Smart flood disaster prediction system using IoT & Neural Networks

Swapnil Bande
Dept. of Electronics & Telecommunication
MIT College of Engineering
Pune, India
swapnilbande11@gmail.com

Prof. Dr. Virendra V. Shete
Dept. of Electronics & Telecommunication
MIT College of Engineering
Pune, India
virendra.shete@mitcoe.edu.in

Abstract—**Floods are the natural disasters that cause catastrophic destruction and devastation of natural life, agriculture, property and infrastructure every year. Flooding is influenced by various hydrological & meteorological factors. A number of researches have been done in flood disaster management and food prediction systems. However, it has now become significant to shift from individual monitoring and prediction frameworks to smart flood prediction systems which include stakeholders and the flood affecting people equally with help of recent technological advancements. Internet of Things (IoT) is a technology that is a combination of embedded system hardware and wireless communication network which further transfers sensed data to computing device for analysis in real-time. Researches in direction of flood prediction have shifted from mathematical models or hydrological models to algorithmic based approaches. Flood data is dynamic data and non-linear in nature. To predict floods, techniques such as artificial neural networks are used to devise prediction algorithms.**

Here an IoT based flood monitoring and artificial neural network (ANN) based flood prediction is designed with the aim of enhancing the scalability and reliability of flood management system. The main aim of this system is to monitor humidity, temperature, pressure, rainfall, river water level and to find their temporal correlative information for flood prediction analysis. The IoT approach is deployed for data collection from the sensors and communication over Wi-Fi and an ANN approach is used for analysis of data in flood prediction.

Keywords—Internet of Things; Flood Prediction; Artificial Neural Network (ANN); Disaster Mangement

I. INTRODUCTION

Floods are the most catastrophic and cataclysmic events of all the natural disasters. World Meteorological Organization has stated that out of all the disasters in the world, floods are the most severe disasters. It largely affects millions of people across the world leading to severe loss of life and colossal damage to property, infrastructure and agriculture. Specifically in India, about 12% of the land is vulnerable to the flood conditions. Heavy unprecedented rainfall results in floods bringing normal life to a standstill. Most of the floods occur during monsoons; however floods can also occur due to dam & levees breaking which further can be triggered by thunderstorms, cyclones, creation of low pressure regions. The Indian monsoon ranges over the four months from June to September. The rivers' in the country discharge waters heavily during these four months increasing the water levels in surrounding regions which leads to flood conditions.

Many states of India suffer from flood disasters every year regularly due to improper early warning system that would alert the people in flood affected regions. For a country like India to grow as a smart nation, it is also important to shift from relief and recovery framework to integrated flood management system which includes all stakeholders and the affecting people equally with recent technological advancements.

With huge technological innovations in the domains of sensing systems, communication networks, cloud computing, machine learning and data analytics, it is readily possible to develop an integrated flood disaster management system which can alert the flood affecting regions effectively. Thus latest technologies have life-saving potential in the flood disaster situations. Internet of Things (IoT) is one such technology for a smart nation. With easily available smart phones and Internet facilities to both urban and rural people in India in the recent years, this media can be utilized for communication with the citizens. The Internet of Things (IoT) is a huge network of physical objects or devices alongwith virtual entities which are generally powered by small batteries and often connect to each other through the Internet. As more number of these devices gets connected to each other, there lies a huge opportunity for development and implementation of such integrated flood disaster management system. It has all become possible due to ubiquitous connectivity, new sensor technologies, and real-time data processing and analysis. In predictive analytics, artificial neural networks (ANNs) provide better results than other methods. In flood disaster management system, it is of utmost importance that data analysis be done for prediction of floods. Many artificial neural network algorithms are being studied and deployed for prediction purposes.

978-1-5386-0569-1$31.00 ©2017 IEEE

In this project, an IoT framework with artificial neural networks has been rendered for the development of flood monitoring and prediction system. The system consists of sensors that sense the surrounding environment, a single board computer which processes the sensed data; a Wi-Fi based communication infrastructure, a cloud server, and data analytics algorithm that would finally help to predict the flood disaster situations.

II. RELATED WORKS

Recent researches in flood prediction depict the use of wireless sensor networks and advanced artificial neural networks. [2]Seal et al. have utilized a wireless sensor network (WSN) to collect data and used a linear regression model with multiple variables for real-time and accurate flood prediction results. Increase in water level indicates flood if it exceeds the flood line. [3] Furquim et al. have also utilized WSN and various types of machine learning classification techniques for flash flood nowcasting. They have made a comparison of the performance of these techniques with different data representations. The multilayer perceptron technique has shown better results in their work. However, some of the used sensors have not been tested in their work.

[4] Nuhu et al. have utilized 6 Low power Wireless Personal Area Network (6LoWPAN) as a communication technology with the help of XM1000 motes for real-time flood monitoring. A water level monitoring is done based on pre-defined rule based system. Though the system shows good accuracy with lower power consumption, the cost of motes in the work is very high. [5] Ancona et al. have discussed an IoT approach for flood monitoring using highly dense grid of rainfall sensors and river gauges to measure water level. 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 the purpose.

[6] Gangopadhyay et al. have implemented wireless IoT framework using Arduino Uno and an array of sensors connected to it. They utilize Xbee transceivers for communication and upload the data on ThingSpeak and Xively cloud servers. Their experiment shows that ThingSpeak is a better IoT cloud platform for this purpose. Also an instant alert is sent to the users through Twitter or the android app developed. However the system cannot accurately predict the event of flood in their work as they have not deployed a model for it. [7] Mitra et al. have proposed an IoT based WSN system for flood forecasting purpose. They have used Zigbee technology for communication between nodes and CC2650 MCU as a central controller. For communication over internet they have made use of GPRS Sim300 module. Further they have proposed use of simple ANN structure with five input parameters and water level as output. They have simulated the entire system and tested ANN model on old satellite data. They have not yet practically implemented the system and have also not used the real-time WSN data for prediction purpose. Also no alert system is developed.

[8] Ruslan et. al. have proposed Nonlinear Auto Regressive with Exogenous Input (NARX) model to mitigate the problem of nonlinear flood prediction problem. The system predicts the occurrence of flood in Kelang River with a lead-time of 10 hours.

In this work, we have developed a ultra low power IoT flood monitoring system using low-power sensors and a dashboard developed by ThingSpeak is used to depict the real-time data collected by the system. The ANN flood prediction model is implemented on the real-time collected data and the prediction of flood event is done. Also an alert system is proposed based on the ThingSpeak messages on registered Twitter accounts.

III. DEVELOPED SYSTEM

In the developed system, a model is designed for monitoring the environmental parameters which has the ability to be used for flood disaster prediction. The environmental parameters like temperature, relative humidity, atmospheric pressure, rainfall etc. are sensed by an array of sensors and the measured data is sent to the microcontroller via Wi-Fi (IEEE 802.11 protocol). Further the relationships between the input data received and the output rainfall is modelled using ANN techniques. A continuous monitoring of changes in environment is done by updating of the old values with new ones after a specified time interval. There is communication between various low power IoT nodes through internet via Wi-Fi module connected to the IoT board. A flood event is predicted beforehand using ANN model and it alerts the people for upcoming disaster according to the increase of rainfall and corresponding water level rising of the low-lying areas near river flow area. The amassed device data is uploaded to cloud database and the information is shared to the people over the smart phone in the form of SMS or tweet notifications.

A. System Design

This system uses a single board computer called Raspberry Pi 3, which is widely used in IoT applications also based on Wi-fi protocol for communication. It is energy efficient because it can operate on lower input/output voltage levels of 3.3V.

The programming language for Raspberry Pi 3 module is Python programming language.

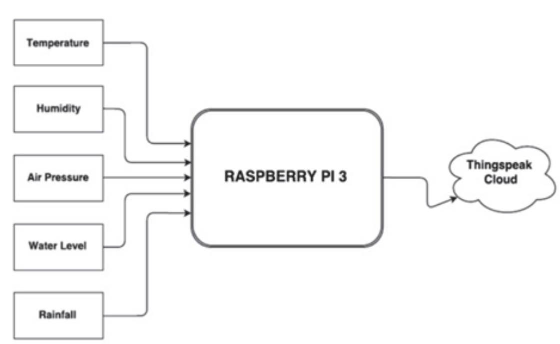

Figure 1Block Diagram of Single IoT Node

Three sensors are connected to each Raspberry Pi module. **LM35** is used as a temperature sensor which is a high precision IC. The output voltage of the sensor is proportional to the temperature in centigrade with 10mV increase in output voltage for each 1 degree centigrade rise in temperature. In this work, the **BME280** sensor is used as an atmospheric pressure sensor which provides digital output. This pressure sensor has high accuracy and the resolution required for environmental monitoring. The sensing range is 300hPa to 1100hPa. This sensor is also utilized as a humidity sensor. The humidity sensor provides fast response time and high accuracy over a wide temperature range. The sensor is interfaced using an I2C interface with the Raspberry Pi 3 module and works on 3.3V power supply. A contactless **FDC1004 sensor** is applied for water level sensing which works on capacitive sensing. The FDC1004 is a high-resolution, 4-channel capacitance-to-digital converter and implements capacitive sensing solutions. Its works with a 3.3V power supply and has a measurement resolution of 0.5fF. It is interfaced using I2C peripheral to the Raspberry Pi 3 module.

B. IoT Framework

Each Raspberry Pi 3 module acts as a single IoT node in network which is connected to Wi-Fi using WLAN technology in a Wi-Fi hotspot and may obtain Internet access using it. Similarly other IoT nodes can be developed with different sensing abilities in the network and can be connected to the Wi-Fi hotspot. The single IoT node sends data to the cloud server over the Internet as shown in Fig. 2.

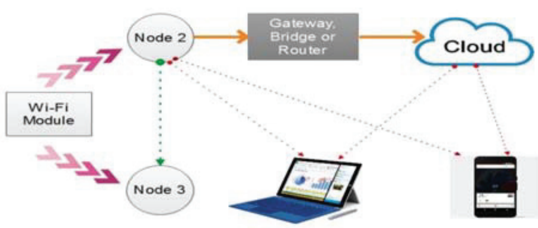

Figure 2 IoT Framework with Cloud Server

The data collected onto the server is analyzed and plotted into graphs on the GUI of ThingSpeak channel created. The complete set of data can be monitored real-time using ThingSpeak server and can be collected into a CSV spreadsheet file. Morever, we can also set the time intervals for reception of data from each IoT node. Fig. 3 and Fig. 4 shows the weather data updated to ThingSpeak channel.

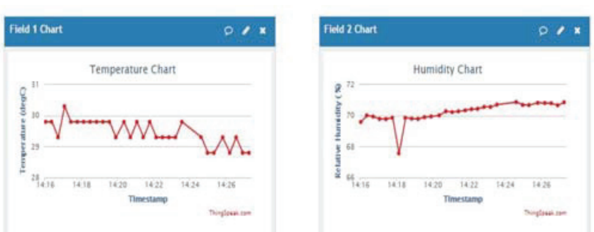

Figure 3 Temperature & Humidity values updated to ThingSpeak

Figure 4 Air Pressure values updated to ThingSpeak

C. ANN Analysis

The collected data in the form of spreadsheet files is given as input to MATLAB.

In this work, ANN is used for prediction analysis. ANN is a neuronal network just as biological neuronal network which computes in parallel and consists of processing elements called neurons connected together in a particular way to get the desired output.

The artificial neural network works upon the non-linear times series data obtained from the sensors' for prediction purpose. Figure 5 shows the basic ANN Architecture which consists of three different layers of neurons called as input layer, hidden layer and the output layer. The three layers are connected to each other by the interconnections between them which have particular weights and the bias values. Each neuron gets fired by an activation function. For nonlinear time series, we have used a nonlinear activation function i.e. sigmoid activation function.

D. NARX Architecture

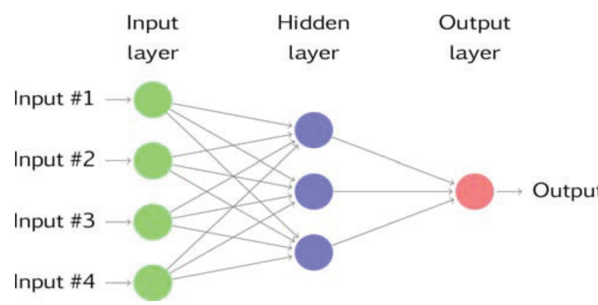

Figure 5 Basic ANN Architecture

Nonlinear **Auto**regressive network with E**X**ogenous inputs (NARX network) is utilized for prediction of flood in this work. NARX is a dynamic recurrent network with feed-forward connections having multiple layers of network. It is mainly applied to input-output modelling of nonlinear dynamic systems such as time-series prediction [1]. NARX is defined by the following function:

$$y(t) = F\begin{pmatrix} y(t-1), y(t-2), \ldots, y(t-ny), \\ u(t-1), u(t-2), \ldots, u(t-nu) \end{pmatrix} \quad (1)$$

where the output vector y(t) is computed as a nonlinear function of the input vectors u(t), u(t - 1), …, u(t - nu) which has a predetermined delay. Besides, the output is affected by a recurrent connection y(t), y(t-1), …, y(t-ny) that goes from the output back to the input layer. Fig. 6 shows the NARX architecture. The input parameters of the network are temperature, relative humidity and atmospheric pressure. The parameter to be predicted is rainfall.

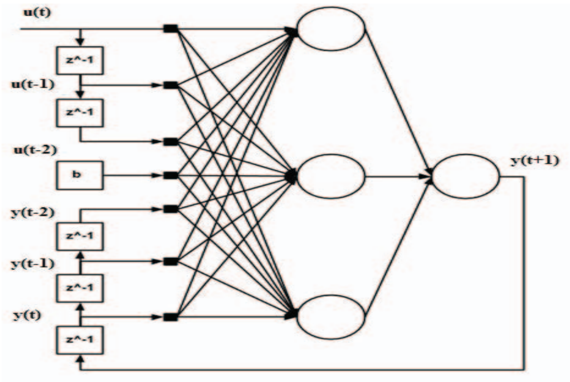

Figure 6 NARX Architecture

The loaded input and target data vectors are then converted into neural network cell array form that is processed by neural network MATLAB code. The basic parameters that need to be set are as follows:

- Training function (algorithm)
- Input delays
- Feedback delays
- Number of Hidden layers

The Gradient descent with adaptive learning algorithm and the Levenberg-Marquardt algorithm are selected as training algorithms for evaluating the performance. The flood dataset is obtained of Chennai region as shown in the Fig. 7 during 2015 floods and consists of 176 samples. The dataset is divided into 3 parts as training, validation and testing. The data is divided in a ratio of 70 % for training, 15% for validation and 15% for testing. Training data is responsible for calculating errors during the training process. Validation dataset is used for having the generalization under control and stopping the training process when it reaches a predetermined value. Testing has no connection to the training process at all and provide an independent check of performance during and after training.

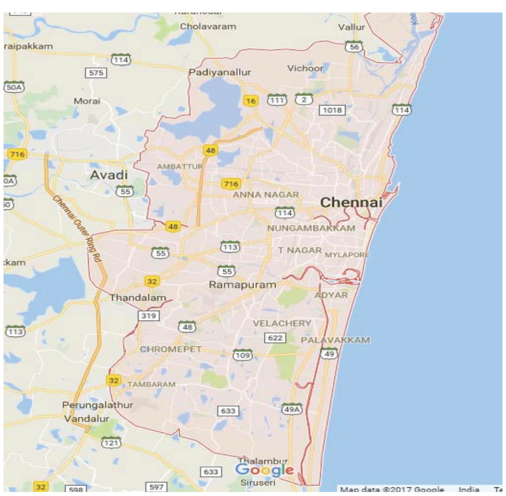

Figure 7 Data samples obtained of Chennai region

Table 1 NARX Architecture Parameters

Architecture Parameters	**Values**
Input Delays	1:4
Feedback Delays	1:4
Number of hidden layers	9
Learning Rate	0.01
Maximum Epochs	1000

IV. Results

The two algorithms are used for evaluating the network final results performance by comparing the mean square error (MSE). The purpose of the error function is to calculate and evaluate differences between the output and the required target given as follows:

$$E = \frac{1}{2}\sum_{p-1}^{p} \sum_{j=1}^{NL}.\,(\mathrm{tj} - \mathrm{aj})^2 \qquad (2)$$

where t_j and a_j are the target and the output signals of a neuron j and N_L defines the number of output neurons. The parameter L represents the numbers of hidden layers. A gradient descent technique is used to minimize the error function.

A. *Gradient Descent With Adaptive Learning Algortihm*

Fig. 8 depicts the regression toward the mean of the real movement (dotted line), the predicted values (black points) and the mean of the predicted values (blue line). For ideal prediction case, the blue line should copy the dotted line and the R parameter value would have to be one. The result of the regression is 0.6838 which equals to approximately 68% similarity between the target and the predicted output.

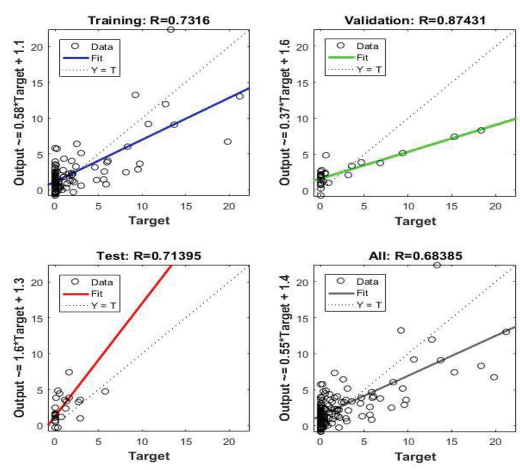

Figure 8 Regression Plot

Fig. 9 depicts the correlated errors in time steps (blue bar lines) and the confidence limit line (dotted lines) which shows limits inside which the prediction is almost perfect. Fig. 9 shows how the predicted errors of the calculated output and the target are related in time. The value 8 at zero lag indicates that the errors are the same if there is no time delay. Other non-zero lags indicate some correlations that indicate inaccuracies during the training process according to the non-zero blue bar lines leading to inaccurate prediction.

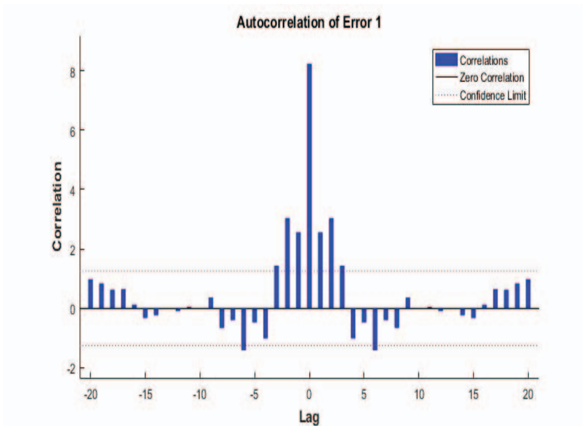

Figure 9 Autocorrelation of Errors

Fig. 10 depicts actual rainfall (blue line) and predicted rainfall (red line) in mm. The trend of the predicted line movement follows the target line but the predicted line suffers from significant jitter. Firstly, this is caused by the vanishing gradient problem during the learning process and secondly this algorithm is unable to predict accurately, although it is generally used for prediction purpose.

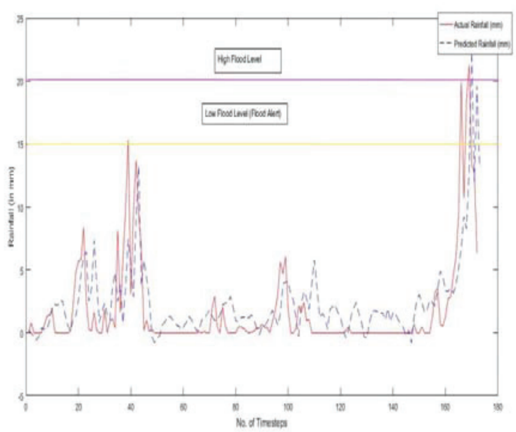

Figure 10 Prediction Plot

B. Levenberg-Marquardt Algorithm

The Levenberg-Marquardt algorithm uses momentum learning instead of the learning rate. Fig. 11 depict the regression performance for this algorithm. In this case, the result shows only few deviations from the mean line which indicates the suitability of this algorithm to be used in real flood prediction events. The result of the regression is 0.8812 that means 88.12% similarity between the target and the predicted output.

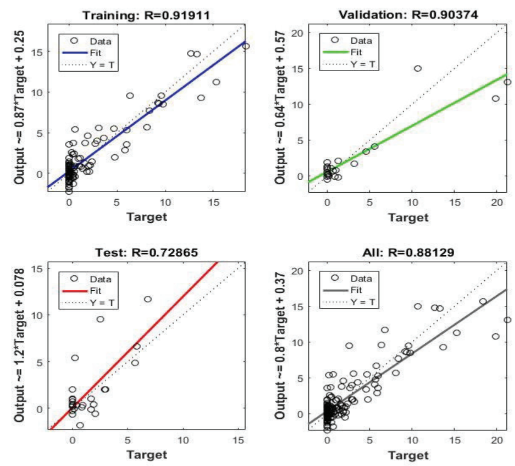

Figure 11 Regression Plot

Fig. 12 depict the correlated errors. In this case, the blue lagged bar lines are all inside the confidence limit that shows a perfect prediction in terms of usage of this algorithm.

Fig. 13 depict actual rainfall (blue line) and predicted rainfall (red line) in mm. The trend of the predicted line movement follows the target line. The predicted line suffers from very small jitter and is ideal for flood prediction events.

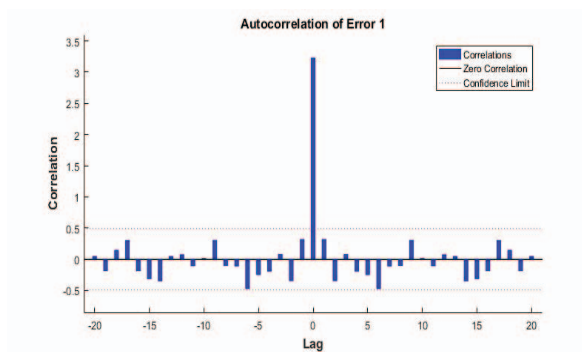

Figure 12 Autocorrelation of Errors

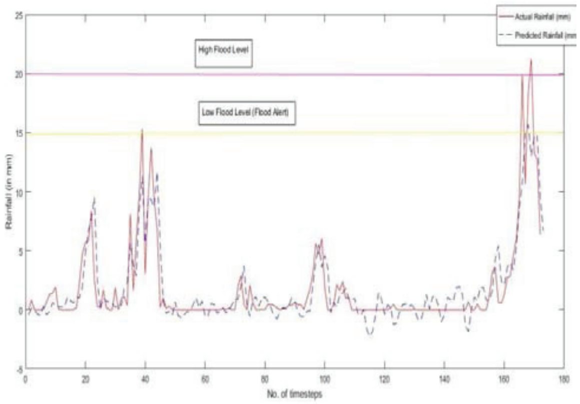

Figure 13 Prediction Plot

C. *Comparison of Results*

The first algorithm does not indicate sufficient resultant accuracy for rainfall prediction. The second algorithm can predict with the accuracy of around 88% which is enough for use case of rainfall prediction and ultimately flood prediction. To sum up all the results, see following Tab. 2.

Table 2 Comparison of Results of two algorithms

Best Performance Parameter	Gradient Descent With Adaptive Learning	Levenberg-Marquardt
R	0.68	**0.88**
Train MSE	8.8671	**2.3106**
Validation MSE	9.9483	**7.2713**
Test MSE	10.6759	**4.8720**
Epochs	32	**6**

D. *Flood Alert in the form of ThingTweet*

The following Fig. 14 shows the flood alert sent by flood management system in the form of tweet which is sent using ThingTweet.

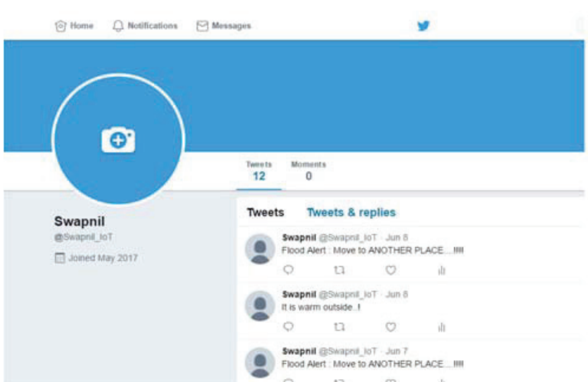

Figure 14 Flood Alert Tweet Sent over ThingTweet

V. CONCLUSION

Thus the smart flood disaster prediction system is relevant in terms of actual deployment and reliability with real time monitoring and updating of environmental parameters and prediction of flood as compared to existing approaches. The integrated approach combines the scalability of IoT and reliability of artificial neural networks to handle data provided by a sensor network and by effective communication between these two components, an early prediction of flood is done. After the experimentation, it has been proved that Levenberg-Marquardt training algorithm with NARX network gives better results and provides real time flood prediction with step-ahead alert.

The prediction chart indicate that the event of flood is predicted one time-step ahead and warns the communities at risk using ThingTweet in simple to understand language with the use of Internet. Thus by harnessing latest technological disruptions such as IoT and machine learning, big data, predictive analytics along with social media and mobility allows effective emergency & disaster management for smart nations.

Acknowledgment

The authors would like to thank the supporting staff of MITCOE for their valuable help in this work. The data samples were obtained from NASA Earth Data Giovanni website.

References

[1] Simon Haykin, Neural Networks – A Comprehiensive Approach.

[2] V. Seal, A. Raha, S. Maity, S. Mitra, A. Mukherjee and M. Kanti Naskar, “A Simple Flood Forecasting Scheme Using Wireless Sensor Networks”, International Journal of Ad hoc, Sensor & Ubiquitous Computing (IJASUC) vol. 3, no. 1, February 2012.

[3] G. Furquim, F. Neto, G. Pessin, Jo Ueyama, J. P. De Albuquerque, M. Clara, Eduardo M. Mendiondo, V. C. B. De Souza, P. De Souza, D. Dimitrova and T. Braun, “Combining Wireless Sensor Networks and Machine Learning for Flash Flood Nowcasting”, 28th International Conference on Advanced Information Networking and Applications Workshops, IEEE, 2014.

[4] B. Kontagora Nuhu, T. Arulogun, I. Adeyanju and Abdullahi I.M., “Wireless Sensor Network for Real-time Flood Monitoring Based on 6loWPAN Communication Standard”, APTIKOM Journal on Computer Science and Information Technologies vol. 1, no.1, 2016.

[5] M. Ancona, A. Dellacasa, G. Delzanno, A. La Camera and I. Rellini, “An “Internet of Things” Vision of the Flood Monitoring Problem”, The Fifth International Conference on Ambient Computing, Applications, Services and Technologies, 2015.

[6] S. Gangopadhyay and M. Mondal, “A Wireless Framework for Environmental Monitoring and Instant Response Alert”, International Conference on Microelectronics, Computing and Communications (MicroCom), 23-25 Jan, 2016.

[7] P. Mitra, R. Ray, R. Chatterjee, R. Basu, P. Saha, S. Raha, R. Barman, S. Patra, S. Saha Biswas and S. Saha, “Flood forecasting using Internet of things and Artificial Neural Networks”, Information Technology, Electronics and Mobile Communication Conference, IEEE, 2016.

[8] F. Ruslan, A. Manan Samad, Z. Md Zain, R. Adnan, “Flood water level monitoring and prediction using NARX neural network: Case Study at Kelang river”, 10th International Colloquium on Signal Processing and its Applications, IEEE, 2014.