

# Design and implementation of the prediction model for floods and drought

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## Abstract:

Due to irregularities in rainfall, many areas in our country suffer from droughts and floods, depending on surplus or less rain. Consequently, we need an algorithm that can analyze this irregularity in past years and predict to some degree, which areas would require special attention in the coming months. So, we proposed a new machine learning model which will indicate the change of drought and floods with the help of dataset we obtained from NASA's Global Modelling and Assimilation Office Online website. This paper works with LSTM and RNN by testing with different architecture and analysed the results with the present and traditional systems.

**Keywords:** Flood forecasting, Drought prediction, machine Learning models, rainfall

## I. Introduction

There exists so many natural calamities on the earth, flood is one of those calamities that cause major damage to the earth, mainly life of people and also their properties. Drought also affects so many lives, as the famine hit areas usually have decreased or negligible amount of ground water and also the land becomes infertile. We can save many lives if we can predict such calamities before they occur. Using a ML model can give very accurate results and hence we will be able to identify and help thousands of lives.

Objectives:

Our objectives are the following-

- To predict areas that might face a long-term or short-term flood.
- To predict droughts due to shortage of rain in areas.

Methods:

There are many ML models that can be used for prediction of these natural disasters.

For flood prediction we need the data of rainfall, temperature and humidity of the certain place and using this data we can build a machine learning model to predict flood and drought.

## II. PROPOSED WORK :

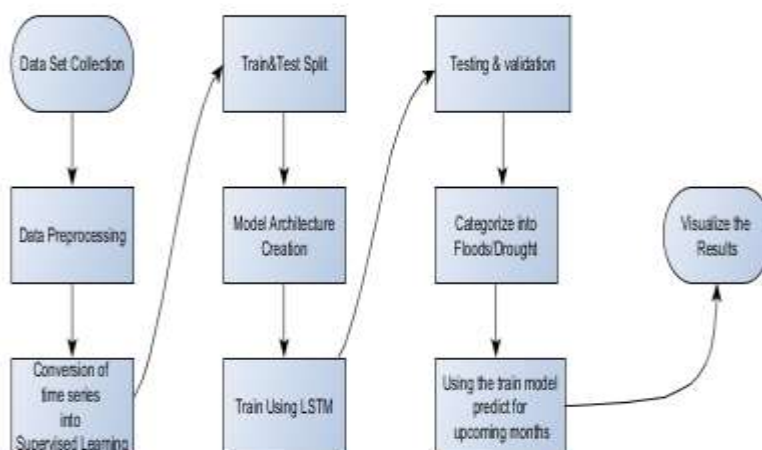
[1] The proposed system is entirely based on a machine learning approach and its architecture includes two main modules, one for text filtering and other for fact extraction. The first module focuses on the selection of news reports about natural disasters, whereas, the second considers the extraction of relevant data from the selected reports. The experimental results demonstrated the pertinence and potential of this solution; using a very small training set it was possible to achieve an F-measure of 98% in the detection of documents about natural disasters, and an F-measure of 76% in the extraction of relevant data from these documents.[2] The paper has proposed a novel DL framework approach with a hybrid of CNNs for deep feature extraction and SVM for classification of different natural calamities. Further, they described four scenarios and selected the best-suited one, thereby obtaining accuracy 82.23%. their proposed framework was observed to outperform the state-of-the-art algorithms.[3] They used 10 flood conditioning factors and 201 flood locations as their model inputs. Eight new hybrid models (Cubic-KNN, Bagging Tree-Cubic KNN, Coarse-KNN, Bagging Tree-Coarse-KNN, Cosine-KNN, Bagging Tree-Cosine-KNN, Weighted KNN, and Bagging Tree-Weighted KNN) were created to analyze and map flood susceptibility. Results based on the relief attribute evaluation metric indicate that distance from the river and slope gradients are the two most important factors for flood occurrence in the Haraz watershed. Among the eight models, it was found that Bagging Tree-Cubic KNN model has the highest predictive power.[4] The study analysed flood susceptibility on a catchment scale in Brisbane, Australia, using two well-known machine learning techniques, DT and SVM. Topographical and hydrological factors (altitude, slope, aspect, curvature, SPI, TWI, TRI, and STI) were obtained from the LiDAR-derived DEM at 5 m spatial resolution, to construct DS1. DS2 included all factors from the first dataset, supplemented by those of geology, soil, LULC and distance from roads and rivers.[5] The predictive ability of the flash-flood conditioning factors was evaluated by using the Correlation-based Feature Selection (CFS) model. The CFS results indicate that among all factors, the Slope angle has the highest Average Merit (0.85). According to the 4 FFPI maps computed by the application of the stand-alone and hybrid models, the total percentage of high and very high FFPI values varies between 16% in the case of FFPIADT-IOE model and 22.5% for FFPIAHP. Another important aspect highlighted by the 4 FFPI maps, is that the areas with a high and very high flash-flood potential are encountered especially in the south-western part of the Suha river basin.[6] Floods are many of the most damaging natural disasters, which might be incredibly complicated to model. The research at the advancement of flood prediction models contributed to hazard discount, coverage inspiration, minimization of the lack of human life, and discount of the property damage related to floods. To mimic the complicated mathematical expressions of bodily processes of floods, during the beyond decades, machine getting to know (ML) methods contributed rather within the development of prediction systems presenting better performance[7] India is the agrarian usa. The typical financial system of our u . S . Is based totally on agriculture. Although the techniques of cultivation are traditional and now not hi-tech as a result extra over seventy five% of our farmers are dependent on monsoon. Prediction of actual monsoon is a undertaking for meteorological scientists. Since the climatic statistics time series suggests pretty non-linear and chaotic conduct as a result its forecast remains an enigma. Thus, forecasting of weather phenomenon is a tough trouble for the researchers spherical the globe. However, it is most important to forecast climatic changes together with Rainfall (day by day rainfall, monthly rainfall, heavy rainfall and so on.), Flood, Drought, minimum and maximum

Temperature, River drift etc.[8] This paper deals with the sensitivity of dispensed hydrological fashions to one-of-a-kind styles that results for the spatial distribution of rainfall: spatially averaged rainfall or rainfall subject. The rainfall statistics come from a dense community of recording rain gauges that cowl approximately 2000 km 2 round Mexico City. The reference rain pattern money owed for the 50 most great events, whose imply duration is about 10 h and maximal point depth a hundred and seventy mm.[9] [9] Rainfall–runoff modelling is one of the key challenges in the field of hydrology. Various approaches exist, ranging from physically based over conceptual to fully data-driven models. In this paper, we propound a new data-driven approach, using the Long Short-Term Memory (LSTM) network, a special type of recurrent neural network. The advantage of the LSTM is its ability to learn long-term dependencies between the provided input and output of the network, which are essential for modelling storage effects in eg catchments with snow.[10] Modeling flood susceptibility in watersheds and reducing the damages caused by flooding is an important component of environmental and water management. ML models such as multivariate discriminant analysis, classification and regression trees, and support vector machines were used for prediction.[11] Floods, as a catastrophic phenomenon, have a profound impact on ecosystems and human life. Modeling flood susceptibility in watersheds and reducing the damages caused by flooding is an important component of environmental and water management.[12]Hydropower is a few of the cleanest assets of electricity. However, the fee of hydropower technology is profoundly stricken by the inflow to the dam reservoirs. In this observe, the Grey wolf optimization (GWO) method coupled with an adaptive neuro-fuzzy inference machine.[13] In the modern-day look at, the ability of 3 data-driven methods of Gene Expression Programming (GEP), M5 model tree (M5), and Support Vector Regression (SVR) were investigated in order to model and estimate the dew point temperature (DPT) at Tabriz.[14] In this paper, we gift a Cluster-Based Approach (CBA) that utilizes the guide vector gadget (SVM) and an synthetic neural network (ANN) to estimate and predict the day by day horizontal international sun radiation. In the proposed CBA-ANN-SVM approach, we first behavior.[15] Snow avalanches are the various maximum unfavourable natural dangers threatening human existence, ecosystems, constructed structures, and landscapes in mountainous regions. The complexity of snow avalanche modelling has been discussed in many research, however its modelling is not properly sufficient.

Floods and Droughts, contrasting in nature, but both of which are equally capable of causing adverse catastrophic effects and can traumatise human lives and their generations. On one hand increased intensity of rainfall causes flood that leads to both economic and social impacts like destruction to properties (such as buildings, bridges, historical sites, etc), loss of crops leading to raise in the price of essential commodities, paves to waterborne diseases, and causes other fatalities. On the other hand increased dryness or reduced rainfall results in a drought condition and its effects are usually long term such as decrease in dairy production, crop cultivation, human health and affect the economic condition of people in all standards.

As we know “Prevention is better than cure”, taking necessary actions beforehand is very essential than to cope with losses. Therefore we seek to predict Floods and Droughts as they allow us to take precautionary actions that can drastically decrease the adverse effects including lives. Hence we propose to build an algorithm that uses LSTM- Long Short Term Memory, for a Time Series Forecast of the next day’s rainfall. For this, we will train a Recurrent Neural Network model as it is most appropriate for our desired outcome.

#### ARCHITECTURE :



## DATASET

The dataset which we are using is obtained from the National Aeronautics and Space Administration (NASA) / Goddard Space Flight Center.

The dataset contains the following features:

Temperature (K) Relative humidity (%) Pressure (hPa)

Wind speed (m/s) Wind direction (deg) Rainfall (kg/m<sup>2</sup>)

Short-wave irradiation (Wh/m<sup>2</sup>)

Water level of four local reservoirs, Poondi, Cholavaram, Red hills and Chembarambakkam (ft)

The data obtained it upto 31st January, 2020, all of which will be used as our input parameters.

## SOLUTION

As we know “Prevention is better than cure”, taking necessary actions beforehand is very essential than to cope with losses. Therefore we seek to predict Floods and Droughts as they allow us to take precautionary actions that can drastically decrease the adverse effects including lives. Hence we propose to build an algorithm that uses LSTM- Long Short Term Memory, for a Time Series Forecast of the next day’s rainfall. For this, we will train a Recurrent Neural Network model as it is most appropriate for our desired outcome.

## TECHNIQUE

Recurrent Neural Network-

Understanding our objective, we can come to the following conclusions:

1. Our model needs to make use of all input parameters.
2. For predicting the rainfall in future, we need to form a sequence of values, which is done by RNN.
3. The sequence is formed as such- Say for predicting any value ‘n’ we need the datas of ‘a’, ‘b’ and ‘c’. Say we get the said value of n. Now, for predicting n+1, we need the values of

a+1, b+1 and c+1. What RNN does, is that it sends the value of the predicted ‘n’ too, in prediction of n+1, making our predictions dependent on the past results too.

Such is the case in our LSTM prediction, that while training, we will use the 6 parameters to predict Rainfall for that day. Now, when we need to predict rainfall for the next day, we will again be using the next day’s six weather parameters, as well as the predicted rainfall for the last day.

This would result in an accurate model.

## WHAT IS THE INNOVATION & NOVELTY

The whole idea of this project is to predict floods and droughts based on rainfall data. We understand that there is a need to predict catastrophes in a much advanced time which the traditional methods fail to do. We can only know floods and droughts based on the water level increase and decrease in rivers. That is, we only know when it attacks us. There is no way to find it even before initial stages start.

ML allows us to do this in a much advanced time based on the location’s weather data.

With our approach, we can find flood-prone and drought-prone areas even before it happens and take necessary actions to prevent it or mitigate the losses.

## LSTM:

LSTM is long short-term memory, an advanced version of RNN, which solves drawbacks of RNN’s.

The focal function of a LSTM model is held by a memory cell known as a 'cell state' that keeps up its state after some time. It tends to be envisioned as a transport line through which data just streams, unaltered.

Data can be added to or taken out from the cell state in LSTM and is controlled by gates. These gateways alternatively let the data stream all through the cell. It contains a pointwise increase activity and a sigmoid neural net layer that help the system.

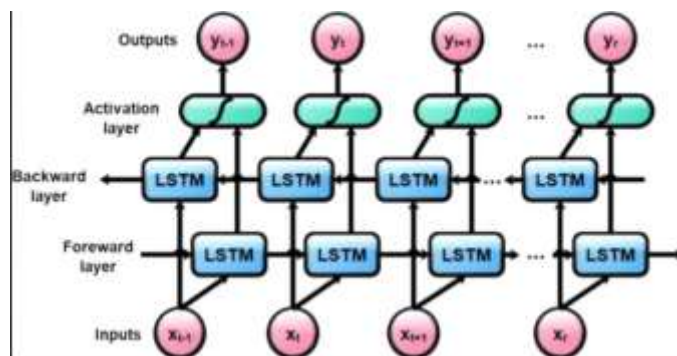
The sigmoid layer gives out numbers somewhere in the range of zero and one, where zero amounts to 'nothing ought to be allowed,' and one signifies 'everything ought to be allowed.'

#### Architecture of LSTM:

There are several architectures of LSTM units. A typical design is made out of a cell (the memory part of the LSTM unit) and three "regulators", normally called gates, of the progression of data inside the LSTM unit: an input gate, a output gate and a forget gate. A few varieties of the LSTM unit don't have at least one of these gates or perhaps have different gates. For instance, gated repetitive units (GRUs) don't have a yield entryway.

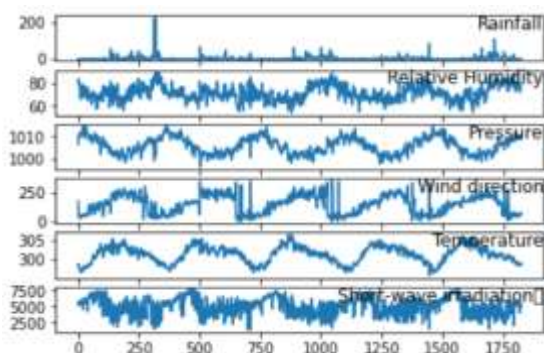
Naturally, the cell is answerable for monitoring the conditions between the components in the information grouping. The input gate controls the degree to which another worth streams into the cell, the forget gate controls the degree to which a worth stays in the cell and the yield door controls the degree to which the incentive in the cell is utilized to register the yield actuation of the LSTM unit. The activation function of the LSTM entryways is frequently the strategic sigmoid capacity.

There are associations into and out of the LSTM entryways, a couple of which are repetitive. The loads of these associations, which should be gotten the hang of during preparing, decide how the entryways work.



#### Methodology:

The dataset is obtained from official NASA's Global Modelling and Assimilation Office. The dataset contains 11 attributes on which the model is going to be trained. The data ranges from past 4 years data (2016-2019). The attributes are Rainfall, Relative Humidity, Pressure, Wind Speed, Wind Direction, Snowfall, Snow-depth and Short-wave irradiation, temperature. The main goal of this is to develop a model which predicts whether a place is likely to have floods or drought on the next day based on the rainfall.



The above plot shows the dependency between the rainfall, Relative Humidity, Pressure, Wind-Direction, temperature, Short wave irradiation. The traditional way of predicting floods or droughts is understanding whether a place has had more than 50% of rainfall than the expected average levels. To understand this better, [16] we can see that Chennai had its last flood in November of 2015 with about 183% higher rainfall than the place is expected to have in the month of November.

So, it makes more sense to predict the rainfall, if there will be any chance of that happening tomorrow based on its conditions for a period of time and then cross checking it with how much rainfall the place was expected to have to understand whether the place is likely to have one of the following conditions: Flood, Drought or Normal. While it makes sense to have a daily analysis for flood prediction, as floods occur in a relatively short span of time, droughts do not occur with just no rainfall in one day. It is more of a monthly analysis. Where there is little or no rainfall for an extended period of time. Therefore, it was more suitable to take daily data to predict the same. To predict the condition of one particular day, we need to know the weather conditions of that place in the past.

**Algorithm:**

We choose LSTM for this project, since for any time series predictions, LSTM proved to be one of the powerful algorithms for better accuracy. LSTM model is known for remembering long term dependencies. While we could assume that only our last day's weather conditions are just enough to predict today's rainfall or any other weather condition, it doesn't make sense. Because an event occurs with a series of changes for a particular time. LSTM can understand long term dependencies because LSTM has a memory cell and reset cell in its structure. Memory cell is known to remember it all while a reset cell is for resetting/clearing LSTM's memory. After every batch of given size while training, an LSTM model's memory will be reset.

We ran the same dataset in two different architectures of LSTM.

### Model-1

```
Model: "sequential_10"
```

| Layer (type)     | Output Shape | Param # |
|------------------|--------------|---------|
| lstm_4 (LSTM)    | (None, 50)   | 11600   |
| dense_39 (Dense) | (None, 1)    | 51      |

Total params: 11,651  
Trainable params: 11,651  
Non-trainable params: 0

In our model, we have given our batch size to be 50 which means that LSTM can understand long term dependencies for 50 days and after every 50 days, it will be reset. This offers great results to predict rainfall at a particular day for our place as it works as a sequential model remembering conditions and their dependencies for every 50 days. Firstly, we gathered the dataset and we have converted it into a time-series data. Time-series data is continuous data that enables a supervised learning for LSTM and has a basic structure like:

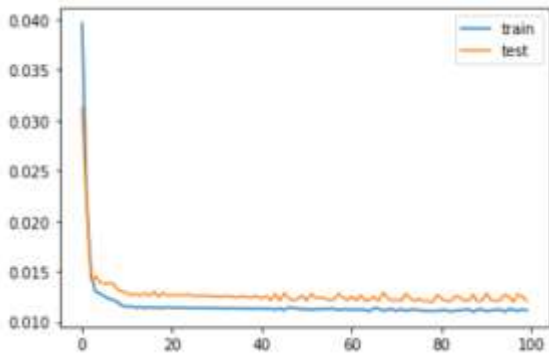
Input: 0th day rainfall, pressure, ...water levels

Output: 1st day rainfall.

We chose our loss functions as mean absolute error (MAE) with Adam optimizer. MAE seemed to be perfect with a flexible optimizer, Adam that lets the model learn with understanding outlier's importance too, as in our case, outliers could be a sudden spike in rainfall that could result in flood. We can observe from the graph and val\_loss that our model has learnt.

### Testing:

After training and predicting



```

0.51392767e-01  0.18935716e-01  6.49250982e-01  3.89626888e-01
4.37066468e-01  7.41853522e-01  6.84534132e-01  8.57949018e-01
8.48909180e-01  6.58763766e-01  7.87437932e-01  5.88950174e-01
6.38182521e-01  5.45389473e-01  4.72545147e-01  4.26342815e-01
3.70483279e-01  3.91435866e-01  8.21085453e-01  4.08981486e-01
2.54839331e-01  2.63750017e-01  4.77995872e-01  6.14412018e-01
0.08524811e-01]
(365,)
(365,)
Test RMSE: 0.198
    
```

We have an actual sequence of 365 days to be predicted and a predicted sequence with 365 days of next day's rainfall. Our root mean square error is around 8.1 which is pretty acceptable for a sequential model. Later, we cross checked our predicted results with the expected conditions for a month. We are supposed to understand if this month could face any drought conditions or not. Whereas, the daily predicted sequence with expected conditions of a month to understand if this month has any flood chance on any day

**Model -2**

In this model we increased the number of layers and using the same optimizer and loss function being mean squared error [MSE].

```
Model: "sequential_7"
```

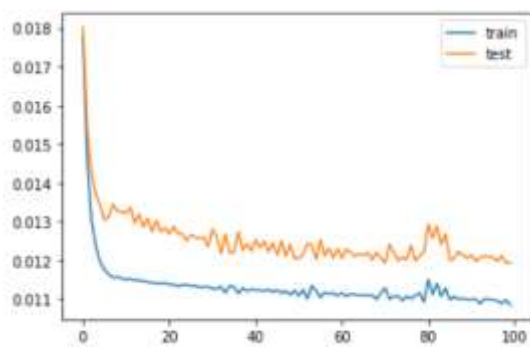
| layer (type)        | Output Shape    | Param # |
|---------------------|-----------------|---------|
| dense_27 (Dense)    | (None, 1, 128)  | 1024    |
| dense_28 (Dense)    | (None, 1, 256)  | 33024   |
| dense_29 (Dense)    | (None, 1, 512)  | 131584  |
| dense_30 (Dense)    | (None, 1, 512)  | 262656  |
| dropout_2 (Dropout) | (None, 1, 512)  | 0       |
| dense_31 (Dense)    | (None, 1, 1024) | 525312  |
| dense_32 (Dense)    | (None, 1, 1024) | 1049600 |
| dropout_3 (Dropout) | (None, 1, 1024) | 0       |
| dense_33 (Dense)    | (None, 1, 512)  | 524800  |
| dense_34 (Dense)    | (None, 1, 512)  | 262656  |
| dropout_4 (Dropout) | (None, 1, 512)  | 0       |
| dense_35 (Dense)    | (None, 1, 256)  | 131328  |
| Flatten_1 (Flatten) | (None, 256)     | 0       |
| dense_36 (Dense)    | (None, 1)       | 257     |

---

```
Total params: 2,922,241
Trainable params: 2,922,241
Non-trainable params: 0
```

**Testing:**

After training and predicting.



```
1.72233450e+00 1.70180165e+00 2.19780880e+00 2.37100909e+00
3.62977529e+00 2.53604794e+00 3.72806001e+00 5.05049593e+00
1.10505472e+00 2.35223815e+00 1.95196297e+00 1.97881209e+00
2.04817533e+00 1.55270875e+00 1.07148468e+00 8.99136576e-01
1.40903950e+00 1.93172455e+00 1.72596359e+00 1.37820001e+00
1.37937260e+00 1.30759537e+00 1.55905378e+00 1.71126115e+00
1.56121732e+00 1.01430180e+00 1.95011718e+00 1.67059640e+00
1.69529080e+00 1.56367254e+00 2.78520918e+00 1.44931567e+00
1.07879364e+00 1.20056208e+00 1.43969107e+00 1.74761307e+00
1.66965199e+00]
(305,)
(365,)
Test RMSE: 8.574
```

This model gave us RMSE of 8.5, which is slightly higher than the previous model, but during the deployment with huge data, these variations will change.



**CONCLUSION:**

Our approach is to use a LSTM model, because studies show that the result of using a neural network is better than using orthodox regression techniques. We used a variety of important parameters that directly affects rainfall for our model and making it diverse. We feed water levels of various reservoirs around Chennai to our model that makes our model better and improves the quality of prediction of rainfall. Other papers show that (in different contexts of flood and drought forecasts) that rainfall prediction plays a important role in determining the status of a particular place in the future. They state that flash floods/short term droughts highly rely on rainfall predictions and min and max temperatures of a place. We use this important parameter to predict both floods and droughts at a time. Our model will be highly accurate in predicting short-term droughts/flash floods, which is ideal for the purpose of prevention of major damages. This model lets us translate the future of rivers and water-bodies around us which might help us to understand which places are severe and require necessary care. Although our ML model predicts, it might not be so accurate because accuracy depends on how valid a dataset is and how many important factors we chose. So, having a dataset that doesn't promise real-time conditions and are old might not produce the best results. Our model uses historical data to develop a prediction algorithm. As it always is in the case of rainfall and weather prediction, our predictions will not be very promisingly accurate. At best we will analyse and be able to formulate a dependable trend.

**REFERENCES :**

- [1] Téllez-Valero, Alberto & Montes, Manuel & Villaseñor-Pineda, Luis. (2009). Using Machine Learning for Extracting Information from Natural Disaster News Reports. *Computacion y Sistemas*. 13.
- [2] Nijhawan, Rahul, et al. "A Novel Deep Learning Framework Approach for Natural Calamities Detection." *Information and Communication Technology for Competitive Strategies*. Springer, Singapore, 2019. 561-569.
- [3] Shahabi, H., Shirzadi, A., Ghaderi, K., Omidvar, E., Al-Ansari, N., Clague, J. J., ... & Rahmati, O. (2020). Flood detection and susceptibility mapping using sentinel-1 remote sensing data and a machine learning approach: Hybrid intelligence of bagging ensemble based on k-nearest neighbor classifier. *Remote Sensing*, 12(2), 266.
- [4] Tehrany, Mahyat Shafapour, Simon Jones, and Farzin Shabani. "Identifying the essential flood conditioning factors for flood prone area mapping using machine learning techniques." *Catena* 175 (2019): 174-192.
- [5] Costache, Romulus, and Dieu Tien Bui. "Identification of areas prone to flash-flood phenomena using multiple-criteria decision-making, bivariate statistics, machine learning and their ensembles." *Science of The Total Environment* 712 (2020): 136492.
- [6] Mosavi, A., Ozturk, P., & Chau, K. W. (2018). Flood prediction using machine learning models: Literature review. *Water*, 10(11), 1536.
- [7] Yadu, A. K., & Shrivastava, G. APPLICATION OF NEURAL NETWORK IN DROUGHT FORECASTING; AN INTENSE.
- [8] Arnaud, P., Bouvier, C., Cisneros, L., & Dominguez, R. (2002). Influence of rainfall spatial variability on flood prediction. *Journal of Hydrology*, 260(1-4), 216-230.
- [9] Kratzert, F., Klotz, D., Brenner, C., Schulz, K., & Herrnegger, M. (2018). Rainfall-runoff modelling using long short-term memory (LSTM) networks. *Hydrol. Earth Syst. Sci*, 22(11), 6005-6022.
- [10] Choubin, B., Moradi, E., Golshan, M., Adamowski, J., Sajedi-Hosseini, F., & Mosavi, A. (2019). An ensemble prediction of flood susceptibility using multivariate discriminant analysis, classification and regression trees, and support vector machines. *Science of the Total Environment*, 651, 2087-2096.
- [11] Mosavi, A. CLIMATE CHANGE PREDICTION: STATE OF THE ART AND CLASSIFICATION OF ARTIFICIAL INTELLIGENCE METHODS.
- [12] Dehghani, M., Riahi-Madvar, H., Hooshyaripor, F., Mosavi, A., Shamshirband, S., Zavadskas, E. K., & Chau, K. W. (2019). Prediction of hydropower generation using grey wolf optimization adaptive neuro-fuzzy inference system. *Energies*, 12(2), 289.
- [13] Qasem, S. N., Samadianfard, S., Sadri Nahand, H., Mosavi, A., Shamshirband, S., & Chau, K. W. (2019). Estimating daily dew point temperature using machine learning algorithms. *Water*, 11(3), 582.

- [14] Torabi, M., Mosavi, A., Ozturk, P., Varkonyi-Koczy, A., & Istvan, V. (2018, September). A hybrid machine learning approach for daily prediction of solar radiation. In *International Conference on Global Research and Education* (pp. 266-274). Springer, Cham.
- [15] Choubin, B., Borji, M., Mosavi, A., Sajedi-Hosseini, F., Singh, V. P., & Shamshirband, S. (2019). Snow avalanche hazard prediction using machine learning methods. *Journal of Hydrology*, 577, 123929.
- [16] [https://en.wikipedia.org/wiki/2015\\_South\\_India\\_floods#cite\\_note-35](https://en.wikipedia.org/wiki/2015_South_India_floods#cite_note-35)
- [17] M. A. Sharma and J. B. Singh, "Comparative Study of rainfall forecasting models," *New York Sci. J.*, pp. 115-120, 2011.
- [18] J. Abbot and J. Marohasy, "Application of Artificial Neural Networks to rainfall forecasting in Queensland, Australia," *Advances in Atmospheric Sci.*, vol. 29, no. 4, pp. 717-730, 2012
- [19] A. Kumar, A. Kumar, R. Ranjan, and S. Kumar, "A rainfall prediction model using artificial neural network," *Control and Syst. Graduate Research Colloq. (ICSGRC)*, pp. 82-87, 2012.
- [20] R. R. Deshpande, "On the rainfall time series prediction using Multilayer Perceptron Artificial Neural Network," *Int. J. of Emerging Technology and Advanced Eng.*, vol. 2, no. 1, pp. 148-153, 2012.
- [21] Soo-Yeon Ji, Sharad Sharma, Byunggu Yu, Dong Hyun Jeong, "Designing a Rule-Based Hourly Rainfall Prediction Model", *IEEE IRI 2012*, August – 2012.
- [22] G. Shrivastava, S. Karmakar, and M. K. Kowar, "BPN model for long range forecast of monsoon rainfall over a very small geographical region and its verification for 2012," *Geofizika*, vol. 30, no. 2, pp. 155-172, 2013.
- [23] C. L. Wu and K. W. Chau, "Prediction of rainfall time series using modular soft computing methods," *Eng. Applicat. of Artificial Intell.*, vol. 26, no. 3, pp. 997-1007, 2013.
- [24] S. K. Nanda, D. P. Tripathy, S. K. Nayak, and S. Mohapatra, "Prediction of rainfall in India using Artificial Neural Network (ANN) models," *Int. J. of Intell. Syst. and Applicat.*, vol. 5, no. 12, pp. 1-22, 2013.
- [25] A. R. Naik and S. K. Pathan, "Indian monsoon rainfall Classification and Prediction using Robust Back Propagation Artificial Neural Network," *Int. J. of Emerging Technology and Advanced Eng.*, vol. 3, no. 11, pp. 99-101, 2013.
- [26] Priya, Shilpi, Vashistha and V. Singh, "Time Series Analysis of Forecasting Indian Rainfall," *Int. J. of Innovations & Advancement in Comput. Sci.*, vol. 3, no. 1, pp. 66-69, 2014. [27] V. K. Dabhi and S. Chaudhary, "Hybrid Wavelet-Postfix-GP model for rainfall prediction of Anand region of India," *Advances in Artificial Intell.*, pp. 1-11, 2014.
- [28] Pinky Saikia Dutta, Hitesh Tahbilder, "Prediction Of Rainfall Using Data mining Technique Over Assam", *Indian Journal of Computer Science and Engineering (IJCSE)*, Vol. 5 No.2 Apr May 2014.
- [29] Pankratz, A., *Forecasting With Univariate Box-Jenkins Models Concepts and Cases*. John Wiley Sons, Inc. New York, pp: 414.
- [30] M. T. Hagan, H. B. Demuth and M. Beale, *Neural Network Design* Thomson Asia Pte. Ltd, Singapore, 2002.