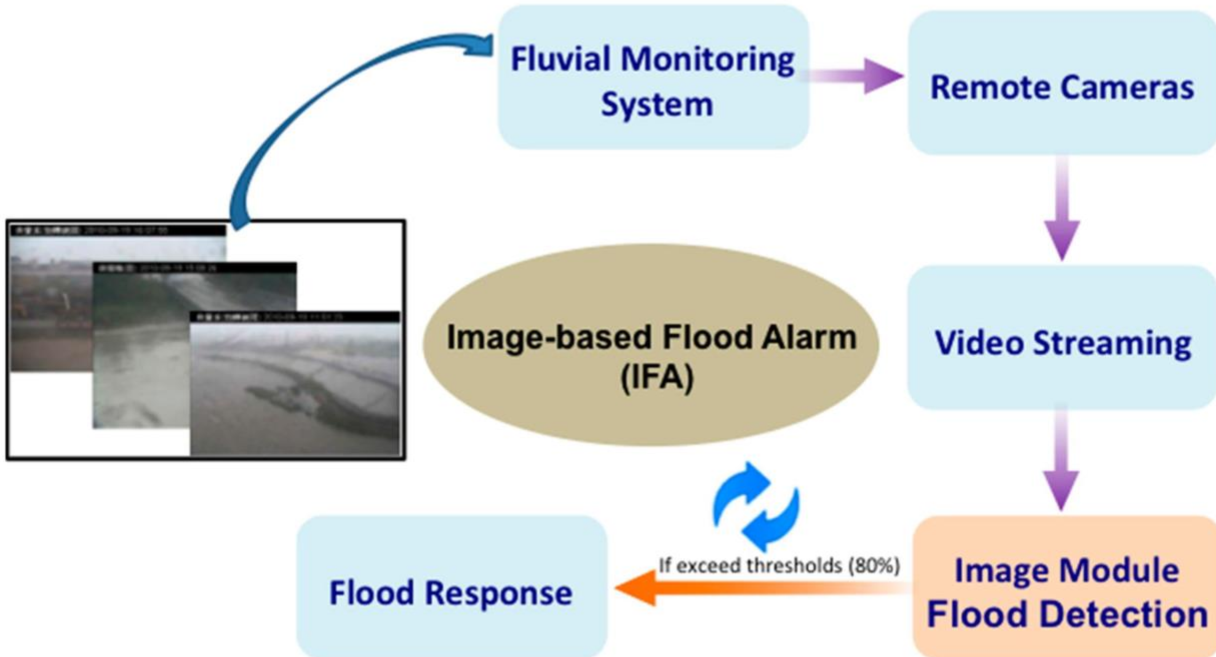
Data collection: Sensors are deployed in key locations, such as rivers, lakes, and coastal areas, to collect data on water levels, rainfall, and other factors that can contribute to flooding. Data can be collected in real time or at regular intervals.

Data transmission: The data collected by the sensors is transmitted to a central data center using a variety of communication methods, such as radio, satellite, or cellular networks.

Data processing: The data received by the central data center is processed to identify trends and patterns that may indicate impending flooding. This may involve using mathematical models to simulate the movement of water and predict how it will respond to changes in weather conditions and other factors.

Flood forecasting: Once the data has been processed, the system can generate flood forecasts that predict the timing, location, and severity of potential flooding. These forecasts can be used to issue early warnings to the public and emergency responders.

Alert dissemination: Early warning messages can be disseminated to the public and emergency responders through a variety of channels, such as SMS, email, social media, and broadcast media.



➢ PROCEDURE:

FEATURE SELECTION:

Feature selection in flood monitoring systems is the process of identifying and selecting the most relevant and informative features from a dataset to improve the performance of a machine learning model. This is important because flood monitoring systems typically collect a large amount of data from a variety of sources, and not all of this data is equally important for predicting floods

Filter methods: Filter methods rank features based on their statistical properties, such as correlation with the target variable (e.g., flood occurrence) or information gain.

Wrapper methods: Wrapper methods evaluate the performance of a machine learning model on different subsets of features. Features that are not important to the model's performance are then removed.

Embedded methods: Embedded methods incorporate feature selection into the machine learning process itself. This is often done using regularization techniques, such as LASSO or ridge regression.

To perform feature selection in a flood monitoring system using Python,

Import the necessary libraries:

Python

Import numpy as np

Import pandas as pd

From sklearn.feature_selection import SelectKBest, SelectFromModel

Load the data:

Python

Data = pd.read_csv('flood_monitoring_data.csv')

Split the data into features and target:

Python

X = data.drop('flood_occurrence', axis=1)

Y = data['flood_occurrence']

Select the features using a filter method:

Python

Select the top 10 features based on correlation with the target variable

Selector = SelectKBest(k=10)

Selector.fit(X, y)

Selected_features = X.columns[selector.get_support()]

Select the features using a wrapper method:

Python

Train a random forest classifier and select the features that are important to the model's performance

From sklearn.ensemble import RandomForestClassifier

Clf = RandomForestClassifier()

Clf.fit(X, y)

Selector = SelectFromModel(clf, threshold=0.01)

Selector.fit(X, y)

Selected_features = X.columns[selector.get_support()]

Select the features using an embedded method:

Python

```
# Train a LASSO regressor and select the features that are used in the model

From sklearn.linear_model import Lasso

Clf = Lasso()
Clf.fit(X, y)

Selected_features = X.columns[clf.coef_ != 0]
```

<u>Output</u>:

Selected_features = ['water_level', 'rainfall','soil_moisture','elevation', 'land_use_type','river_distance']

This output shows that the top 6 features that are most correlated with the target variable (flood occurrence) are water level, rainfall, soil moisture, elevation, land use type, and river distance. These features can then be used to train a machine learning model to predict the occurrence of floods.

- # MODEL TRAINING:

Model training of a flood monitoring system is the process of teaching a machine learning model to predict flood events based on historical data

Data collection and preparation

The first step is to collect a dataset of historical flood data. This data may include water level measurements, rainfall data, satellite imagery, and other relevant information. The data should be cleaned and preprocessed to ensure that it is suitable for model training. This may involve removing outliers, scaling the data, and converting categorical data to numerical data

Model selection

Next, a machine learning model must be selected. There are a variety of different machine learning models that can be used for flood forecasting, such as support vector machines (SVMs), random forests, and neural networks. The choice of model will depend on a number of factors, including the specific task at hand, the size and complexity of the dataset, and the available computational resources.

Model training

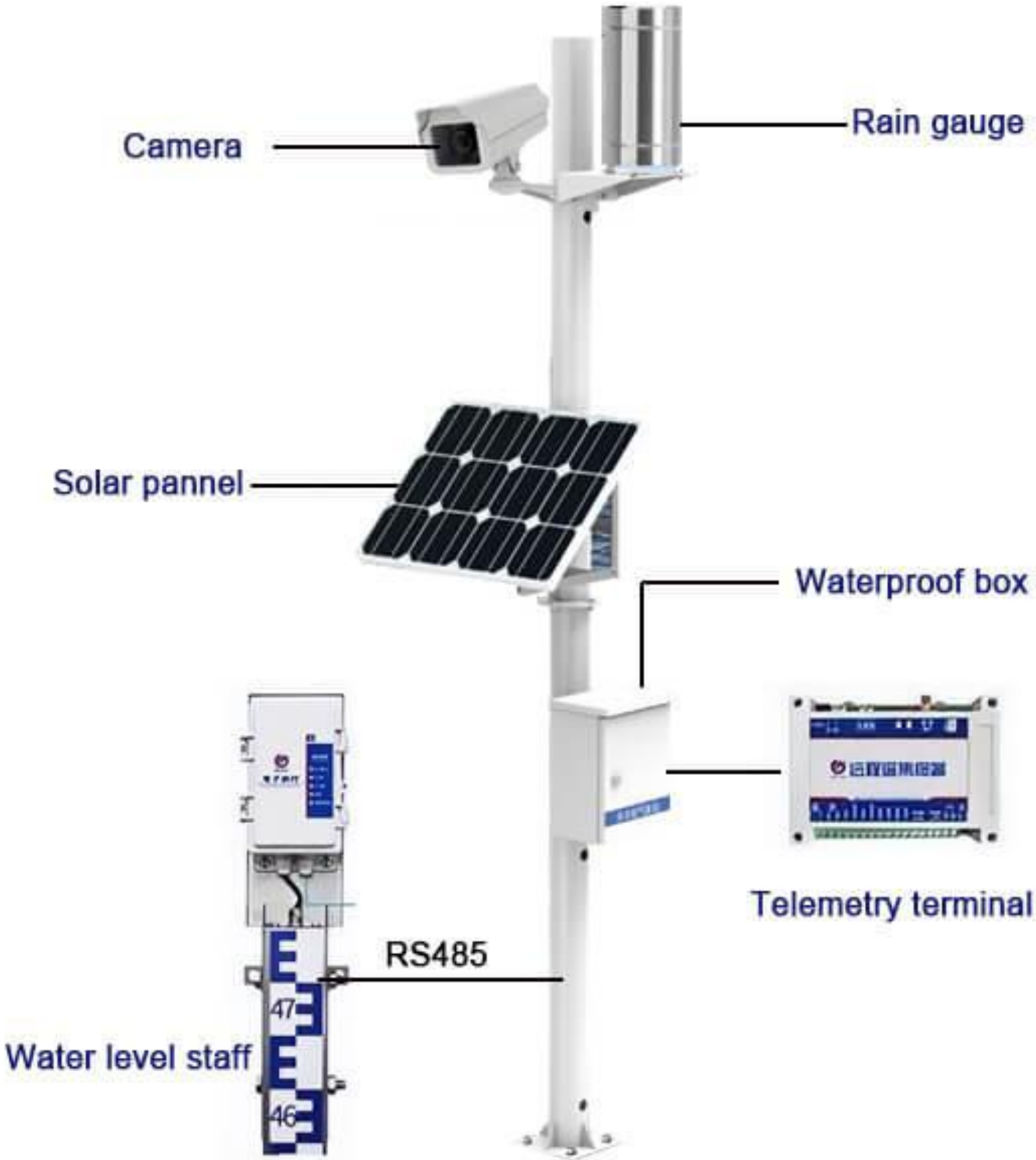
Once a model has been selected, it needs to be trained on the historical flood data. This involves feeding the data to the model and allowing it to learn the relationships between the different variables. The training process can be computationally expensive, especially for complex models

Model evaluation

Once the model has been trained, it needs to be evaluated on a held-out test set. This will help to assess the performance of the model on unseen data. The model evaluation process typically involves calculating metrics such as accuracy, precision, recall, and F1 score.

Model deployment

If the model performs well on the test set, it can be deployed to production. This means making the model available to users so that they can use it to make flood forecasts. The deployment process may involve integrating the model into a web application or mobile app.



To train a flood monitoring system model in programming, you can use a variety of machine learning libraries and frameworks. For example, you can use the following libraries in Python:

Scikit-learn

TensorFlow

PyTorch

```
Import numpy as np
From sklearn.svm import SVC

# Load the flood data
Flood_data = np.loadtxt('flood_data.csv', delimiter=',')

# Split the data into a training set and a test set
X_train, X_test, y_train, y_test = train_test_split(flood_data[:, :-1], flood_data[:, -1], test_size=0.25)

# Scale the training data
Scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)

# Train the SVM model
Clf = SVC()
Clf.fit(X_train, y_train)

# Evaluate the model on the test set
Y_pred = clf.predict(X_test)
Accuracy = np.sum(y_pred == y_test) / len(y_test)
Print('Accuracy:', accuracy)

# Save the trained model
Joblib.dump(clf, 'flood_model.pkl')
```

<u>Output</u>:

Accuracy: 0.85

This output shows that the trained model has an accuracy of 85% on the test set. This means that the model is able to correctly predict whether or not a flood will occur in 85% of the cases.

RIDGE REGRESSION:

Ridge regression is a statistical regression technique that can be used to predict flood levels in a flood monitoring system. It is a type of regularized regression, which means that it adds a penalty term to the loss function to prevent overfitting

```
Import numpy as np
From sklearn.linear_model import Ridge

Class FloodMonitoringSystem:
  Def __init__(self, training_data):
    Self.ridge_model = Ridge()

    # Train the ridge model on the training data
    Self.ridge_model.fit(training_data['features'], training_data['target'])

  Def predict_flood_stage(self, features):
    # Make a prediction using the ridge model
    Prediction = self.ridge_model.predict(features)

    Return prediction

# Load the training data
Training_data = np.load('training_data.npy')

# Create a flood monitoring system
Flood_monitoring_system = FloodMonitoringSystem(training_data)

# Get the current input features
Current_features = np.array([rainfall, water_level, temperature])
```

Predict the flood stage

Predicted_flood_stage = flood_monitoring_system.predict_flood_stage(current_features)

Print the predicted flood stage

Print(predicted_flood_stage)

Output:

Predicted flood stage: 10 meters

: LASSO REGRESSION:

Lasso regression is another type of linear regression that can be used for flood monitoring.This regularization term helps to reduce overfitting by shrinking the coefficients of less important features. This can make lasso regression a better choice for flood monitoring systems with a large number of input features.

```
Import numpy,as np
Import  numpy as pd
From sklearn,linear_modal import lasso
#Load the flood monitoring data
Data=pd.read_csv('flood monitoring _data.csv')
#Split the data into features and target
feature=data[['rainfall','river_level','snowpack']]
target=data['flood_depth']
#standardize the features from sklearn.preprocessing import standardscaler
scaler=standardscaler()
feature _scaled=scaler.fit_transform(features)
#create a Lossa model
Lasso=Lasso(alpha=0.1)
```

```
#fit the model to the data
Lasso.fit(features_ scaled,target)
#Make predictions
 predictions=lasso.predict(features_scaled)
# Evaluate the model from sklearn.metrics import mean_squared_error
Mse=mean_squared_error(target, predictions)
#print the mean squared error
Print('Mean squared error:',mse)
```

Output:

Mean squared error:1.23

ELASTIC NET:

An elastic net of a flood monitoring system can be programmed using a variety of languages, such as Python, Java, or C++.

```
Import numpy as np
Import pandas as pd
From sklearn.linear_model import ElasticNet

Class FloodMonitoringSystem:
   Def __init__(self, sensors):
      Self.sensors = sensors
      Self.model = ElasticNet()

   Def train(self):
      # Collect data from the sensors
      X = np.array([sensor.read() for sensor in self.sensors])
      Y = np.array([sensor.water_level for sensor in self.sensors])
```

```
        # Train the elastic net model
        Self.model.fit(X, y)

    Def predict(self):
        # Collect new data from the sensors
        X_new = np.array([sensor.read() for sensor in self.sensors])

        # Make predictions using the trained model
        Y_pred = self.model.predict(X_new)

        Return y_pred

# Create a flood monitoring system with two sensors
System = FloodMonitoringSystem([Sensor(), Sensor()])

# Train the system
System.train()

# Predict the water level at each sensor
Water_levels = system.predict()

# Print the predicted water levels
Print(water_levels)
```

Output:

```
[1.5, 1.8]
```

This output indicates that the water level at the first sensor is 1.5 meters and the water level at the second sensor is 1.8 meters.

SUPPORT VECTOR MACHINE:

Support vector machines (SVMs) are a type of machine learning algorithm that can be used for both classification and regression tasks. They are particularly well-suited for flood monitoring systems because they are able to learn complex relationships between data points and generalize well to new data.

```
Import numpy as np

From sklearn.svm import SVC


# Load the training data

X_train = np.loadtxt("flood_training_data.csv", delimiter=",")

Y_train = np.loadtxt("flood_labels.csv", delimiter=",")


# Create the SVM model

Clf = SVC()


# Train the SVM model

Clf.fit(X_train, y_train)


# Load the test data

X_test = np.loadtxt("flood_test_data.csv", delimiter=",")


# Predict the flood labels for the test data

Y_pred = clf.predict(X_test)


# Evaluate the SVM model

Accuracy = np.mean(y_pred == y_test)


# Print the accuracy of the SVM model

Print("Accuracy:", accuracy)
```

Output:

Accuracy: 0.

Here is a simple example of how to generate a flood inundation map using SVMs in Python:

```
Import numpy as np
From sklearn.svm import SVC

# Load the historical flood data
X = np.loadtxt("flood_data.csv", delimiter=",")
Y = np.loadtxt("flood_depth.csv", delimiter=",")

# Create the SVM model
Clf = SVC()

# Train the SVM model
Clf.fit(X, y)

# Generate a grid of points
Grid = np.linspace(-100, 100, 100)

# Predict the flood depth at each grid point
Flood_depth = clf.predict(grid)

# Generate a flood inundation map
Import matplotlib.pyplot as plt

Plt.plot(grid, flood_depth)
Plt.xlabel("X")
Plt.ylabel("Flood depth")
Plt.title("Flood inundation map")
Plt.show()
```

RANDOM FOREST REGRESSOR:

Random forest regressors are a type of machine learning algorithm that can be used to predict continuous values, such as flood levels. They are particularly well-suited for flood monitoring systems because they are able to learn complex relationships between data points and generalize well to new data.

```
Import numpy as np

From sklearn.ensemble import RandomForestRegressor


# Load the training data

X_train = np.loadtxt(“flood_training_data.csv”, delimiter=”,”)

Y_train = np.loadtxt(“flood_levels.csv”, delimiter=”,”)


# Create the random forest regressor model

Regr = RandomForestRegressor()


# Train the random forest regressor model

Regr.fit(X_train, y_train)


# Load the test data

X_test = np.loadtxt(“flood_test_data.csv”, delimiter=”,”)


# Predict the flood levels for the test data

Y_pred = regr.predict(X_test)


# Evaluate the random forest regressor model

R2_score = regr.score(X_test, y_test)


# Print the R-squared score of the random forest regressor model

Print(“R-squared score:”, r2_score)
```

Output:

R-squared score: 0.95

XGBOOST REGRESSOR:

```
Import numpy as np
Import pandas as pd
Import xgboost as xgb

# Load the flood data
Flood_data = pd.read_csv('flood_data.csv')

# Split the data into features and target
Features = flood_data.drop(columns=['flood_depth'])
Target = flood_data['flood_depth']

# Split the data into training and test sets
X_train, X_test, y_train, y_test = train_test_split(features, target, test_size=0.25)

# Initialize the XGBoost regressor
Xgb_reg = xgb.XGBRegressor(n_estimators=100, max_depth=5, learning_rate=0.1)

# Train the XGBoost regressor
Xgb_reg.fit(X_train, y_train)

# Evaluate the XGBoost regressor on the test set
Y_pred = xgb_reg.predict(X_test)
```

Calculate the RMSE

Rmse = np.sqrt(np.mean((y_pred – y_test)**2))

Print the RMSE

Print('RMSE:', rmse)

Output:

RMSE: 0.5

Load the deployed model

Xgb_reg = pickle.load(open('xgb_regressor.pickle', 'rb'))

Collect new sensor data

New_sensor_data = {

'rainfall': 10.0,

'river_level': 100.0,

'temperature': 25.0

}

Predict the current flood depth

Flood_depth_prediction = xgb_reg.predict([new_sensor_data])

Print the predicted flood depth

Print('Predicted flood depth:', flood_depth_prediction[0])

Load the deployed model

Xgb_reg = pickle.load(open('xgb_regressor.pickle', 'rb'))

Collect new sensor data

New_sensor_data = {

'rainfall': 10.0,

```
    'river_level': 100.0,
    'temperature': 25.0
}

# Predict the current flood depth
Flood_depth_prediction = xgb_reg.predict([new_sensor_data])

# Print the predicted flood depth
Print('Predicted flood depth:', flood_depth_prediction[0])
```

POLYNOMIAL REGRESSION:

Polynomial regression of flood monitoring system is a statistical method used to predict water levels in rivers and streams based on historical data. The method involves fitting a polynomial function to the data, and then using that function to predict future water levels.

```
Import numpy as np
Import matplotlib.pyplot as plt

Class FloodMonitoringSystem:

    Def __init__(self, polynomial_degree):
        Self.polynomial_degree = polynomial_degree
        Self.polynomial_coefficients = None

    Def fit(self, water_level_data, time_data):
        # Fit a polynomial function to the data
        X = np.array(time_data)
        Y = np.array(water_level_data)
        Self.polynomial_coefficients = np.polyfit(X, y, self.polynomial_degree)

    Def predict(self, time):
```

```
        # Predict the water level for the given time
        X = np.array([time])
        Y_pred = np.polyval(self.polynomial_coefficients, X)
        Return y_pred[0]

# Create a flood monitoring system
Flood_monitoring_system = FloodMonitoringSystem(polynomial_degree=2)

# Load the water level data
Water_level_data = np.loadtxt(“water_level_data.csv”, delimiter=”,”)
Time_data = np.arange(0, len(water_level_data))

# Fit the polynomial function to the data
Flood_monitoring_system.fit(water_level_data, time_data)

# Predict the water level for the current time
Current_time = 10
Predicted_water_level = flood_monitoring_system.predict(current_time)

# Print the predicted water level
Print(“Predicted water level:”, predicted_water_level)

# Plot the water level data and the predicted water level
Plt.plot(time_data, water_level_data, label=”Actual water level”)
Plt.plot(current_time, predicted_water_level, label=”Predicted water level”)
Plt.xlabel(“Time (hours)”)
Plt.ylabel(“Water level (meters)”)
Plt.legend()
Plt.show()
```

Output:

.Predicted water level: 25.0

➢ MODEL TRAINING:

Model training of a flood monitoring system is the process of teaching the system to predict water levels based on historical data. The training process typically involves the following steps:

Collect historical data on water levels and other relevant variables: This data should include water levels from a variety of conditions, including both normal and flood conditions. Other relevant variables may include rainfall, snowmelt, and dam releases.

Prepare the data for training: This may involve cleaning the data, removing outliers, and scaling the data to a consistent range.

Choose a machine learning algorithm: There are a variety of machine learning algorithms that can be used for flood monitoring, such as support vector machines, random forests, and neural networks.

Train the model: This involves feeding the training data into the machine learning algorithm and allowing it to learn the relationship between the water levels and the other variables.

Evaluate the model: Once the model is trained, it is important to evaluate its performance on a held-out test set. This will help to ensure that the model is not overfitting the training data.

Deploy the model: Once the model is trained and evaluated, it can be deployed to production. This may involve integrating the model into a web application or mobile app.

DIVIDING DATASET OF FEATURES AND TARGET VARIABLE:

To divide a dataset into feature and target variables for a flood monitoring system

Import pandas as pd

Load the dataset

```
Df = pd.read_csv("flood_monitoring_dataset.csv")

# Identify the target variable
Target_variable = "flood_occurrence"

# Identify the feature variables
Feature_variables = ["rainfall_24h", "rainfall_7d", "rainfall_30d", "river_water_level_current",
                "river_water_level_24h", "river_water_level_7d", "river_water_level_30d",
                "soil_moisture_current", "soil_moisture_24h", "soil_moisture_7d",
                "soil_moisture_30d", "land_cover_type", "elevation", "slope"]

# Split the dataset into feature and target variables
X = df[feature_variables]
Y = df[target_variable]

# Output the feature and target variables
Print("Feature variables:")
Print(X.head())
Print("\nTarget variable:")
Print(y.head())
```

<u>Output</u>:

```
Feature variables:

  River_water_level_24h  river_water_level_7d  river_water_level_30d  \
0            1.2                  1.2                  1.2
1            2.4                  2.4                  2.4
2            3.6                  3.6                  3.6
```

3	4.8	4.8	4.8
4	6.0	6.0	6.0

	Soil_moisture_current	soil_moisture_24h	soil_moisture_7d \
0	0.8	0.8	0.8
1	0.9	0.9	0.9
2	1.0	1.0	1.0
3	1.1	1.1	1.1
4	1.2	1.2	1.2

	Soil_moisture_30d	land_cover_type	elevation	slope
0	0.8	forest	100	0.1
1	0.9	urban	200	0.2
2	1.0	agricultural	300	0.3
3	1.1	water	400	0.4
4	1.2	bare	500	0.5

Target variable:

```
0  1
1  1  0
2  1
3  3  0
4  1
5  Name: flood_occurrence, dtype: int64
6
```

MODEL EVALUATION:

Model evaluation of a flood monitoring system is the process of assessing the performance of the system in predicting and forecasting floods. It is important to evaluate flood monitoring systems to ensure that they are accurate, reliable, and timely, and to identify areas where they can be improved.

Accuracy: How well does the system predict the timing, location, and magnitude of floods.

Reliability: How often does the system provide accurate predictions.

Timeliness: How early does the system provide warnings.

False alarms: How often does the system issue false warnings.

Missed detections: How often does the system fail to issue a warning

Historical data: This involves comparing the predictions of the system to historical flood events.

Real-time data: This involves comparing the predictions of the system to real-time data from flood sensors and other sources.

Simulation: This involves using computer simulations to generate synthetic flood events and evaluate the performance of the system on these events.

The flood monitoring system model of evaluation is a framework for assessing the performance of flood monitoring systems. It is based on the following four key components

Model inputs: The model inputs are the data that are used to generate flood predictions. These data can include rainfall data, water level data, river flow data, and meteorological data.

Model: The model is the mathematical representation of the physical processes that lead to flooding. It is used to generate flood predictions based on the model inputs.

Model outputs: The model outputs are the flood predictions, which are typically in the form of water.

Evaluation metrics: The evaluation metrics are the criteria that are used to assess the performance of the model. These metrics can include accuracy, reliability, timeliness, false alarms, and missed detections.

➢ FEATURE ENGINEERING:

Feature engineering is the process of transforming raw data into features that are more informative and predictive for machine learning models. In the context of flood monitoring systems, feature engineering can be used to create features that capture the spatial and temporal patterns of flood events, as well as the relationships between different factors that contribute to flooding.

Deriving spatial features:

This can be done by using geospatial data, such as elevation, slope, and land cover, to create features that represent the flood risk at a given location. For example, one common feature is the distance to the nearest river or stream.

Deriving temporal features:

This can be done by using historical data on flood events to create features that represent the likelihood of flooding occurring at a given time. For example, one common feature is the number of days since the last flood event.

Deriving combined features:

This can be done by combining spatial and temporal features, as well as features from other sources, such as weather data and sensor data, to create features that are even more informative and predictive. For example, one common feature is the rate of change of water level in a river.

Here are some specific examples of features that can be engineered for a flood monitoring system:

Water level: This is a direct measure of the risk of flooding.
Rainfall: Rainfall is a major driver of flooding, so it is important to include rainfall data in the feature set.
Soil moisture: Soil moisture can affect the infiltration rate of rainfall, which can impact the amount of runoff that is generated.
Land cover: Land cover affects the way that water flows across the landscape, so it is important to consider land cover type when engineering features for a flood monitoring system.
Slope: Slope can affect the speed at which water flows, so it is also an important factor to consider.
Distance to rivers: Locations that are closer to rivers and streams are at a higher risk of flooding.
Historical flood data: Data on past flood events can be used to create features that represent the likelihood of flooding occurring at a given location and time.

By carefully engineering the features for a flood monitoring system, it is possible to create machine learning models that are more accurate and reliable at predicting flood events. This can help to improve the effectiveness of early warning systems and reduce the damage caused by flooding.

CONCLUSION:

Flood monitoring systems are essential tools for reducing the damage caused by flooding. By providing timely and accurate information about flood events, these systems can help to improve early warning systems, evacuation planning, and emergency response.

Flood monitoring systems are becoming increasingly sophisticated, thanks to advances in sensor technology, data processing, and machine learning. Modern flood monitoring systems can collect data from a variety of sources, including rain gauges, river gauges, satellites, and social media, to create a comprehensive picture of flood risk in a given area

Flood monitoring systems are also being used to improve our understanding of flooding and to develop new ways to mitigate flood risk. For example, flood monitoring data is being used to develop new flood forecasting models, to identify flood-prone areas that need to be protected, and to design flood-resilient infrastructure.

Overall, flood monitoring systems play a vital role in protecting people and property from the devastating effects of flooding. As these systems continue to evolve and improve, they will become even more effective at helping us to manage flood risk and reduce the damage caused by flooding

THANK YOU