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Evaluation on NTM based Predictive Analytics on Rainfall and Flood Disaster Management

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ABSTRACT

In this Research article, we presented a new approach for predicting the flood through the advanced Machine learning Algorithm which is one among the Neural networks class that outperforms itself in best data operations and predictive analytics. This Research article discusses in detail about the prediction of flood occurrences evaluation process. We interpreted the Research with many algorithms that is existing, and the Research work have been dealing with different research works inculcated and compared with different Research approaches. On Comparing to the Previous Researches its observed that the Neural Turing networks have been performing the prediction of the rainfall and flood-based disasters for the consecutive year counts of 10,15 and 20 with 93.8% accuracy. Here the Research is analyzed with various parameters and Comparing it with the other researches which is implemented with other machine learning algorithms. Comparing with the previous researches the Idea of the research have been described and evaluated with the different evaluation parameters including the number of iterations or Epochs.

KEYWORDS: *Rainfall disaster, Machine learning, Neural Turing Networks, Evaluation parameters*

I. Introduction

Although water is fundamental to life, its overabundance (i.e., flooding) can cause significant harm and death toll. Since 1970, more than 7000 significant flooding and dry season occasions have caused around $2 trillion in harms and 2.5 million in setbacks as per Research observations from World Water Assessment Program, 2009 [25]. Among the various kinds of flooding, trans boundary flooding happens when floodwaters move along a global waterway from an upstream country to a country downstream. At the point when high precipitation aggregation happens in upstream countries and isn't conveyed to downstream countries in close continuous, it gets trying for downstream countries to deal with the flooding. While trans boundary waterway floods just gets peak to 9.9% of all flooding occasions, they represent 32% everything being equal, practically 60% of influenced people, and 14% of monetary harm [15]. The unbalanced connection among event and contact with trans-boundary floods is fundamentally due to the absence of correspondence between nations with respect to precipitation.

This Research focuses on flood observing dependent on satellite precipitation assessment and its hydrologic displaying to process the surface overflow. From the easiest hydrologic model to the most mind boggling, precipitation is the key info that drives the precision of the overflow yield vital for flood determining. As of late, the NTM-based precipitation has been consolidated into close to continuous hydrologic model that decides the overflow profundity created along a determined stream way with measurement esteem for flood potential. This framework is known as the NTM-based Flood Detection System (FDS).

Since the FDS has just been in activity since 2006, there isn't a lot of work in writing that exhibits the presentation of the framework against in situ estimations. However, the nonstop watch on floods the world over by the FDS has gigantic potential for profiting society where such data is inadequate. In the latest flood harm by Cyclone Nargis over Myanmar in 2014, it was accounted for that the Red Cross utilized FDS yield to help distinguish overwhelmed territories and plan relief activities. Henceforth, evaluation of the FDS is significant in facts that interpret the viability of the framework, which is basic to upgrade its presentation what's more, to make future model enhancements.

The machine learning techniques produce maximum accuracy, and its efficiency is proven in solving several analysis tasks.

II. Literature Review

Recent researches high prediction depict the employment ofwireless sensor networks and advanced artificial neural networks. The Researches have utilized a wireless sensor network (WSN) to gather data and used a rectilinear regression model with multiple variables for real-time and accurate flood prediction results [2]. Increase in water level indicates flood if it exceeds the flood line. The Researches have also utilized WSN and various types of machine learning classification techniques for flash flood broadcasting. They necessitate making a comparison of the performance of those techniques with different data representations. The multilayer perceptron technique has shown better ends up in their work.

The challenges with near real time data communication are often observed with lack of analysis from the ground work in infrastructure and data sharing analysis between nations or borders along the same river. Many nations have an improper ground network or infrastructures necessary to log water or to gauge rivers and rainfall monitoring operations [21]. In United states of America due to lack of maintenance and Resources ground gauging is getting declined [18]. For nations with some ground-estimated information, there is frequently an absence of correspondence among riparian countries because of nonappearance of a helpful component [18]. An outreaching audits of fresh water arrangements on flooding has demonstrated that there at present exists no deal that tended to the sharing of estimated stream or precipitation information in close to ongoing among riparian countries of a global waters and Resources[16]. Though the system shows good accuracy with lower power consumption, the price of motes within the work is extremely high. The Researches have discussed an IoT approach for flood monitoring using highly dense grid of rainfall sensors and river gauges to live water level [5]. It also discusses about the integration of sensors' infrastructure with various IoT cloud platforms. It also speaks of development of ultra-low power sensors or devices for this aim. Several researches have been implemented wireless IoT framework using Embedded kits like Arduino Uno and an array of sensors connected [6].

In this work, the research got developed as ultra-low power IoT flood monitoring system using low-power sensors and a dashboard developed by Thing Speak is employed to depict the real-time data collected by the system with embedded mechanisms. The ANN flood prediction model is implemented on the real-time collected data and also the prediction of flood event is completed. Also an alert system is proposed supported by the Thing Speak messages on registered Twitter accounts which is integrated to the system developed. Evaluation of this research can be performed only through various parameters and observations in the Research database.

At present it's optimum to use machine learning methods to determine a particular identification. Their final aim is to get trained algorithms that facilitates the flood and pain fall based disaster predictions in advance. These algorithms can be utilized by meteorological scientists as auxiliary tools to enhance the predictability of Rainfall and flood based disaster alerts. According to the International Agency for analysis on Meteorology there have been concerning 4% (1,590 thousand) deaths of the total range of deaths every year due to water based disasters. Whereas in current scenario the death poll rate due to water based disasters has been increased to 35%.

III. Research methodology

Based on the previous researchers all the researches have been taken with the evaluation parameters of the machine learning algorithm, Neural Turing Networks. Turing Machine or networks [26] is a sub-set of computing models. This Turing model can respond to the following interpretations:

1) Is there any machine able to determine whether to stop or continue its function through its own memory tapes?

2) Is there any machine able to determine that another machine can ever print symbol on its tape [27].

Based on these approaches we have intended to use neural turing machines in the research to reduce the memory consumption of the data. The research is made to reduce the involvement of big data and Hadoop concept to integrate large sets of data and to avoid noises that is caused due to data transmission from one software environment to other.

Turing machine takes the first overview that can be considered as signal receptor or data receptor for fast computing. Hence in the concept of Machine learning approach the idea have been developed for a fast processing easy accessible machine that plays a major role in the Turing process. Neural computing Research is a base in visualizing human brain on data processing or information systems. This system works completely with the concept of features or parameters that segregates the characteristics of the information received. Memory plays a major role in data processing since we use information processing based on feedback or prediction are processed which is also called as computing systems and this operates in different channels like Order of the computation, Prediction strategy or cost functions and theoretical logics [14]. Similar to this Neural Turing machines Recurrent neural networks also plays a major role in development of the system predictive efficiency [3]. On the other words the other way of prediction of information can also be anticipated with Recurrent Neural Networks with maximum effectiveness [22].

The Algorithms considered in the Research are K-NN, Support vector Machine, Gradient descent with Adaptive learningwith Neural Turing Machines. The Algorithms have been considered with various different researches and utilized with Prediction based Concepts in most of the Researches.

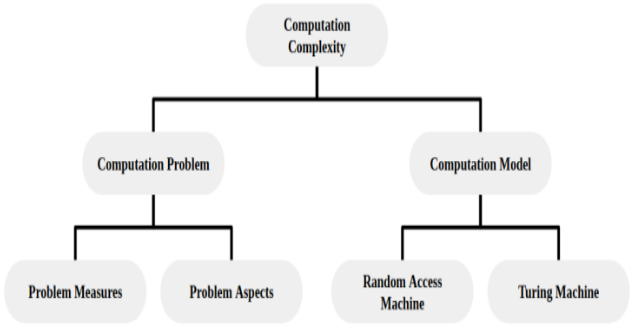

Fig 1 Computation Complexity Research

K-NN

K-Nearest Neighbor (KNN) is a collective classification tool deployed in data mining applications. It is a nonparametric learning algorithm that makes no assumptions about the primary dataset. This is important to be noted when molding hydrological processes such as floods and stream flow, for which there is little knowledge of the data distribution. Additionally, these methods are nonlinear and heterogeneous with noisy data that challenge common statistical assumptions such as those sustaining linear regression models. The optimal case is the one with the maximum similarity indices. In KNN, the optimal choice of the selected number of neighbors (K) hinge on on the metrics used for classification and regression purposes. In the case of continuous variables, the most common distance metric is Euclidean distance, also known as the straight-line distance. In opposition, for discrete variables, the overlap metric is often used. Other metrics that have been used are correlation coefficients, such as the Pearson and Spearman correlation coefficients. The K value is sensitive to the chosen dataset and fluctuates between datasets. The number of neighbors can be altered to govern the best performance of the KNN algorithm. There are four KNN classifiers introduced by MATLAB given as follows.

1. Coarse KNN: The number of neighbors is 100. The classifier is well-defined as the nearest neighbor among all classes.
2. Cosine KNN: The cosine distance metric is the nearest neighbor classifier. It is generally used as a metric for distances when vector magnitudes are irrelevant.

The following equation is used to measure the distance between two vectors, u and v:

$$1-\frac{u.v}{|u|.|v|'}$$

3. Cubic KNN: The number of neighbors is 10, and the cubic distance metric is the nearest neighbor classifier. The following equation is used to measure the distance between two n-dimensional vectors, u and v:

$$\sum_{i=1}^{n}|u_i - v_i|$$

4. Cubic KNN: The number of neighbors is 10, and the cubic distance metric is the nearest neighbor classifier. The following equation is used to measure the distance between two n-dimensional vectors, u and v:

$$\sqrt{\sum_{i=1}^{n} w_i (x_i - y_i)^2}$$

Where 0< w_i <1 and $\sum_{i=1}^{n} w_i$ =1.

SVM

SVM-based hierarchical two-level structure is introduced for traffic flooding attack detection, in which an one-class SVM distinguishes attack traffic from normal traffic at the first layer, then, at the next layer, a multi-class SVM classifies the type of attacks in detail: TCPSYN flooding, UDP flooding, ICMP flooding, etc. Recently, the support vector learning method has emerged as a promising tool in the area of intelligent systems, since it has shown an excellent performance for pattern classification and function approximation, by ensuring the global optimum for a given problem. However, it has the intrinsic structural limitation of the binary classifier. There are three major known types of approaches for multi-class SVM: one against-all, one-against-one, and DAGSVM in the form of combining many binary SVMs. In general, the number of datasets necessary for training varies according to the amount of normal traffic and attack traffic. Hence, the resulting training may not be independent of other classes, due to the unbalanced size of training data. In addition, it may not be true that the current training data represents the whole classes, since new types of attack are increasingly emerging. Thus, the binary classifier SVM may suffer from misclassification of novel attack data, by creating a decision boundary including an unobserved area. Accordingly, it is preferable to select a decision boundary function using a one-class SVM which expresses the corresponding class independently (one of the most well-known one-class SVMs is a support vector data description (SVDD)). The multi-class SVM based on SVDD is described as follows:

Given a K-data set of N k patterns in ad-dimensional input space, $D_k = \left\{ x_i^k \in R^d \mathrm{I} i = 1,..,N_k \right\}$, k= 1, …, K, the multi-class SVM based on SVDD is defined as the problem of obtaining a hyper-sphere which contains as many training datasets as possible, while keeping the radius small.

IV. Results and Discussion

Based on the Analysis with different database its observed that the prediction accuracy have been considered with various evaluation parameters like Receiver Operations Characteristics, Mathews Correlation Coefficient, Mean Square Error and Validation of Epochs. With Mathews correlation based analysis the approach have been established with effective data redundant in Neural Turing Machines than the existing algorithms like ANN and RNN.

In this research the objective have been established with proper data recovery and analysis of the data convolution of different machine learning approaches. The developed Adaptive NTM implementation learns to solve all three of the five crucial objectives in the NTM algorithm proposed [4] that is analysed. LSTM and NTM have been providing similar results whereas the Epochs considered have been reduced to major levels than the analytical data representations.

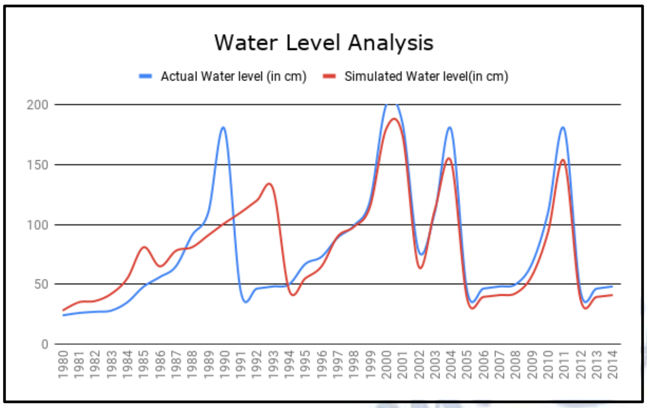

Fig 2 Water level vs No. of Data samples with Actual water level and Simulated Water level

The Research have been considered with different Machine learning algorithms to analyze the evaluations with different Perspectives. Based on these considerations we have used k means classifier which is one of the famous algorithms in prediction based Researches.

scenarios. In this Research various Database have been considered and found the results adaptive for the selected algorithms. Since selection of Algorithm is most critical process in Machine learning researches this research not only makes the prediction efficient but also the memory processing faster. Here are the various algorithms have been considered with all the critical evaluation parameters.

Based on the analysis of different algorithms the research has been estimated with variations in the data and approach has been established with the data retrieval part. Fig 2, 3 and 4 describes about the variations happened in actual and observed level of historical data whereas 80% of data is considered as training plot and have been trained with different combinations at almost 150 epochs of variable sampling method and obtained the training plot with 20% of the total data to estimate the complete sampling of the data and the data retrieval process is justified by Database with at most of 93% - 97%.

Performance Metric	KNN K=1	KNN K=5	SVM	GD	LM	**NTM**
R	0.75	0.62	0.58	0.68	0.88	**0.9351**
Validation MSE	7.65	6.53	5.85	8.86	2.31	**2.25**
Train MSE	7.95	8.1	7.65	9.94	7.27	**6.54**
Test MSE	8.56	9.25	11.25	10.67	4.87	**3.82**
Epochs	50	30	30	32	6	**10**
Mathews Correlation Coefficient	0.87	0.75	0.72	0.65	0.85	**0.92**
Receiver Operations Charecteristics	0.62	0.75	0.5	0.35	0.3	**0.8**
Area Under ROC	0.5	0.45	0.75	0.35	0.5	**0.85**

Table 1 Evaluation Result of Various Machine Learning Predictive Scoped Algorithms

Based on the above research its observed that the Neural Turing Machine is providing better results than comparison with the other Machine learning Predictive scoped Algorithms.

In general the conception of NTM is incredibly robust however restricted by weak coaching algorithms [18]. Due to its memory, it's ready to surmount several continual neural networks. The structural changes concerning the methods mentioned during this article square measure is tabulated in Table 1, wherever all have external memory and also the neural network is applied. The comparison square measure created against one among is the most effective than the recurrent neural networks.

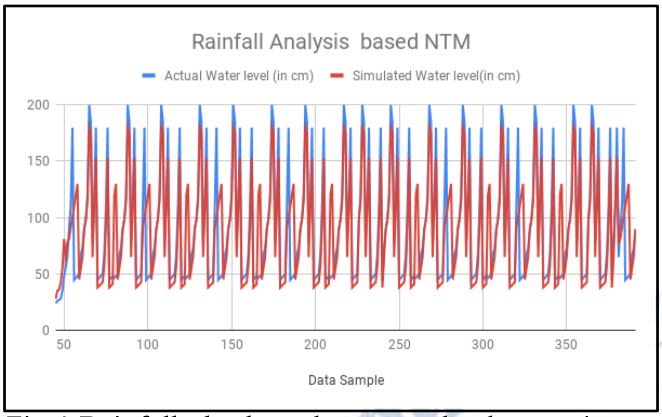

Fig 4 Rainfall plot based on sample observations

Flood modeling and prediction exploitation with different Machine Learning Algorithms was successfully developed and Evaluated. The flood water level at downstream river around referred to as the flood location area unit with success foretold with minimum of 10.833 hours prior time with sensible prediction results. The effects of physio graphical factors like basin space, length of main stream and mean slope were neglected during this Evaluation process. Therefore for future works, NTM may be applied to other hydrological issues like rainfall-runoff prediction and stream flow forecast that area unit unaccustomed the researchers around the world.

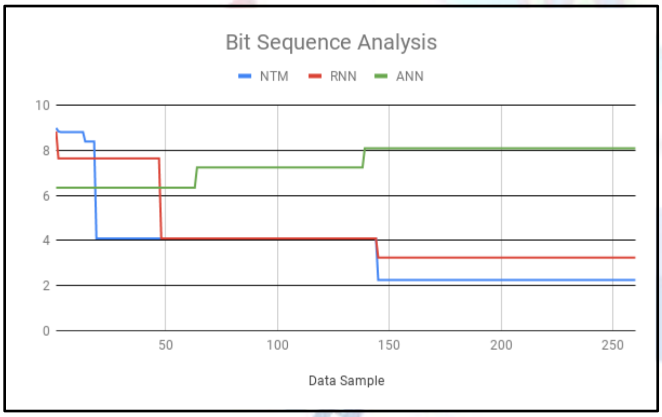

Fig 5 Bit Sequence Analysis with Data samples

Bit Sequence Analysis between NTM, RNN and ANN have been Evaluated and the analysis explains that the approach of the research objective to be stabilized data and occurrences observed through the Analysis process. The Data samples have been established with the different observations with 50,100,150 and 300 epochs of data and observed that the bit sequence rate is processed with Equilibrium data in the Data sequence plot which makes the Accuracy of the Machine learning algorithm enhanced than the existing algorithm.

NTMs are associate degree exciting new neural network approaches that reach crucial performance on a spread of artificial tasks. However the specification of a NTM has developed opportunities that makes customization of Algorithm very effective and no ASCII text file or logical barriers that makes the algorithm implementation dependent to a condition or many which makes the development of adaptive algorithm very simple and effective.

V. Conclusion

This research presents an innovative approach for predicting the flood by means of advanced Machine Learning algorithm. Flood modeling and prediction exploitation with different Machine Learning Algorithms was successfully developed and evaluated. The Research have also examined that Bio inspired algorithm like Cuckoo Search Algorithm, Random Forest Algorithm and Particle Swarm Optimization where the Results are not adaptive for different scenarios. NTM is found to be presumptively well fitted to a number of area units. Thus the sensible flood disaster prediction system has proved to be relevant in terms of actual preparation and responsibleness with real time monitoring and change of environmental parameters and prediction of flood as compared to existing approaches. The integrated approach combines the measurability of IoT and reliability of artificial neural networks. This handles information provided by a sensing element network and effective communication between these 2 elements.

After the experimentation, it's been established that Neural Turing machine-based Algorithm predicts flood one time-step ahead and warns the communities in danger. Therefore, by harnessing latest technological disruptions such as IoT and machine learning, big data, prophetical analytic along with social media and quality permits effective emergency & disaster management for sensible nations.

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