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Identifying Flood Prediction using Machine Learning Techniques

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Abstract:- Flood is the most devastating and destructive that can destroy everything on land. These floods will cause further flooding in affected areas. Flood prediction models are being researched to reduce risk, think strategically, reduce human life and reduce property damage from floods. Over the last two years, AI techniques have improved the forecasting process, resulting in better execution and financial planning stability. First of all, these events can take everyone's feelings into account. Artificial intelligence models for flood prediction are crucial for flood warning, flood mitigation or prediction. Machine learning programs have become ubiquitous due to their computational needs for limited information. We believe that collecting only a small amount of data can help representative vector, best scores. The selected tree was successful due to better than expected accuracy and best score. Machine learning algorithms used in this flood prediction are decision trees, logistic regression, etc. For evaluation and comparison. Logistic regression can provide more accurate results than other algorithms and provide high efficiency and improvement. Floods are perhaps the most destructive event in the world, can cause irreversible damage and cause great suffering to humanity. Generally, most farmers are the most disturbed people in the world because their hard work can suddenly fail, causing their hearts to become melancholy. To measure water level and velocity over a large area, it is important to provide an exposure model that includes safety. These models can be aimed to improve the prediction by using different methods. Additionally, these models provide accurate predictions of flood events in a year, but do not provide much understanding and detail of the options needed.

Keywords:- *Forecast, Flood Forecast, ML Model, Flood Decision, Flood Research, Expiration Date.*

I. INTRODUCTION

Floods are one of the most devastating natural disasters that cause mass death, devastation and devastation worldwide. Traditiona flood forecasting methods rely on historical data and decision models.

Machine learning provides a powerful way to improve the accuracy of flood forecasting and predictions by leveraging weather forecast and historical flood data (including the time scale of time). Machine learning algorithms can extract relationships from this data to improve predictive models.

- *Flood Forecasting Requires Different Types of Informati on:*

- The amount of rainfall occurring on real-time basis.
- The rate of change in river stage on real-time basis, which can help indicate the severity and immediacy of the threat.
- Knowledge about the type of storm producing the moisture, such as duration, intensity and areal extent, which can be valuable for determining possible severity of the flooding.

Floods are the most devastating among natural disasters and cause great damage to human life, so the government is under pressure to improve the security of the area and it is flooded. However, the timing of the flood and its prediction depends on the nature of the weather.

This article explores the use of various machine learning methods in flood forecasting, highlighting their advantages, limitations and potential to improve flood management.

Machine learning enables authorities to issue timely warnings, allocate resources efficiently and minimize damage to the environment.

II. LITERATURE SURVEY

- *Flood Forecasting:*

This review provides the current state of flood forecasting worldwide, including various methodologies.

- *Flood Detection:*

The detection of flood is important when the water level raises where the people living near that area.it detects the flood before it arises in the prone areas.

- *Flood Alerts:*

The alerting of flood has been done by wireless sensor network (WSN) which is cheaper and affordable and easy to maintain. The model uses simple calculations which are easy to understand.

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➢ *Early Flood Warning:*

The system is developed to warn the people when floods arrive. the user can make emergency cells and also send messages. The inclination drop with versatile learning calculation portrays the relapse toward the mean of the genuine development.

III. METHODOLOGY

➢ *Data Collection:*

Collect relevant data including historical flood data as a forecast model. Cleaning and prioritizing information regarding defects, irregularities and violations. Proven design skills to find solutions to past security challenges.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P
1	SUBDIVISION	YEAR	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC	ANNUAL RAINFALL	FLOODS
2	KERALA	1901	28.7	44.7	51.6	160	174.7	824.6	743	357.5	197.7	266.9	350.8	48.4	3248.6	YES
3	KERALA	1902	6.7	2.6	57.3	83.9	134.5	390.9	1205	315.8	491.6	358.4	158.3	121.5	3326.6	YES
4	KERALA	1903	3.2	18.6	3.1	83.6	249.7	558.6	1022.5	420.2	341.8	354.1	157	59	3271.2	YES
5	KERALA	1904	23.7	3	32.2	71.5	235.7	1098.2	725.5	351.8	222.7	328.1	33.9	3.3	3129.7	YES
6	KERALA	1905	1.2	22.3	9.4	105.9	263.3	850.2	520.5	293.6	217.2	383.5	74.4	0.2	2741.6	NO
7	KERALA	1906	26.7	7.4	9.9	59.4	160.8	414.9	954.2	442.8	131.2	251.7	163.1	86	2708	NO
8	KERALA	1907	18.8	4.8	55.7	170.8	101.4	770.9	760.4	981.5	225	309.7	219.1	52.8	3671.1	YES
9	KERALA	1908	8	20.8	38.2	102.9	142.6	592.6	902.2	352.9	175.9	253.3	47.9	11	2648.3	NO
10	KERALA	1909	54.1	11.8	61.3	93.8	473.2	704.7	782.3	258	195.4	212.1	171.1	32.3	3050.2	YES
11	KERALA	1910	2.7	25.7	23.3	124.5	148.8	680	484.1	473.8	248.6	356.6	280.4	0.1	2848.6	NO
12	KERALA	1911	3	4.3	18.2	51	180.6	990	705.3	178.6	60.2	302.3	145.7	87.6	2726.7	NO
13	KERALA	1912	1.9	15	11.2	122.7	217.3	948.2	833.6	534.4	136.8	469.5	138.7	22	3451.3	YES
14	KERALA	1913	3.1	5.2	20.7	75.7	198.8	541.7	763.2	247.2	176.9	422.5	109.9	45.8	2610.8	NO
15	KERALA	1914	0.7	6.8	18.1	32.7	164.2	565.3	857.7	402.2	241	374.4	100.9	135.2	2899.1	NO
16	KERALA	1915	16.9	23.5	42.7	106	154.5	696.1	775.6	298.8	396.6	196.6	302.5	14.9	3024.5	YES
17	KERALA	1916	0	7.8	22	82.4	199	920.2	513.9	396.9	339.3	320.7	134.3	8.9	2945.3	YES
18	KERALA	1917	2.9	47.6	79.4	38.1	122.9	703.7	342.7	335.1	470.3	264.1	256.4	41.6	2704.8	NO
19	KERALA	1918	42.9	5	32.8	51.3	683	464.3	167.5	376	96.4	233.2	295.4	54.1	2501.9	NO
20	KERALA	1919	43	6.1	33.9	65.9	247	636.8	648	484.2	255.9	249.2	280.1	53	3003.3	YES
21	KERALA	1920	35.2	5.5	24.1	172	87.7	964.3	940.8	235	178	350.1	302.3	8.2	3303.1	YES
22	KERALA	1921	43	4.7	15	171.3	104.1	489.1	639.8	641.9	156.7	302.4	136.2	15.8	2719.9	NO
23	KERALA	1922	30.5	21.4	16.3	89.6	293.6	663.1	1025.1	320.6	222.4	266.3	293.7	25.1	3267.6	YES
24	KERALA	1923	24.7	0.7	78.9	43.5	80	722.5	1008.7	943	254.3	203.1	83.9	41.6	3484.7	YES
25	KERALA	1924	19.3	2.9	66.6	111	185.4	1011.7	1526.5	624	289.1	176.5	162.9	50.4	4226.4	YES
26	KERALA	1925	4.1	16.5	76.9	93.4	258.2	688.8	593.5	554.1	158.8	295.4	223.7	98.8	3062.1	YES
27	KERALA	1926	28.6	5.8	23.1	55.8	222.6	563.9	885.2	536	322.7	216.7	88.8	16.2	2965.4	YES
28	KERALA	1927	18.8	35.3	49.6	86.5	265.4	720.2	888.2	315	335.6	135.8	137.6	6.8	2994.7	YES
29	KERALA	1928	12.7	65.9	51.3	121.1	81.9	590.7	420.6	553.2	75.9	321.5	155.2	52.7	2502.8	NO
30	KERALA	1929	12.8	29.8	58.9	210.7	148	946.6	844	293.9	268.9	350.4	158.2	39.4	3361.6	YES
31	KERALA	1930	10.8	10.8	39	102.7	404.9	633.1	401.7	273.4	411.5	433.9	207	89.2	3018	YES
32	KERALA	1931	3.3	0.3	19.2	126.9	131.7	541.7	653.9	1199.2	163.2	149.3	164.3	106.5	3259.6	YES
33	KERALA	1932	0.1	19.3	28.6	113	646.5	341	716.4	423.2	317.3	543.2	223.2	31.3	3403	YES
34	KERALA	1933	1	9.3	36.9	139.5	738.8	859.3	773.4	479.5	469.7	397	126.1	42.3	4072.9	YES

Fig 1 Historical Flood Data

➢ *Feature Selection:*

- Identify the most important features for flood prediction using techniques such as PCA.
- Remove other features that may capture the relationship between variables, such as temporal patterns.

➢ *Methods used:*

Here we use logistic regression machine learning algori thm for flood prediction.

➢ *Model Training:*

Logistic regression is an algorithm in control learning. It is used to use the self-regulation method to predict unabated changes in the church. Here we use LR to predict floods with 95% accuracy.

The output will be 0 or 1, Yes or No, True or False. Returns the probability that the quality is between 0 and 1. Strategy degeneracy is used to solve representation problems. Here we can fit the capacity of the s-module calculation.

➢ *Equation:*

$$Y = b0 + b1x1 + b2x2 + b3x3 + \ldots\ldots\ldots\ldots +bnXn$$

$$y / y\text{-}1;\ 0 \text{ for } y = 0,\ 1 \text{ when } y = \text{Unlimited}$$

$$\log[y/y\text{-}1] = b0 + b1x1 + b2x2 + b3x3 + \ldots\ldots .+bnXn$$

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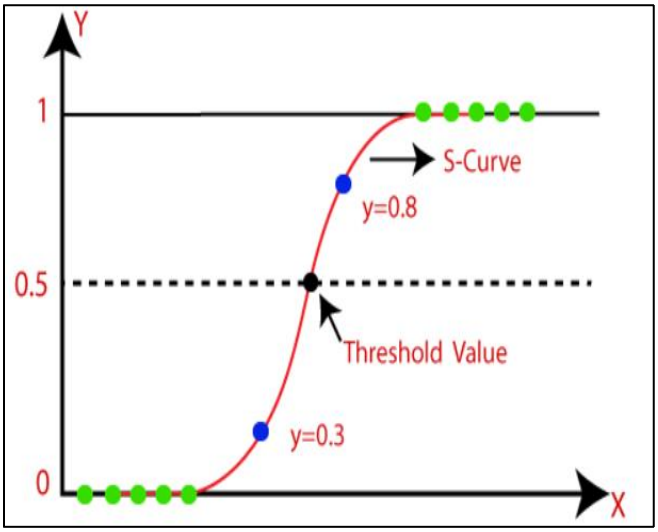

Fig 2 Graph for Logistic Regression

➢ *Applying the Logistic Regression Algorithm:*

The code below shows us that we can train and test the data by applying LR.

```
[15]: x_train_std = minmax.fit_transform(x_train)
      x_test_std = minmax.transform(x_test)

[16]: from sklearn.model_selection import cross_val_score
      from sklearn.linear_model import LogisticRegression

      lr = LogisticRegression()
      lr_clf = lr.fit(x_train_std,y_train)

      lr_accuracy = cross_val_score(lr_clf,x_test_std,y_test,cv=3,scoring='accuracy',n_jobs=-1)

[17]: lr_accuracy.mean()

[17]: 0.75
```

Fig 3 Training the Data using Logistic Regression

➢ *Applying the KNN Algorithm:*

```
[18]: clf = neighbors.KNeighborsClassifier()
      knn_clf = clf.fit(x_train,y_train)

[19]: y_predict = knn_clf.predict(x_test)
      print('predicted chances of flood')
      print(y_predict)

      predicted chances of flood
      [1 0 0 1 0 1 0 1 1 0 0 0 1 1 0 1 0 1 0 0 0 1 1 1]

[22]: from sklearn.model_selection import cross_val_score
      knn_accuracy = cross_val_score(knn_clf,x_test,y_test,cv=3,scoring='accuracy',n_jobs=-1)
      knn_accuracy.mean()

[22]: 0.8333333333333334
```

Fig 4 Training the Data using KNN Algorithm

We use the KNN algorithm to detect or predict floodin g with 91% accuracy. 3. Apply the decision tree algorithm:

➢ *Applying Random Forest Algorithm:*

```
[26]: from sklearn.ensemble import RandomForestClassifier
      rmf = RandomForestClassifier(max_depth=3,random_state=0)
      rmf_clf = rmf.fit(x_train,y_train)
      rmf_clf

[26]: ▾ RandomForestClassifier
      RandomForestClassifier(max_depth=3, random_state=0)

[27]: rmf_clf_acc = cross_val_score(rmf_clf,x_train_std,y_train,cv=3,scoring="accuracy",n_jobs=-1)

[28]: rmf_clf_acc

[28]: array([0.9375    , 0.70967742, 0.74193548])

[29]: from sklearn.metrics import accuracy_score,recall_score,roc_auc_score,confusion_matrix
      print("\naccuracy score:%f"%(accuracy_score(y_test,y_pred)*100))
      print("recall score:%f"%(recall_score(y_test,y_pred)*100))
      print("roc score:%f"%(roc_auc_score(y_test,y_pred)*100))

      accuracy score:70.833333
      recall score:72.727273
      roc score:70.979021
```

Fig 5 Training the Data using Random Forest Algorithm

➢ *Comparison of all Flood Prediction Algorithms:*

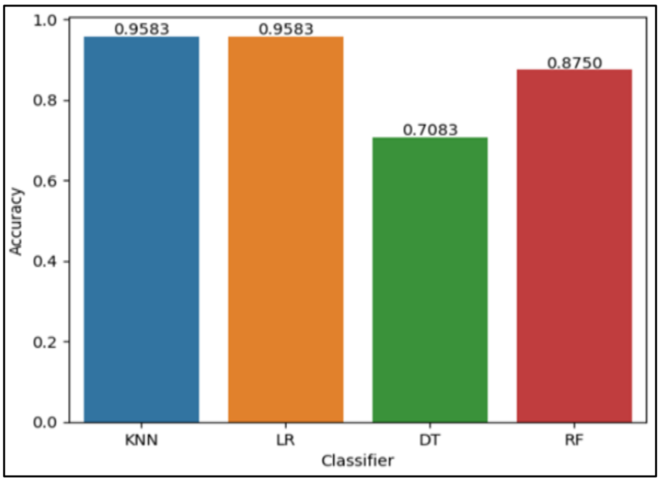

Fig 6 Comparison Graph for all Flood Protection Algorithm

IV. CONCLUSION

By comparing flood prediction algorithms among them, flood prediction can be made through transportation. The higher the accuracy, the easier the prediction. Therefore, we prefer LR to predict the probability of flooding.

Advances in computer innovation have enabled significant advances in machine learning; From this, many unsustainable models emerge that rely on customers and the questions they seek answers to that already exist (flood expectations, infrastructure), Water assets and their managers.

This article demonstrates the need for flood prediction models. It is based on intelligence. Four different intelligence models, KNN, were determined by tree selection, iterative counting, and cutting to measure scores (such as precision, accuracy, inspection, and F1 score) using

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the support vector machine, and the results show that recycling is the best model. highest review score. The article also recommended collaboration of the intelligence model with intelligence design; the model shows global and nearby promises for flood and non-flood cases respectively. Future work will look at deep learning models and human-machine interfaces that will enable users to find answers to help predict recent floods.

This report focuses on meta-analysis, which is described in a new article on flood forecasting, and the program is widely used in times of need. Based on the above analysis, written research and integration, it can be concluded that the measurement strategy using NARX can provide unique and useful results for flood measurement. This study is useful in explaining the process of these plans and how they influence each other, so that it can be understood which strategy is better and what to do and how.

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