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Flood Prediction Analysis Using Explainable Artificial Intelligence

Siva Sathyanarayana Movva

*sivasathya@gmail.com

ABSTRACT

This paper presents flood prediction models for the state of Kerala in India by evaluating the monthly rainfall data and applying machine learning algorithms including Logistic Regression, K-Nearest Neighbors, Decision Trees, Random Forests, and Support Vector Machine. Despite demonstrating high accuracy in predicting flood occurrences within a given year, these models lack both quantitative and qualitative explanations for their prediction decisions. The paper addresses this gap by illustrating how underlying features influencing the prediction decisions are identified. Additionally, the study extends its insights by incorporating explainable artificial intelligence modules such as SHAP and LIME to provide a detailed understanding of the models. The results obtained affirm the validity of the findings revealed by these explainer modules, based on the historical monthly rainfall data related to floods in Kerala

Key words: machine learning algorithms, predictive decision, artificial intelligence, flood prediction, accuracy (key words)

INTRODUCTION

Presently, natural calamities like floods exert a significant influence on both humans and infrastructure. The expenses associated with these disasters have risen substantially, encompassing not only economic ramifications but also detrimental effects on the environment and human lives. This escalating cost is attributed to various factors, including population growth and alterations in land use patterns. Additionally, the recent surge in global warming has contributed to an increased frequency of floods worldwide. India, particularly Kerala, has been severely impacted by these floods, with 2018 being a notable year. The Central Water Commission (CWC) of India reported extensive flooding in Kerala during August 2018, affecting millions and causing over 400 deaths. According to the Associated Chambers of Commerce and Industry of India (ASSOCHAM), the estimated damage incurred by Kerala due to this disaster amounts to 15,000 to 20,000 crores. The coming years are anticipated to continue presenting significant challenges in this regard. In the forthcoming years, it is imperative to devise a solution capable of forecasting floods well in advance to mitigate potential damage. Traditionally, models were employed for predicting events like storms, rainfall, and natural calamities, yielding satisfactory results but demanding extensive processing units and substantial computational power, which hindered timely predictions. The implementation of traditional models also necessitated profound knowledge of hydrological study parameters, and despite their complexity, these models exhibited failures in accurately predicting floods, as exemplified by an incident in Queensland, Australia, in 2010. Numerical prediction models similarly proved unreliable due to logical errors. Recent technological advancements offer numerous methods for developing more precise and accurate applications to enhance flood predictions. Among these advancements, Artificial Intelligence (AI) and machine learning have garnered significant attention due to their cost-effectiveness, minimal coding requirements, low resource needs, and the ability to quickly and accurately learn from past events, leading to early predictions. While machine learning models have demonstrated benefits in the technological industry, end users often have limited insights into the internal workings of these models, resulting in a "black-box" effect. As these models increase in complexity, it becomes challenging to identify biases and errors in the prediction process. Failure to address this issue can lead to a reduction in trust among users, potentially leading to rejection of these models in real-time scenarios. This is where Explainable Artificial Intelligence (XAI) becomes crucial. The authors note a lack of research aimed at making flood prediction models more transparent and interpretable for users. Therefore, the paper's contributions include the development of a flood prediction system coupled with model explainability, the assessment of prediction model accuracy, and the analysis of findings uncovered by explainer modules based on historical flood data. Machine learning algorithms such as Logistic Regression, K-Nearest Neighbors (KNN), Decision Trees, and Support Vector Machine have been chosen for the flood prediction system's development and model explainability using XAI techniques such as Shapley Adaptive Explanation (SHAP) and Local Interpretable Model-Agnostic Explanation (LIME).

EASE OF USE

A. Area of study

The chosen area under investigation is the state of Kerala, situated in southern India. In August 2018, Kerala experienced highly uncommon flooding characterized by continuous rainfall from the 8th to the 17th of August. Despite possessing an extensive coastline and numerous reservoirs, the state encountered challenges in retaining water within riverbanks, resulting in significant overflow in the Periyar river and Vembanad Lake. According to the Chamber of Commerce India, the financial toll on the state due to the floods is estimated to be around 2000 crores.

B. Data

The dataset utilized for constructing the flood prediction model pertains to the state of Kerala, spanning a duration of 115 years, commencing from 1901 to 2015. This dataset comprises 118 entries with 16 distinct columns of information, delineating monthly rainfall. Additionally, one column explicitly indicates whether a flood occurred in a given year, denoted as either "Yes" or "No." Model predictions are based on the occurrence of monthly rainfall within a specific year. A comprehensive analysis was conducted, focusing on the average monthly rainfall from 1901 to 2015. This analysis is visually represented in Fig. 2, portraying a bar graph that highlights months with the highest and lowest rainfall. As depicted in Fig. 2, a substantial concentration of rainfall is observed particularly in June and July. It's important to note that this outcome is derived from the average rainfall over the 116-year period.

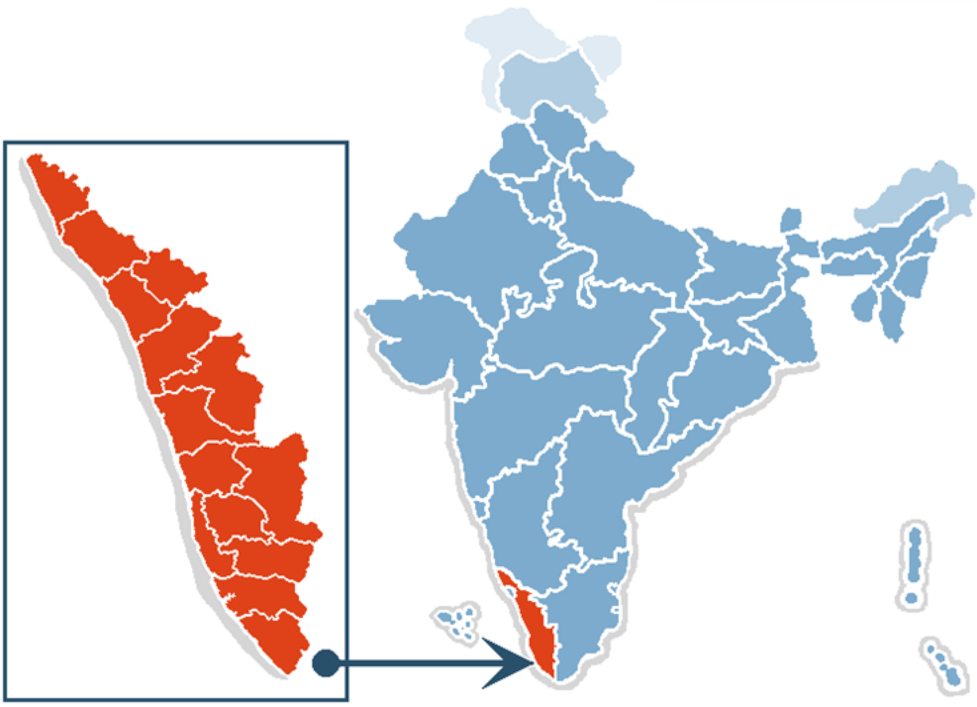

Figure 1: Map of Kerala

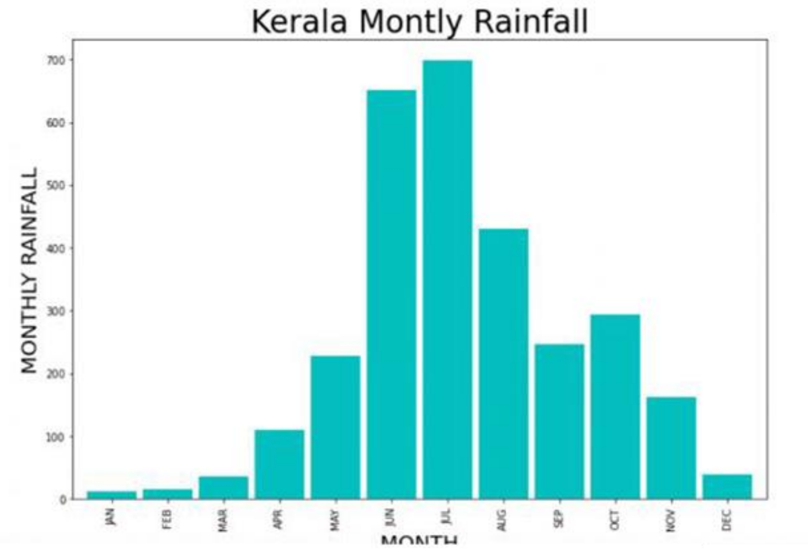

Figure 2: Monthly rainfall analysis

FLOOD PREDICTION MODELS

AI is essential for enhancing flood prediction accuracy and preventing errors in forecasting. Traditional flood prediction systems often fall short in delivering precise forecasts due to insufficient information. This lack of accuracy can result in adverse consequences, jeopardizing residents who may be unable to make timely evacuation decisions, thereby putting their lives at risk.

Machine Learning (ML) utilizes mathematical expressions and algorithms to predict floods. The models are data-driven, relying on historical data to enhance prediction systems and deliver accurate results in a cost-effective manner. To implement a successful prediction model, the initial step involved preprocessing the dataset by addressing null values. Subsequently, descriptive data in the dataset was converted into numerical format since ML models cannot directly handle categorical data. Once the data was encoded numerically, the dataset was split into a training dataset (70%) and a test dataset (30%) to assess the model's performance by comparing results on trained and test data.

A. K-Nearest Neighbours

K-Nearest Neighbors (KNN) functions as a supervised machine learning algorithm applicable to both classification and regression tasks. However, it is predominantly employed as a classification model in most scenarios. KNN operates on labeled data, classifying it according to the attributes of its neighboring data points. The 'K' in KNN denotes the quantity of nearest neighbors considered when classifying new data. This model relies on the Euclidean distance formula to determine the proximity between two points in a plane with coordinates (x, y) and (a, b), expressed as:

$$\sqrt{(x-a)^2+(y-b)^2} \tag{1}$$

The algorithm calculates the distance between a particular data that requires to be classified and its nearest neighbors. Basing on the nearest neighbors distance it is classified into that class of data.

B. Logistic Regression

Logistic Regression is one of the most simple and commonly used Machine Learning algorithms for two-class classification. It is easy to implement and can be used as the baseline for any binary classification problem. Its basic fundamental concepts are also constructive in deep learning. Logistic regression describes and estimates the relationship between one dependent binary variable and independent variables. Logistic Regression is a supervised learning model which is used for solving classification problems. It is used when the output is necessary to be present in the 0 or 1, Yes or No, True or False, High or Low. This algorithm works based on the equation below:

$$\log\left[\frac{y}{1-y}\right] = b_0 + b_1x_{1+}b_2x_2 + \cdots + b_nx_n \quad (2)$$

C. Decision Trees

Decision tress are supervised learning models with flexibility of the usage in both regression and classification kind of problems. It consists of root nodes, internal nodes, and leaf nodes. The decision tree works by making the question for decision as the root node and based on the question the tree is extended until the least level of entropy is reached. The formula for entropy is given as

$$\sum_{i=1}^{k} P(value_i).\,log_2(P(value_i)) \quad (3)$$

where k represents the numbers of elements present in the dataset, P is the probability of an element. Decision tree gave an accuracy of 75% which is relatively low meaning this would not be the most recommended algorithm for the flood prediction purpose.

C. Support Vector Machines (Svm)

The Support Vector Machine (SVM) is a supervised learning algorithm applicable for both classification and regression tasks. Employing the kernel trick, it transforms data, enabling the formation of an optimal boundary (hyperplane) to discern between potential outputs. SVM operates by categorizing data into support vectors, subsequently drawing an optimal hyperplane between them while maximizing the distance between the hyperplane and the vectors.

FLOOD EXPLAINERS

While machines have demonstrated superior performance compared to humans, there remains skepticism regarding the reliability of solutions provided by machine learning models. The extensive calculations performed by these models for predictions often lack transparency, making it challenging for humans to comprehend. Addressing this issue, Explainable AI (XAI) models play a crucial role. XAI facilitates the interpretation of machine learning models in a format understandable by humans, offering transparency and clarity. As a component of Artificial Intelligence (AI), XAI contributes to providing explicit explanations for human comprehension [25]. Additionally, XAI helps establish trust in the model by revealing the influential data affecting prediction results, displaying features of utmost importance. This paper focuses primarily on XAI methods, specifically LIME and SHAP.

A. Shapley Additive Explanation

The SHAP methodology is based on the game theory concept of Shapley values, which was introduced by Lloyd in 1952. This concept aims to address scenarios where a combination of elements, forming an entity X, results in an output Y, and seeks to determine the individual contributions leading to this outcome. SHAP primarily seeks to elucidate the extent to which each individual feature contributes to achieving the outcome. In SHAP, additivity is defined as follows: Given a set of inputs x and a model f(x), along with a simplified local input x' and an explanatory model g, it is important to ensure that if x' is approximately equal to x, then g(x') should also be roughly equal to f(x'), and g must take on the following form:

$$g(x') = \varphi_0 + \sum_{i=1}^{N} \varphi_i x_i' \quad (4)$$

B. Local Interpretable Model Explanations (Lime)

Local Interpretable Model Explanation (LIME) checks if the prediction that has been made is close to the expected model results or not. The LIME focuses on local interpretability, which is determined by accessing only one input feature that fits in a line of linearity using a regularization constraint applied to a linear regression model. LIME takes a single data input and checks for all the features in the data that are made responsible for the prediction of the machine learning models and classified them into two categories on either side of a line where the left-hand side of the line shows the features in the dataset that are having negative impact on the model prediction and the right-hand side of the line represents the features that are having a positive impact on the machine learning model predictions. In this way the LIME builds the trust on the results by clearly displaying the interior working of the machine learning models. The mathematical interpretation of the LIME model is as follows:

$$E(x) = \underset{g \in G}{\operatorname{argmin}} L(f, g, \pi_x) + \Omega(g) \quad (5)$$

RESULTS, ANALYSIS AND VALIDATION

A. Model Selection

All prediction models will be evaluated in terms of the accuracy, precision, recall and F1-score. Table I shows the performance of the prediction based on 70% training and 30% test dataset. It can be noticed from Table I that logistic regression has shown am accuracy of 0.95, recall score of o.95 meaning that there are very less chances of falsely predicting a positive value and the F1 score of o.95 shows that there is a very good balance between the precision and recall scores meaning that the overall performance of Logistic Regression is very good for the prediction of floods. While the other model KNN shows the least accuracy of 0.75 with very less precision, recall and F1-scores of 0.8, 0.66, and 0.72. The remaining two models' decision trees and support vector machine also do not show expected efficiency when we look at their metric scores. From the above study it can be clearly seen that the Logistic Regression has outperformed the remaining three machine learning models, making it the best recommendable machine learning model for the accurate prediction of floods. Hence, it will be used to analyze the relevance of features.

Table 1: Prediction results on test dataset

Model	Accuracy	Precision	Recall	F1-score
Logistic Regression	0.95	1.0	0.91	0.95
KNN	0.75	0.8	0.66	0.72
Decision Tree	0.83	0.9	0.75	0.81
SVM	0.87	0.91	0.84	0.87

B. Flood analysis with Explainable AI

After performing the implementation of the machine learning algorithms by training and testing the data Logistic regression looks to perform the best with an accuracy of 0.95. But to understand the internal working of the logistic regression model it important to open the Blackbox and learn its working with the help of SHAP and LIME.

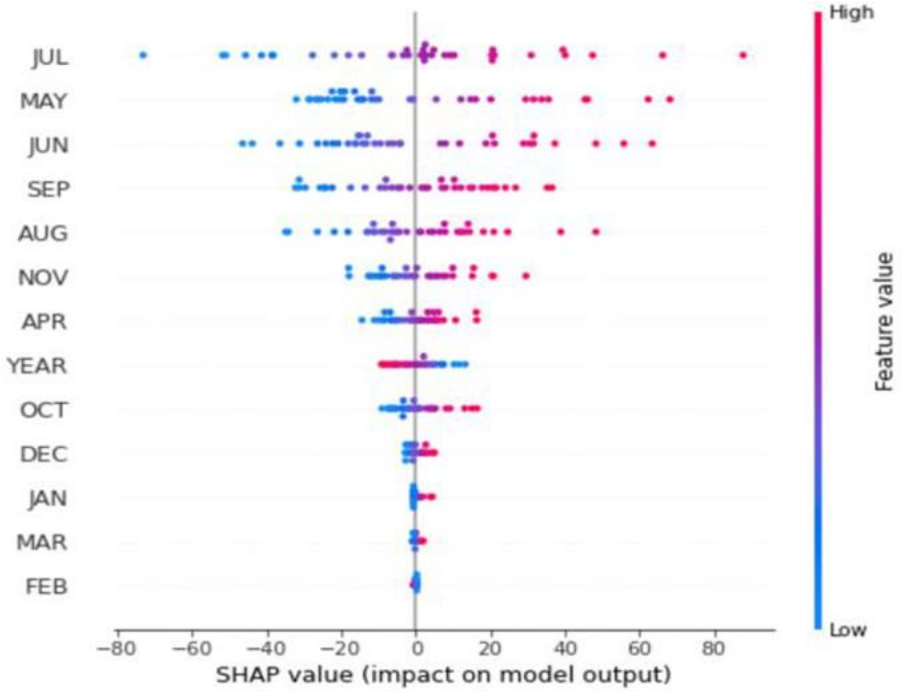

Figure 3: Features contribution to flood and no-flood from 1901 to 2015 by SHAP

SHAP: The SHAP has been used to identify the feature importance in the model prediction. Specifically, it highlights the influence of each month's rainfall data on the machine learning model's ability to forecast floods or non-floods. As depicted in Figure 3, the SHAP analysis ranks the months based on their impact on the model output, with July's rainfall data exerting the greatest influence, followed by May, June, September, and August. November, April, and October contribute moderately to the model's predictive accuracy, while January, February, and March have the least impact. This analysis provides a comprehensive overview of feature contributions from 1901 to 2015 as unveiled by SHAP.

LIME: After implementing the LIME, the following results have been identified. In 1947, there was a flood in Kerala. LIME output the explanation and analysis in Fig. 4.

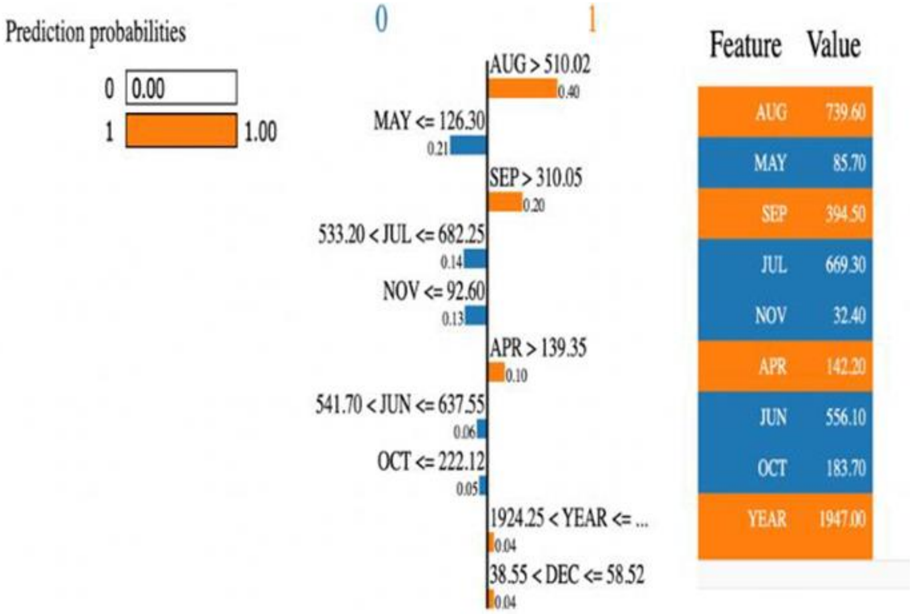

Figure 4: Features contribution to flood and no-flood in 1947 by LIME

Fig. 4 shows that the year 1947 has the complete possibility of flood as the months August contributes 739 meters of rainfall which is greater than the threshold value of 510.02 that has been set by the lime to classify into month that causes flood or not. Similarly, September can be seen as the month with heavy rainfall causing the result to be as flood. The April month contribution also contributed to flood and the December contributed the least to the prediction of floods in that year. It is interesting to note that LIME reveals the local analysis of feature contributions for the particular year.

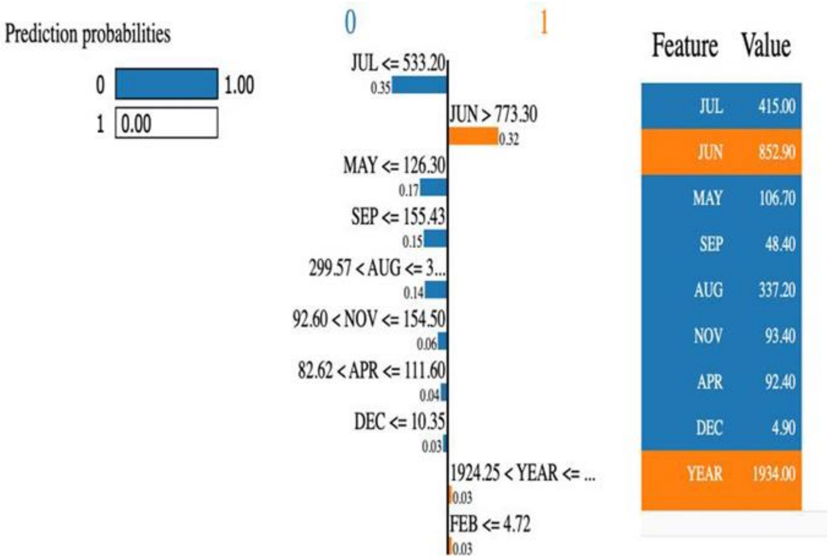

Figure 5: Features contribution to flood and no-flood in 1934 by LIME

Comparing the results that have been identified in LIME with the overall results provided by the SHAP, the months August, September are among the top five months and April contributes at medium for the prediction of the model results in SHAP. The same is seen in the LIME results which show the month August and September contributing the highest to the model output in the year 1947 for a flood occurrence. Fig. 5 depicts the LIME prediction which shows that there is no flood in the 1934. This is validated by the fact that July has the highest contribution to the model results with the month having rainfall of 415.0 which is very less leading to the prediction as no floods in the 1934.Comparing the SHAP and LIME results, SHAP shows that July, June, August, May, and September contribute the highest to the model output and similarly in LIME the same months are responsible for the correct prediction of the output. Comparing the results of the SHAP and LIME, both the models project the months May, June, July, and September as the months with the highest impact on the model prediction.

CONCLUSION

The paper highlights the necessity for a predictive model based on machine learning to forecast floods. It compares four distinct machine learning models – KNN, Decision Tree, Logistic Regression, and Support Vector Machine – based on various metric scores, including accuracy, precision, recall, and F1-score. The findings indicate that Logistic Regression stands out as the superior model with the highest metric scores. Additionally, the paper validates the machine learning model's functionality using Explainable AI models, namely SHAP and LIME. These models respectively disclose global and local feature contributions to predicting flood and no-flood scenarios. The future direction of the research involves exploring deep learning models and integrating human-machine interaction. This framework aims to empower users to discover solutions facilitating earlier flood forecasts in the years to come.

REFERENCES

[1]. G. Di Baldassarre, in: Floods in a Changing Climate: Inundation Modelling, (2012).

[2]. C. Field, V. Barros, T. Stocker. And O. Dahe, in: Managing the Risks of Extreme Events and Disasters Advance Climate Change Adaptation, Cambridge Univ. Press, (2012).

[3]. L. Bouwer, in: Observed and Projected Impacts from Extreme Weather Events: Implications for Loss and Damage. Loss and Damage from Climate Change, pp.63-82, (2018).

[4]. D. Coumou and S. Rahmstorf, in: A decade of weather extremes. Nature Climate Change, 2(7), pp.491-496, (2012).

[5]. V. Mishra, S. Aaadhar, H. Shah, R. Kumar, D.R. Pattanaik, and A.D. Tiwari, in: The Kerala flood of 2018: combined impact of extreme rainfall and reservoir storage. Hydrology and Earth System Sciences Discussions, [online] pp.1–13, (2018).

[6]. M. Zhao and H. Hendon, in: Representation and prediction of the Indian Ocean dipole in the POAMA seasonal forecast model. Quarterly Journal of the Royal Meteorological Society, 135(639), pp.337-352, (2009).

[7]. D. Borah, in: Hydrologic procedures of storm event watershed models: a comprehensive review and comparison Hydrological Processes, 25(22), pp.3472-3489, (2011).

[8]. P. Costabile, C. Costanzo, F. Macchione, in: A storm event watershed model for surface runoff based on 2D fully dynamic wave equations. Hydrological Processes, 27(4), pp.554-569, (2012).

[9]. L. Cea, M. Garrido, and J. Puertas, in: Experimental validation of two-dimensional depth-averaged models for forecasting rainfall–runoff from precipitation data in urban areas. Journal of Hydrology, 382(1-4), pp.88-102, (2010).

[10]. J. Fernández-Pato, D. Caviedes-Voullième and P. García-Navarro, in: Rainfall/runoff simulation with 2D full shallow water equations. Journal of Hydrology, 536, pp.496-513.

[11]. P. Nayak, K. Sudheer, D. Rangan, and K Ramasastri, in: Short-term flood forecasting with a neurofuzzy model. Water Resources Research, 41(4), (2005).

[12]. B. Kim, B. Sanders, J. Famiglietti and V. Guinot, in: Urban flood modeling with porous shallow-water equations: A case study of model errors in the presence of anisotropic porosity. Journal of Hydrology, 523, pp.680-692, (2015).

[13]. R.van den Honert, and J. McAneney, in: The 2011 Brisbane Floods in: Causes, Impacts, and Implications. Water, 3(4), pp.1149-1173, (2011).

[14]. T. Lee and K. Georgakakos, in: Operational Rainfall Prediction on Meso-γ Scales for Hydrologic Applications. Water Resources Research, 32(4), pp.987-1003, (1996).

[15]. D. Shrestha, D. Robertson, Q. Wang, T. Pagano, and H. Hapuarachchi, in: Evaluation of numerical weather prediction model precipitation forecasts for short-term streamflow forecasting purpose. Hydrology and Earth System Sciences, 17(5), pp.1913-1931, (2013).

[16]. V. Bellos, G. Tsakiris, in: A hybrid method for flood simulation in small catchments combining hydrodynamic and hydrological techniques. Journal of Hydrology, pp.331–339, (2016).

[17]. A. Adadi, and M. Berrada, in: Peeking Inside the Black-Box: A Survey on Explainable Artificial Intelligence (XAI). IEEE Access, 6, pp. 52138–52160, (2018).

[18]. The Black Box Society. (2015). Harvard University Press.

[19]. https://github.com/amandp13/Flood-Prediction-Model/blob/master/kerala.csv

[20]. J. Sunkpho, in: Real-time flood monitoring and warning system. Songklanakarin J. Sci. Technol, 33(2), (2011).

[21]. A. Mosavi, P. Ozturk, and K. Chau, in: Flood Prediction Using Machine Learning, Literature Review, (2018).

[22]. K. Taunk, S. De, S. Verma, and A. Swetapadma, in: A Brief Review of Nearest Neighbor Algorithm for Learning and Classification, (2019).

[23]. Mady, in: Chapter 4: Decision Trees Algorithms. [online] Medium, (2017).

[24]. Rushikesh Pupale, in: Support Vector Machines (SVM) — An Overview.

[25]. Lent, Michael & Fisher, William & Mancuso, Michael, in: An Explainable Artificial Intelligence System for Small-unit Tactical Behavior. 900-907, (2004).

[26]. Lundberg, Scott & Lee, Su-In, in: A Unified Approach to Interpreting Model Predictions, (2017).

[27]. S.S.M. Ribeiro, and C. Guestrin, in: “why should i trust you?” explaining the predictions of any classifier, (2016).

[28]. N. Tengtrairat, W.L. Woo, P. Parathai, C. Aryupong, P Jitsangiam, D. Rinchumphu, in: Automated Landslide-Risk Prediction using Web GIS and Machine Learning Models. Sensors 2021, 21(13), 4620

[29]. B.H.D. Koh, C.L.P. Lim, H. Rahimi, W.L. Woo, B. Gao, in: Deep Temporal Convolution Network for Time Series Classification. Sensors 2021, 21(2), 603

[30]. W.L. Woo, in: Human-Machine Co-Creation in the Rise of AI. IEEE Instrumentation and Measurement Magazine, 23(2), pp. 71-73, (2020)