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Investigation of Flash Floods on Early Basis: A Factual Comprehensive Review

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ABSTRACT Ultimate extreme flash floods can be acknowledged as a main reason of high casualties and infrastructure loss in many countries like Pakistan, Malaysia, Philippines, Southern France, India, Bangladesh, China, Nepal, Canada, United States of America and others. Run offs can devastate huge buildings and personal belongings within fraction of seconds. Flash floods usually occurs due to many reasons like higher precipitation velocity, melting of ice debris in ocean, high wave current at sea shore, broken reservoir (dam), Cloud to ground flashes, thunderstorm and hurricane inside the ocean. More than one hundred and twenty thousand casualties resulted due to the flash floods during the 1992 and 2005. According to the literature review deadliest flash floods have been observed in past history. Many approaches have been completed to investigate the flash floods accurately and precisely with less false alarm rate. Disaster management authorities are unable to forecast the natural disasters accurately and precisely like tsunami, flash floods, hurricanes and seismic events due to the poor efficiency of the sensors and transmission of missed information. It has also been observed that during the wireless data transmission of sensors to the controller unit some bits of the data are missed, due to these phenomena data is not transmitted properly or indicate the wrong observations. Several diversified approaches have been made to identify the run offs more accurately and precisely. Generally, the approaches can be classified into two categories a) Engineering Based b) Non-Engineering Based. Engineering techniques based on the construction of the dams and reservoirs to store the excess water which causes severe run offs. Designing of various Artificial Intelligence Based competent algorithms to predict the flash floods vigorously can be considered as non-engineering based approaches. Authors have tried their best to summarize and portray all the successful techniques that can be used for the early prediction of flash floods. Scientists can be benefited by this research paper as this research paper is the detailed capsulization of all the approaches that has been carried out for the robust investigation of flash floods. Extensive literature review has been done to observe the comparative analysis for the investigation of flash floods identification accurately. Literature review has been categorized into following types; 1. Sensory Fusion based 2. Artificial Intelligence Based methods 3. Radar and Satellite based approaches 4. Modeling and Nowcasting. According to the exhaustive literature review it can be concluded that swarm intelligence weights optimization for multi-layer perceptron neural network configuration performed better among all the forecasting approaches and recommended as the future enhancement.

INDEX TERMS Flash floods forecasting, false alarm, artificial intelligence, sensors, radar, satellite, system modeling.

I. INTRODUCTION

To predict any kind of natural disaster like flash floods, tsunamis and seismic events accurately and vigorously a powerful competent early warning system is strongly needed. Highly utmost flash floods can be acknowledged as a main reason of high casualties and infrastructure loss in many countries like Pakistan, Malaysia, Philippines, Southern France, India, Bangladesh, China, Nepal, Canada, United States of America and others. Run offs can devastate huge

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TABLE 1. **Country wise flash floods list (last ten years) (Wikipedia).**

Country Name	Year	Death Toll
Indonesia	2ND January 2019	Around 500
China Floods	2017	203+
Gujarat, Rajasthan, India	2017	240
India	2016	8000
Tamil Nadu Floods	2015	431
Southeast Europe	2014	80+
Argentina Floods	2013	75+
Nigeria	2012	72+
Southeast Asian Floods	2011	2828

FIGURE 1. **Glimpses of disaster after flash floods.**

buildings and personal belongings within fraction of seconds. More than one hundred and twenty thousand casualties resulted due to the flash floods during the 1992 and 2005 [1]. Deadliest flash floods have been observed in past history some of them which occurred in last ten years are given below:

Several diversified approaches were performed to investigate the run offs vigorously. Generally, the approaches can be classified into two types:

a) Engineering Based

b) Non-Engineering Based

TABLE 2. **Comparative investigation of sensors, radar and satellite based estimation of flash floods [3].**

Evaluation Parameters	*GAUGE*	*RADAR*	*SATELLITE*
Cost Effectiveness	High	Medium	Low
Installation Complexity	High	Medium	High
Calibration Complexity	Low	Medium	Medium
Data Assimilation	Low	Medium	High
Dimensional Resolution	Low	Medium	Medium
Short Range Monitoring	Low	Medium	Medium
Long Range Monitoring	High	Medium	High

Engineering techniques are based on the construction of the dams and reservoirs to store excess water which causes severe run offs. Development of various Artificial Intelligence based competent algorithms to predict the flash floods vigorously can be considered as non-engineering based approaches [2]. The forecasting of the flash floods can be categorized by the direct measurement of sensors and transducers, radar imaging and X-band images from satellite. A generic comparative analysis has been obtained from the extensive literature review and published [3].

Table no. 2 represents the estimation methods which can be adopted as a yardstick to measure the floods accurately. The suitability of an appropriate estimation method can be judged by the comparative analysis [3]. Several case studies and research analysis have been implemented to identify the actual event of run offs. Many of the researchers used direct measurement method from sensors and some of them utilized the combination of radar and satellite imaging. Morphological and other image processing strategies were applied to further enhance the clarity of radar and satellite based informative images for the rigor evaluation of flash floods and tsunamis [4]. It has been noticed that radar and satellite images also contain some ambiguity. To eliminate the false alarm and errors due to the ambiguity, multi-feature fusion classifier algorithm based on extraction and segmentation was applied to the radar and satellite images [5]. Partial Differential Equation was applied to the system to estimate the wave pattern and velocity of tsunami. An adequate false alarm free system was needed for the prediction of flash flood on early basis so that evacuation exits and emergency announcements [6]. Usually to build a model to forecast the flash floods can be acknowledged as most difficult task as sewages discharge are the most complex composition of multiple factors, the factors can also be the intricate land structure, rainfall magnitude and time of rainfall. Prediction models may also differ due to the false alarm in the modeling systems [7]. Direct measurement from the sensors

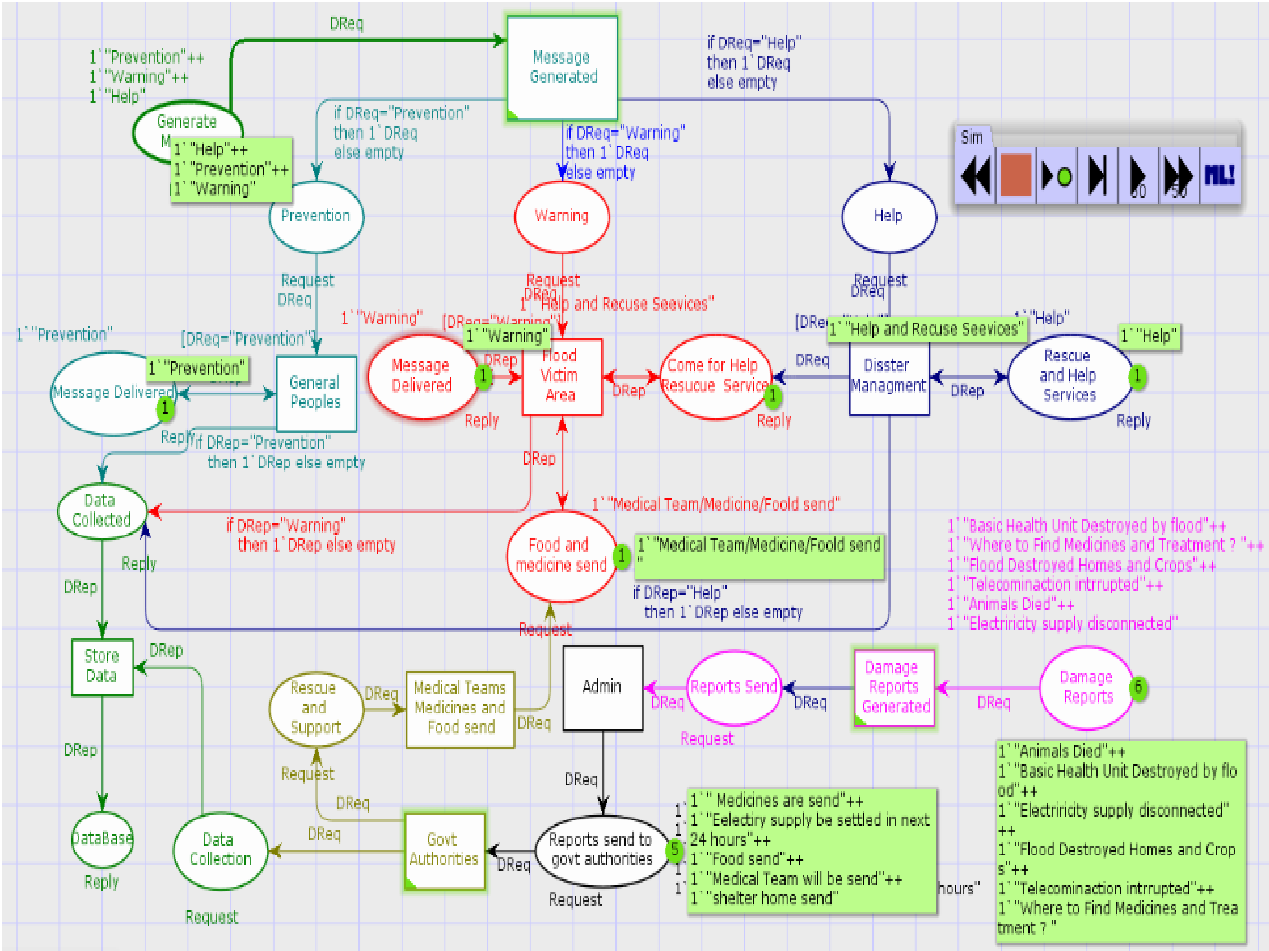

FIGURE 2. CPN model of disaster management authorities [10].

can be considered as more reliable compared to other methods. Transducers like seismic, acoustic, passive infra-red, magnetic and pyroelectric transducers are acknowledged as unattended ground sensors (UGS) for the continuous surveillance of illegal intrusion. Commonly Unattended ground sensors (UGS) have more number of false alarms due to the poor performance of prediction algorithms. Unattended ground sensors (UGS) may miss some true event information due to less battery backup and data redundancy in fixed and semi-fixed systems. Less battery backup can also be acknowledged as an apical issue during the reconnaissance data transmission [8]. In langrangian sensing, discrete sensors were spread on particular sea surface which has to be observed. These micro sensors monitor the different parameters to estimate the floods. Micro sensors detect the change, record it and transmit it to the receiver. To receive the data properly with greater reliability, receiver must be in range with these micro sensors. Fake alerts were found in langrangian sensing therefore some artificial intelligence based algorithm was applied on the system [9]. Many countries' economy depends on the crops and crops rely on the water of irrigation. Irrigation system of any country depends on numerous big rivers, mini rivers and canals. In Pakistan, agriculture can be considered as a back bone of country therefore it has been given a lot of significance. Generally, the water of the river relies on glaciers. Glaciers and heavy precipitation in monsoon season increase the upstream level of dams, lakes and rivers to the critical levels that causes the floods. Colored Petri-nets (CPNs) models have been designed to monitor the floods. CPN is acknowledged as a mathematical graphical language that has the capability to develop executable model of the system. Flood situation and real time status can be estimated using indicators wind velocity, wind direction, precipitation velocity, dams' level and river levels. These parameters identify the flash floods using CPNs models. CPNs model covers approximately all the aspects that are related to the flood for example reliable communication with the people of the vicinity that can be affected by floods and immediate propagation of early warning to the people of that particular area. During the event an alert can be sent to the concerned authorities of disaster management and evacuation routes and shelter locations must be announced by CPNs model. CPNs may also have the tendency to generate the detailed event report for the disaster management authorities and people on real time basis. The detailed report event may include the number of casualties, number of wounded people, number of animals died, irrigation situation, disconnection of electric connection and flood affected areas. The disaster management reviews the detailed report and arranges rescue teams and provides shelter locations [10].

Continuous heavy rainfall for over one week and severe rainfall for short time causes floodplains in northern areas of Thailand. Intense floods with greater speed have the ability to end the human and cattle lives. Alleviation of flash floods and upstream levels of river must be forecasted in order to announce the warning and precautions to the villagers. The water level monitoring stations have been setup to predict the floodplains but unfortunately the threshold and ranges varies every year as river situation changes annually. Many researches stated that water level prediction may be performed using artificial intelligence with the parameters input layer, hidden layer and threshold of previously measured water level. An algorithm was needed to automatically set the threshold of water level to forecast the floodplains. A suggested water level prediction was estimated using particle swarm optimization to predict the floodplains of Thailand occurred in the northern region [11]. The phased array radar at National Weather Radar Test bed (NWRT) had the diameter of 12ft (3.7m), max. transmitting power of 750 kW and operating frequency of 3.2 GHz. Pulse compression and all newest waveform technologies (a signal processing approach usually used by radar, sonar and echography to enhance the range resolution as well as the signal to noise ratio by modulating of a low level signal to a higher signal) are being used in armed forces but rarely used for the investigation of weather because of the scattered behavior of the water precipitation and vapor (Explained by IEEE 686-2008, Standard Radar Definitions). Usually the main data contains from Polari metric radar (transverse waves) spectral motion of reflection, mean, average radial velocity, spectrum width, cross correlation coefficient, phase difference and linear depolarization ratio. For the pulse compression example an in house PX-1000 radar (Polymetric X-band radar was established in 2008). Atmospheric Imaging Radar (AIR) was deployed for the rapid scanning of intense thunderstorms and cyclones. Radar beam forming principle is normal to the surface. The prototype radar possesses operational range of 2.7 to 3.1 GHz in S-band and transmission power of 1.5 kW. For identification of earth and atmospheric changes radar can be regarded as an important instrument as it is capable to scan reliably in very harsh environment and surroundings [12].

A. FALSE ALARM IN FORECASTING FLASH FLOODS

Basically false alarm rate is the estimation of fraction of predicted events that could not happen and key yardstick metrics for the validation and verification of National weather service (NWS) alerts [13]. Automated Target Recognition Algorithms produce more false alarms as they are dependent on the surroundings and environment where they are deployed and installed. False alarm rate is related with the complexity and anisotropy of sea floor [14]. Several sensor fusion algorithms have been developed in many predictive applications to increase the accuracy in detection and investigation of false alarm. Fusion algorithm of sensors permits the combination of different data type of sensors to achieve higher accuracy and precision. Particularly if we take an example of PIR (Passive infrared sensors) in which many sensors output from PIR sensors were taken to investigate the presence of the real target and to identify the false alarm [15]. The evacuation announcements in emergency situation are affected due to the false alarm. Frequent warning announcements may reduce the significance and performance of the early warning systems. Incompetent prediction algorithms and poor sensitivity of sensors may generate false alarms. It is very hard to differentiate the actual positive targets like finding the digging and walking activity while tracking earthquake using seismic sensors [16].

II. LITERATURE REVIEW SYNTHESIS

Table no. 3 portrayed fresh and novel flash flood investigation methods with higher accuracy results.

III. RECENT ESTIMATION APPROACHES FOR PREDICTION OF FLASH FLOODS

Extensive literature review has been done to investigate the flash floods identification accurately. Literature review has been categorized into following types;

a) Sensors and gauges based measurement
b) Artificial Intelligence based methods
c) Radar and Satellite based observation
d) Modeling and Nowcasting

A. SENSORS AND GAUGES BASED MEASUREMENT

Weighted average of the various sensing units reading has been recorded as it varies and changes. DAG (Directed Acyclic Graph) and dynamic threshold scheme was developed which helped to eliminate the false alarms. Different location conditions and the sensing devices were acknowledged as nodes of DAG. DAG introduced the Bayesian network and probability distribution after each variable. A sensory fusion algorithm was proposed using Dempster Shaffer theory. This technique elaborated the combined relationship of changing site conditions and response of sensing units. Heat, wind and rain have been considered the main instrument for the most appropriate combination of sensors was selected using probability tables depending on different environmental and terrain conditions. Simulation has been performed in the MATLAB. The false alarm was investigated in MATLAB by considering an array of 100×100 which contained numbers that has been generated randomly. Decision theory has been applied to validate the presence and no show of target by comparing the signal to the threshold value. Dempster-Shaffer is a generalization of Bayesian inference. Dempster-Shaffer not only defined the probability of single variable but also to the mixture of the variables therefore it was considered appropriate for the sensor fusion [17].

TABLE 3. Extensive literature review synthesis.

Research	Technique	Features	Domain
1.N. A. Rohaimi, "3 Hours ahead of time flood water level prediction using NNARX structure: Case study pahang" **2016**	Neural network autoregressive model with exogenous input (NNARX) technique	ST1, ST2, ST3 and ST4 that shows four higher stream and dy/dk represents the variation of water level at the flood occurred location	Neural Networks
2.G. Boni *et al.*, "The OPERA project: EO-based flood risk management in Italy," **2009**	It can produce change maps and maps of flooded area using CSK (Cosmo Skymed Mission).	High resolution 3-d virtual model of city, climatic and atmospheric change, soil moisture level	Satellite based images and communication
3.Simulator to Evaluate Tsunami Warning Performance for Coastal HF Radars **2016**	Coastal HF Radars	Tsunami wave pattern, Tsunami Height and Orbital Velocity	Model designing by using second order differential equation (PDE)
4."Development of Particle Swarm Optimization Based Rainfall-Runoff Prediction Model for P ahang River, Pekan," **2016**	PSO	Multiple Perceptron (MLP) with ANN, average data of water level from 5 stations.	AI, Particles were trained and learnt from its own knowledge and neighbor particle knowledge.
5.A. Macrander, V. Gouretski and O. Boebel, "PACT — a bottom pressure based, compact deep-ocean Tsunameter with acoustic surface coupling," **2009**	Pressure gauges can measure, recognize and investigate the differences less than a centimeter occurred in deep ocean sea-level using acoustic link.	Seismometers and GPS provided the accurate and reliable movements (horizontal and vertical).	On-board computing performs the pressure measurements and tsunami recognition and modern control
6."A movement prediction method of CG(Cloud to Ground) flashes based on lightening and convective clouds clustering and tracking technology" **2014**	Movement prediction method of CG flashes based on satellite nephogram (cloud image).	Fuzzy C means (FCM) for clustering	Improved lightning clustering and technology
7."Detection of Thunderstorms using data mining and image processing" **2015**	Clustering and wavelet transform	Data mining, wavelet transform	Data mining and image processing
8.Lizhen Lu, Shuyu Zhang, "short-term water level prediction using different artificial intelligent models" **2016**	Hourly water level prediction	ANN, SVM, ANFIS	Artificial intelligent model
9.Iztok Fister,	Cuckoo search	Cuckoo search with variants	Comparative Analysis

TABLE 3. ***(Continued.)*** **Extensive literature review synthesis.**

Dušan Fister, "A comprehensive review of cuckoo search: variants and hybrids", **2013**			
10.L. S. Solanki, S. Singh and D. Singh, "An ANN approach for false alarm detection in microwave breast cancer detection, " **2016**	ANN	Antenna for Biological sensing was designed	Positive False Alarm Detection Negative False Alarm detection
11.F. Guan, J. Shi, X. Ma, W. Cui and J. Wu, "A Method of False Alarm Recognition Based on k-Nearest Neighbor," **2017**	k-Nearest Neighbor	K-means is simple clustering based	False alarm recognition based on KNN, KNN Classification
12.P. Sun, Z. Wu, H. Yang, X. Liu and K. Chen, "Sensors Validation Based on Bayesian Classifiers," **2017**	Bayesian Classifiers	Tree Augmented Naive Bayesian classifier was applied	Comparative analysis was performed between NBC and TAN
13.Ankur Kulhari, Avinash Pandey, "Unsupervised Data Classification Using Modified Cuckoo Search Method" **2018**	Cuckoo search with probability distribution	Clustering	Unsupervised data classification
14.Aishwarya Palaiah a1, Akshata H Prabhu a2, "Clustering using Cuckoo Search Levy Flight" **2016**	Cuckoo Search Levy flight	Cluster formation	Positive False Alarm Detection Negative False Alarm detection
15.Suwannee Phitakwinai, Sansanee Auephanwiriyakul*, "Multilayer Perceptron with Cuckoo Search in Water Level Prediction for Flood Forecasting", **2016**	MLP-CS	Hybrid Algorithm Multilayer perceptron with the combination of cuckoo search	Flood prediction based on water level detection
Qi Chen, Amanda Whitbrook, "Data Classification Using the Dempster-Shafer Method: **2014**	Dempster Shafer	Dempster Shafer	Data classification

TABLE 3. *(Continued.)* **Extensive literature review synthesis.**

Ngo, P. T., Hoang, N. D., Pradhan, B.A Novel Hybrid Swarm Optimized Multilayer Neural Network for Spatial Prediction of Flash Floods in Tropical Areas Using Sentinel-1 SAR Imagery and Geospatial Data. *Sensors* **2018**	Hybrid algorithm comprising of firefly and ANN	12 input process variables, SAR images	Prediction of flash floods using swarm optimized multiple neural network.
Thanh Wan Hoang, Tien Yin Chou, Ngoc Thach Nguyen, Yao Min Fang, Mei Ling Yeh, Quoc Huy Nguyen, Xuan Linh Nguyen, MDPI 2019	Thomas Saaty's analytic hierarchy process (AHP).	River density, forest density, soil, geomorphology, landslide density, mean slope of tributes, topographic wetness index and mean annual precipitation index was estimated for the identification of flash floods on early basis.	Mapping

Sensor fusion algorithm are recommended for the higher accuracy, precision and resolution in investigation the false alarm and degradation in false alarm rate compared to the single transducer. Particularly if we take an example of PIR (Passive infrared sensors) in which many sensors output from PIR sensors were taken to investigate the presence of the real target and to identify the false alarm. Data was collected from shielded room to minimize the unwanted noise. Room was fitted with eight manually developed sensor modules on the walls. Time series issues were found to be the signal model for both the background noise signal and possible intrusion event signals were unknown. CDF (Cumulative distribution function) was applied and as soon as signal exceeded the threshold an intrusion was detected. Frequency domain results were better than the time series. Sensor fusion algorithm has been developed to eliminate false alarm. The PCA dimension was selected to record at least 95 % of the variance and PCA coefficients were Gaussian distributed. The results were taken from post processing data that was recorded and observed by the test bed particularly analysis was performed on MATLAB [15]. Nistara was a device interfaced with different sensors (thermal, fire, seismic) was installed at different points for sending signals to the main computer which implemented the fuzzy logic-based decisions. Images and other important information could also be propagated using cellular phones. The research included various sensors, master computer placed in a safest zone and in case of disaster there must be backup of master computer with others various functions like camera and voice recognition. The multipurpose device for disaster management can be installed in malls, schools and hospitals as well [18]. Cloud server was built to gather data on cumulative basis and to investigate huge data of long time for the decision making. Gradients servers have been expanded and installed on various river locations. Transducers like ultrasonic, optical flow and liquid level sensors were interfaced with Arduino and connected wirelessly to the gradient server.

Two schemes were designed for the cloud server:

1) Server was lightly loaded which indicated the recent web server load located in Flood forecasting center.
2) Server was loaded heavily (assume a situation of flood occurrence) and many hits to the central server then government servers can be used to propagate the data.

Cloud based system was validated with the cost and response time [19]. NEPTUNE, VENUS and CAMBRIDGE Bay have been administered by Ocean Networks Canada (ONC – oceannetworks.ca). Tremendous number of transducers was connected to the surface by undersea cables [20]. Recently data can be accessed through more than 200 online equipment and can be preliminary seen on Oceans 2.0. WARN received data as an input from pressure observer (lower surface of ocean), accelerometers and evaluated to identify the signs of seismic waves from earth. The practical example comprised of concrete software design to gather, analyze and discriminate the data from noise. Hydrographic radars were utilized to identify tsunami up to 150km. Dr. Carlos from University of British Columbia designed economical accelerator whose main motive was to discriminate the P wave (elastic wave). That observation also included the magnitude of earthquake and acceleration, orientation and height of the tornados and tsunamis [20], [21]. Another research explained the assessment and analysis of the post seismic effects means to observe that the building structures are really affected or not. During real time transmission scenario, data latency rate of communication can be considered more important as out dated information could provide garbage and unnecessary information. Many research applications have been developed to reduce the effect of seismic waves as they are generally non predictive. Several WSN based approaches have been applied to monitor the

TABLE 4. **Comparative analysis of different approaches [25].**

Model	L∞(cm)	RMSE	Training time	Prediction time	Error Std.
Naïve compensation	15.3	0.0547	0	5.3	0.0504
ARMAX	4.9	0.0164	0	272.3	0.0152
Fuzzy Logic (ML)	2.59	0.0413	168.6	5.5	0.0377
NL Regression (ML)	2.57	0.0082	28	5.7	0.0083
Decision Trees (ML)	2.15	0.0158	26.6	5.9	0.0158
NN(ML)	0.6	0.0058	975	5.2	0.006

building structures after earth quake [22]. For the successful recognition of disaster, it is mandatory that data of the event must be transmitted timely with higher reliability therefore two network QoS metrics were adopted. For simulation a set of five different cases of traffic flow on nodes based on Back-off algorithm was applied to reduce the collisions. Battery backup was also the major problem but data discontinuation cannot be neglected. Recorded data was classified into three types a) In first type there would be no data will be recorded and observed as the building didn't suffer any kind of damage. b) Secondly the standing structure with the recorded data as it suffered damage. c) Destroyed and completely devastated structures that shows and represent that building has been collapsed. The Ptolemy II/Visual sense framework was designed for the simulation [23]. Initially Global Positioning System (GPS) modules were deployed at the east coast of Peninsular Malaysia to find out the intense weather hazards like heavy flooding. The high frequency of rainfall may decrease the soil tendency resulting in flash floods. GPS were located in the west coast of Peninsular Malaysia. Rainfall data has been selected from the department of irrigation and drainage (DID). GPS and meteorological data have been processed to find out the PWV (Precipitable water vapor) by using Trowav 2.0 designed in MATLAB. The weighted mean temperature was utilized to accurately change zenith wet delay (ZWI). Statistical reading of minimum and maximum values of GPS was taken as an average. The average value is higher during pre-phase for overall the cases. The high peak of rainfall could cause the weather hazards with a contribution from wind and water cycle activities. Minimum peak of GPS PWV can be suggested as an early indicator. It was observed that extreme minimum value of GPS PWV was observed in the evening within two to three days before the flash floods and the average level of GPS PWV was maximum during the event of flash flood [24].

Table 4 represented the comparative analysis of six prediction models. The prediction models have been compared in terms of root means square error (RMSE), training time, prediction time and the error [25]. Piezoelectric transducer is generally acknowledged as ''shock sensor'' or instant material. Microphone can be adopted for the sound input and usually they do have more false alarm. Car alarms are the examples as it starts buzzing in the rain as well. The simple approach like glass broken parameter may also be added as a combination with the simple sensor so that all other false alarm may be reduced. The transducer that was connected with base plate have higher sensitivity than the suspended transducer to sounds propagated in the base plate while suspended transducer had higher sensitivity than the fixed one in the air around the sensor [26].

B. ARTIFICIAL INTELLIGENCE BASED METHODS

Varieties of design techniques have been followed to discriminate the true signal from false signal for example Extended Kalman Filtering (EKF) to improve the accuracy in identification of false alarms. Wavelet Transform Technique was applied to identify the fake alerts in ventricular tachycardia [27]. Fake alerts in arterial blood pressure (ABP) were minimized by utilizing morphological and timing information. Data mining approach was also applied to reduce the false alarms and close calls. FA (positive), FA (negative) and classification accuracy were considered as the evaluation parameters. Decision Tree is a machine learning tool for classification and regression. It performed like SVM (support vector machine). Bagged decision is same as decision tree. The only difference is that it doesn't take the whole data as input for the forecasting model [28]. Sudden heavy rainfall is very common in Mediterranean domain which causes many casualties and infrastructure losses. It had become genuine problem such as in the department of GARD, 23 casualties and 1.2 billion Euros loss were reported. This loss can be extended more than 15000 Euros in rural areas. Radar images were not accurate and trustworthy while precipitation measuring device did not work appropriately with consistency as they needed maintenance on regular basis. The research was applied on Garden de Mialet a mini basin of the Gardon d'Anduze. The designed watershed was around 220 square kilometers and its height ranged from 147 meters to 1170 meters with 36% ramps. Soil is light, rugged and underground soil contained 94 percent of mica-schists. The event time period was from 26 hours to 143 hours and was equally scattered at intervals of less than 48 hours. Average aggregate rainfall was observed between 44 mm to 462 mm. It has been observed that in heavy torrents the received signals comprise of high rate of errors and noise. Rainfall can be considered as the most authentic and precise instrument but efficiency is around 20%. TOPMODEL enveloped almost all the scenarios related to hydrological and meteorological parameters like moisture and ramps. Multi-layer perceptron model was developed for this proposed research model for universal assessment and stinginess related to deviating non-linear models. Multi-layer perceptron was applied with feed forward neural network comprised of one layer of deviating nonlinear neurons and one output linear neuron. Linear and non-Linear parameters were calculated that worked accurately [29]. Generally, UGS (Unattended Ground sensors) have high false alarm rate due to the less quality of detection algorithms and they do have also less battery backup of sensors operation and communication. It has been very complex to classify such activities like (digging, walking) from only seismic sign in real time with low SNR (Signal to noise ratio). Geophones have been fitted in two 3-axis so that digging and walking may be identified and classified. MSTSA (Multi-scale symbolic time series analysis) detects at the faster time scale. Seismic time series was changed to zero mean signal and down sampled to 1KHz from 4KHz means de-noised. Activity detection was done by taking transverse of window of 2S over the seismic signal with 30% overlap. Dominant and high peak was monitored by auto correlation [30]. To handle the water resources explicit and error free rainfall data is mandatory. For sure it is the most difficult exercise to interpret and design the model because of the perplexity of the climatic process. ANN has the capabilities to easily understand and interpret from the previous examples to contribute a useful solution if the data comprises of error or missed information. Almost All ANN are able to easily classify the pattern of rainfall for rainy period, moreover model can't perceive the parameters that is not fed into the system. Due to this fact it can only assess the time duration of a rainfall. Neural network can be regarded as a branch of AI that was matured in 1960 depending on the biological behavior and architecture of brain. Information and data have been gathered from the Malaysian Meteorological Department situated in Petaling Jaya. Previous data from the period of (2007 o 2010) that was analyzed by rain gauges was taken. After the assessment of data, it was decided that to train the network data of this period (1 Jan 2010 to 31st Jan 2010) will be used. Data that was taken from the department contained error, noise and missed information having N/A and −33.3 values. Data cleaning task can be utilized to recover the missed data values or deviations. N/A and −33.3 were replaced by 0 and 0.1. It's necessary to improve the deficiencies of data for the smooth and proper validation and testing. The model having the minimum error was chosen to estimate in contrast with the actual results. Mean Square error was calculated to observe the error, MSE value was 0.2.A system was developed using SCADA (supervisory control and data acquisition) technology to avert flash floods, in first and second model (A and B) forward back propagation (type of neural network) were used. The third layer used the multi-layer perceptron (MLP) having structure of five nodes in first layer and one node in second layer having output layer (5-5-5-1) [31]. ANN is most and widely used tool for the identification and locating the different type of the fields. After the demonstration of the ANN training by Rosenlatt in 1958 ANN is recognized as a discovery model. Flood water level has been forecasted by using neural network autoregressive model with exogenous input (NNARX) technique. This model was developed using MATLAB neural network toolbox. Rainfall intensity is based on various factors (variables) like pressure, temperature, wind, speed and direction, therefore the flood forecast warning system must be very accurate and intelligent to provide an initial warning [32]. The procedure was an extension of ARX model; five inputs were feed to the NNARX model to guess the hazard (flood water level). The forecasting time can be modified at any normal water level so that, the rapid enhancement in level may be identified. ST1, ST2, ST3 and ST4 that demonstrated four higher stream and dy/dk defined the changing of water level at the flash flood location. The data which was used for testing, validation and simulation was taken from 1st nov.2014 to 1st dec.2014 from department of irrigation and drainage Malaysia. Patterns of data were classified by training, validation and testing the proposed algorithm. Basically, NNARX used numerical method to examine in contrast with simulated and actual data. Initially it was observed that water levels are higher than the predicted modeling but after sometime it was near the actual water level that proved that this prediction model was reliable [33]. Tornados and heavy floods are the most hazardous troubles that caused casualties and loss of infrastructure in several countries. For the cost-effective solution of an early warning system a smart equipment that determine the crucial time must associate with the network so that it may be connected to servers all the time. It has been observed that watercolor can be yardstick to discriminate the flashflood. In normal situation water color is white-blue tone but it turns to red tone in tornados. If the water crossed the threshold of the water level and color was changed then photograph of the water was sent to the server with all other observed data. Automated Local Evaluation in Real Time (ALERT) in US and HYDRATE in Europe are the practical implementations of recording the data on a higher scale specifically for the heavy rain fall and precipitations named as "Flash flood monitoring & Prediction" (FFMP) [34]. Android part would be observing the water level constantly. Image of photograph was captured and evaluated by the android. If the water level exceeded the threshold limit and after the identification of the event android began to communicate with the server using 3G. It took input from the thermal transducer and echolocation sensor (echoes are sent and waited to be reflected back) also utilized the GIS (Geographic information system) data and images. HC-SR04 echolocation sensor has been used to observe the water level. Sensors give the echo time of sound and this PWM is changed into the length data. The sensor comprised of two parts, transmitter and receiver. Field testing was performed in Nang Rong waterfall that was heavily influenced by thunderstorm in 2013. It was observed and recorded that high rate of inaccurate estimation was achieved as high level of noise due to the temperature change, continuously precipitations and heavy winds [35]. In whole world natural disaster happen on yearly basis. Overflow forecasting has been very useful and beneficial for early warning system. Pekan River data was used to train the particle swarm optimization. Early warning system in managing overflow system was required for the exit routes safely. Natural disasters of floods over flow have been happening since a long time therefore they can be regarded as an important research topic in hydal engineering [7]. Various optimization algorithms are available in neural networks. Bayesian Regulization and Back propagation is one of the popular NN algorithms, sometimes network and feeding training stops due to huge data. It also required more time to process simulation as particles are received slowly.

It usually occurred with the biggest data size. Particle Swarm Optimization (PSO) can be used in most complicated medical areas like breast cancer and heart diseases. PSO's simplicity can be regarded as most important merit. Particles have been trained and learnt from its own knowledge and neighbor particle knowledge. Ackley's function can investigate and estimate the expression vigorously. Average data that has been noted down hourly from five stations were selected for the input. Output was declared as water level. Data during 2012 and 2014 floods were selected for the experiment. Multiple Perceptron (MLP) is type of ANN. It comprises of three parts named as input layer, hidden layer and output layer. There are joined and interconnecting weights among them. There are two factors which can be estimated a.) Number of iteration b.) Optimum number of particles. 300, 350, 400 and 450 were the maximum number of iterations. Numbers of particles in hidden neuron were 3, 6 and 10. A funnel was shaped by the optimization technique. Therefore, it was concluded that overflow and drainage of water model can be investigated by applying PSO with huge data size in very less processing time [36]. Early identification can be considered as the most important factor for the breast cancer affected woman. X-Ray, Mammography can detect breast tumor at early stage level. Almost 10-30% cancers are not detected by mammographic screening. Video pulse radars were used to identify the buried structure like pipes, cables and mines [37]. The breast was modeled with tumor. Spherical tumor was placed 30 mm inside the depth. EM wave antenna was placed over rectangular surface of breast. The back of antenna was filled with the lossy di-electric medium with similar di-electric properties having the same di-electric properties like normal healthy breast issues. The simulation was performed by utilizing ANN on the MATLAB. The false positive rate (FP) was acknowledged as a positive alarm rate. The negative false rate (FN) is the data that was categorized falsely negative. Fake alerts were minimized from 22% to the 2% with the variation of the signal to noise ratio from 1db to 40 db [38]. The electro cardiogram (ECG) signal was used widely to analyze the heart health. Arrhythmias can be regarded as physical variations. Investigation of irregular pattern is mandatory for prevention of heart. HRV (Heart rate variability) analysis is very fruitful in finding heart health [39]. Many approaches has been carried out like ANN with fuzzy, support vector machine and generalized discriminant analysis [40], [41].

C. RADAR AND SATELLITE BASED OBSERVATIONS

The phased array radar at National Weather Radar Test bed (NWRT) possessed the diameter of 12ft (3.7m), maximum transmitting power of 750 kw and operating frequency of 3.2 GHz. Pulse compression and most of the new waveform technologies (a signal processing approach generally used by radar, sonar and echography to enhance the resolution range as well as the SNR by modulating low level signal to a higher signal) has been used in armed forces but rarely used for the investigation of weather because of the scattered behavior of the water precipitation vapor (defined by IEEE 686-2008, Standard Radar Definitions) .Usually the main data contained from Polari metric radar (transverse waves) spectral motion of reflection, mean, average radial velocity, spectrum width, cross correlation coefficient, phase difference and linear depolarization ratio. For the pulse compression example an in house PX-1000 radar (Polymetric X-band radar was established in 2008) [4]. Atmospheric Imaging Radar (AIR) was used for the rapid scanning and observe the intense thunderstorms and cyclones [42]. Radar beam forming principle is normal to the surface. The prototype radar possessed operational range of 2.7 to 3.1 GHz in S-band and transmission power of 1.5 kW. For identification of earth and atmospheric variations radar can be acknowledged as an important tool as it is capable to scan in very harsh surroundings. Approximately 40 years ago development of tsunami detection by coastal based HF radars was analyzed. Only 26 observations assured the merit of this approach [43], [44]. HF radars discriminated the tsunami signal by calculating the periodic orbital velocity of low surface water on the coast line as it increases and decreases by diminished bottom of the seashore. The Seasonde (continuous surface current mapping and wave monitoring system) is working successfully in many continents on a large-scale network. Following consequences has been faced by using HF radar-based technique:

1. Tsunami wave current pattern order must be calculated and estimated with the previous wave pattern data; first metric would be probability of detection.
2. Haphazard extrinsic turbulence and communication signals can interfere the second achievement metrics: probability of false alarm.

Keeping in the mind these two problems there were two main parameters that estimated the higher discovery domain and early prediction time

1. Strength of tsunami.
2. Depth of the river with respect to the surface of the coastal.

Designing of a model having hyperbolic second order differential equation (PDE) that investigates the tsunami height and orbital velocity. It ignites or triggers the tsunami at the particular coastal area having all the bathymetry of that particular seashore. The 2D velocity can be converted into radials. Data is saved on radar site. Amplitude shows the tsunami power in testing. The order of the waves (tsunami and non-tsunami) are examined in the form of Q-factor spikes to set the threshold and then transmitted to the tsunami warning center (TWC). Threshold level must be set adequately high so that false alarm may be minimized. CODAR (Coastal Ocean Dynamics Application Radar) Ocean Sensors (COS) was linked with HF Radar programs to determine the tsunami early warning at New Jersey [45]. Another research paper is related to the weather forecasting of flash floods based on the images taken by grounded radar systems. Rainfall prediction can be further elaborated by the numerical weather predictive model approach or by the ground-based radar images. The numerical method was developed for the calculation of temporal distances, more than three hours elapsed time was required for the data processing to train the data values in a model. A nowcasting system comprised of two main categories. The First one calculated the recent direction and second one predicted the rainfall position and volume. Motion calculation based upon three sequential radar-based observations that were named as Ae1, Ae2 and Ae3. Ifi represented the predicted image and Afi represented the image received by radar at the same date. These two images were examined in contrast to each other. Generally, X band images were imported from ground radars after every five minutes having angular resolution of one degree and radial resolution of 150 meters. The bounced readings have been remodeled into humidity rates by using Z-R formula and second transformed from polar grid to the Cartesian [46]. CASA (Collaborative adoptive sensing of the atmosphere) in affiliation with U.S National Science Foundation (NSF) were joined together on a single agreement to analyze the weather changes and prediction of dangerous accidents due to the weather variations by utilizing a network of tiny radars that consumes deplete less power to estimate the atmospheric and climatic variations. These small radars having less power consumption have been setup around 30 km away from each radar. The radar system which was deployed at DFW Urban test bed used the latest technology and research that is done by CASA. A very high detailed geographical and dimensional resolution was achieved due to the precise range and nearly installed radar to each other. Important objectives that had to be accomplished by DFW.

1. For the recognition of heavy winds, cyclone, water floods, a very detailed high resolution and multi-dimensional mapping has been determined.
2. For the protection of human from harm early warning should be developed so that there should be remarkable advantage of saving human lives.
3. The estimation of the result will have to be the combo of x-band radar networks, transducers, efficiency metrics and decision making.
4. Designing of a model for the federal, municipal and private departments to analyze the changes in the weather.

Radar network comprised of 8 nodes, multi Doppler, dual radiated polarization that included 12 countries of 6.5 million people in Metropolex. CASA worked with the additional transducers like WSR-88D, TDWR and rain gauges for the testing and validation purpose [46]. Another research has indicated the utilization of Earth Observation satellites to observe and monitor the torrents. Committee on Earth Observation Satellites (CEOS) explained the design solutions for the trouble management during tornados. There can be two modes of remote measurement or sensing.

1. For the evaluation of the event and input into the design model, accurate and definite mapping was needed.
2. Pointing out the accurate location of the flood covering all the aspects on big scale.

Remotely measured observations calculated the terrain properties of coastline like ramps, slopes, direction, bumpiness and the distance covered by the river that is usually available on government scale as well. The satellite-based data consisted of length of the land; water spread area, area covered by snow, ground moisture, humidity in rainfall and evaporation. Remotely measured observations and other transducers-based data to the end users must be unified to give the research and development-based concept for watershed models to record the torrents, tornados, dams, landslides and storm. High resolution based Geographic Information System, better coverage frequency, high resolution of data, increased coverage access, data transmission, delivery for the microwave link-based transducers and proper link of satellites must be unified to predict the flash floods [48]. Vigorous flash flood management must have the capabilities to determine the change in the process: the hydro atmospheric and climatic development that causes flood waves and land metropolitan exposure that leads to causalities. The OPERA covered all the aspects of different phases of flood risk management (prediction and post event estimation). Temporary data and transmission distribution model were used for the transmission of data of various satellites and sensors to administer the central and outside function centers. OPERA basic aim was to provide civilian safety from floods based on the earth analysis obtained from the space in combination with the ground data. The opera provided the following services; maps of deadly alarming and critical infrastructures and maps of hydro-mechanical structures related to ocean changes. Mapping of river beds and flow of discharge was also made visible at the user end. High resolution 3-D virtual model of city climatic and atmospheric change was designed. The second main feature was soil moisture observation and analysis for the identification of flash floods. The third facility would be flood alarming and continuous observation. The fourth element of opera was disaster management and post event evaluation. The representation setup was dependent on real-time nonstop parallel running of two particulars 1. Forecasting of flood and 2. Evaluation chains. High resolution images of X-band can be used for producing the functionalities which have been discussed earlier. Conventional case of this was high resolution, meter scale, designing of Digital Elevation Model (DEM) of highly affected areas, quick evaluation of actual flooded areas and early warning of the land position changes. The competency of this system design model has been tested successfully for the Tanaro river flood happened on April 28, 2009. It produced maps of flooded area using CSK (Cosmo Skymed Mission) [49], [50]. Power plants that were located near watershed started to design an early warning system for tsunami and tornados after the occurrence of Tohoku-Pacific Ocean earth tremors in 2011. A DBF based radar system was considered suitable to observe the current arrangement pattern in a precise time. The motive of the proposed research was the combined analysis of DBF radar located at oceans with VHF band in real time situations (field observation). A real time system has been flourished named as DRAGON to audit the wave currents along the seaside by using DBF radar and VHF band having the dimensions of 0.5 km and the velocity of 2.13 cm/s. DBF radar transmitted 512 pulses with repeated time of 0.64 msec.

Dragon was installed at two sites (Site A: Omaezaki and Site B: Hamaoka) 8 km away from the Enshu Seashore. Accuracy and precision have been determined by comparing the wave current acceleration with the current measuring equipment (meter). Impact of current by the heavy wind or air can be easily minimized by the current meter data. DBF radar based data and current meter data were correlated to estimate the tsunami [51]. Serious weather conditions and heavy rainfall, torrents, cyclone and rainstorms lead towards the casualties and infrastructure loss. Lightening is one of the most dangerous hazards. It is also china's threat that causes the damage of transmission lines in china. CG flashes are commonly identified by lightening detection network (LDN). Different thunderstorm measuring equipment like field mill, radar, nephogram (images of clouds), and images received from satellites were incorporated with cloud to ground flashes system that forecasted motion of tornados with various algorithms. The main motive was to provide cost effective solution based on CG flashes and images of clouds (nephogram). Lightening occurs independently and haphazardly therefore it's complicated to forecast. Charged clouds generate lightening effect which was investigated through satellite received images by researchers. Severe weather (thunderstorm) cannot be predicted by only lightening as lightening occurs randomly. Remote sensing of the tornados and heavy rainstorm can be done by taking images and information from the satellites. Nephogram (pictures of clouds) are also mandatory to forecast the motion of flashes. Meoscale convective complex (MCC) was introduced by Maddox for the analysis of thunder clouds. Remote sensing images were refined by minimizing hindrances and unwanted distortion to determine the convective clouds. The movement can be forecasted by summarizing the lightning flashes and recognition of thunderclouds. Resemblance of both lightening and clouds at the same time will determine the next movement of the activity by identifying the group and estimating the final vector of the motion as probability of the prediction at the same time of both events is one [52]. There are various ways for the suppression of azimuth ambiguities [53]. High resolution images may contain much vagueness due to several other targets. Finite pulse repetition frequency and non-ideal antenna pattern maximizes the false alarm rates in ship identification applications. ''Asymmetric mapping and selective filtering'' technique was used for the filtering of azimuth ambiguities in map SAR (synthetic aperture radar) images. Processing time of SAR image is around 20 seconds. Azimuth ambiguity filtering method was applied as an initial step of standard ship detection algorithm that depends on adaptive threshold cell averaging CFAR (constant false alarm rate) method. This algorithm computed the ratio between small box centered in the target and the mean intensity of the large area. CFAR may produce many false alarms at coastal areas. CFAR was optimized to minimize this issue. For the verification comparison was performed between non-filtered and filtered images for ship detection algorithm. First image showed that almost every ship has been identified, second image showed that ghost ship has been identified. The results proved that false alarm rate reduced drastically [54], [55]. Automatic Target Recognition Algorithms produce more false alarms as they are dependent on the environmental conditions where they are installed. ATR generates more fake alerts due to the Mine Like Textures (MLTs) and regions with high clutter density. ATR can identify in flat surfaces very accurately. False alarm depends on the correlation with the complexity and anisotropy of the sea-floor Nelson and Kingsbury [56]. These complexities can be utilized to feed and educate the neural network. Dual Tree Complex Wavelet Transform (DTCWT) is used to measure the textural characteristics like areas of the sea having same design and patterns. Clutter characteristics are investigated by Markov Random Field (MRF). Haar-cascade ATR is trained to identify the truncated cones, wedges and cylinders in the data sets B-D. ATR was compared with the sea-floor filter. A lesser effect was observed in the results proving that this approach can be used to minimize the false alarm in the ATR. Sea-floor classification can be used to detect the mines and Autonomous Underwater Vehicles (AUVs) as a future enhancement [57], [14]. Assessment of satellite-based rainfall measurement error can be acknowledged as a very complex task because this factor is related to the multiple reasons containing natural variation in rainfall occurrence, analysis error and incompetent algorithms and sampling ambiguity. Diversified high accuracy techniques have been applied like Tropical Rainfall Measuring Mission (TRMM), multi-satellite precipitation analysis (TMPA), Climate Prediction Center morphing (CMORPH), precipitation estimation from remotely sensed imagery using artificial neural networks (PERSIANN) and Global Satellite Mapping of Precipitation Moving Vector with Kalman filter (GSMaP-MVK) [59]–[61]. Minor researches have been carried out to resolve the problem of precipitation measurement in complicated landscape and topography without errors [62], [63]. Analysis was performed at mountains Trentino-Alto Adige region, situated in the eastern Italian Alps for error observation. The area was around 13607 km^2 of complicated landscape region along with the altitude 65 meter to almost 4000 m. Parameters were calibrated and measured again by using CMORPH (2000-2005) data, PERSIAN data and 3B4RT data for the detailed error investigation [64]–[66].

D. MODELING AND NOWCASTING

Sewerage system of Karachi has been deadly stuck and damaged by the haphazard urbanization infringements on the natural sewerage channels that altered the land use/land cover (LULC). Congestion in sewerage lines caused the discharge on daily basis in Karachi. Urbanization affects the exterior hydrology and damages the natural water path as well. Karachi flow comprises of 2 basic river systems, Malir and Lyari. Both of rivers are used to clean out the flow of water of the rainfall and thunderstorm. These river sides have been covered by the yields of crops, illegal mound to hold water and illegal construction. Main aims of this study were to evaluate the leading LULCs that caused to obstruct the Malir

River and to draw a graphical model for the sample of Malir River by utilizing the water science related to earth (hydrology), movement based on fluids pressure and past precipitation values. Satellite based pictures of the land were utilized to obtain Land use/Land cover (LULC) of the Malir River watershed. To design the model of heavy rainfall and flow of precipitations HEC-RAS/GeoRAS was used and for the simulation of thunderstorm and rainfall HEC-HMS/GeoHMS was utilized. Models of tornados and torrents during the 2009 to 2013 have been designed along with HEC-RAS hydraulic model. Various diseases and viruses can be spread out by the polluted, contaminated and blighted region [67]. Modeling research indicated the utilization of Earth Observation satellites to observe and monitor the torrents. Committee on Earth Observation Satellites (CEOS) explained the design solutions for the trouble management during tornados. There can be two modes of remote measurement or sensing for the evaluation of the event and input into the design model, accurate and definite mapping is needed. Pointing out the accurate location of the flood covering all the aspects on big scale. Remotely measured observations calculated the terrain properties of coastline like ramps, slopes, direction, bumpiness and the distance covered by the river that is usually available on Government scale as well. The satellite-based data comprised of length of the land, water spread area, area covered by snow, ground moisture, humidity in rainfall and evaporation. Remotely measured observations and other transducers-based data to the end users must be unified to give the research and development-based concept for watershed models to observe the torrents, tornados, dams, landslides and storm. High resolution based Geographic Information System with better frequency, high resolution of data, increased coverage access, data transmission for the microwave link-based transducers and proper link of satellites must be there to investigate the flash floods properly [48], [68]. Weight matrices usually evaluate the architecture of artificial neural network. Synthetic aperture radar (SAR) images were used to determine the flash floods. Machine learning approaches firefly algorithm (FA), Levenberg–Marquardt (LM) backpropagation, and an artificial neural network (named as FA-LM-ANN) were developed to build predictive mode for the investigation of flash floods. Case study was performed at an area named as The Bac Ha Bao Yen (BHBY) in the northwestern region of Vietnam. Geographical information system (GIS) was designed using 12 input process variables. Hybrid approach comprising of firefly algorithm (FA), Levenberg–Marquardt (LM) backpropagation achieved better results [69].

Hydro-numerical and hydrodynamic predictive modeling for the rainfall and flash floods was completed. Risk based early warning system case study was carried out at the German city of Achen. Georeferenced files consisted the following data for GIS design, precipitation velocity, timings, precipitation intensity, affected area, video and images of flood with time and actual depth of the flow rate [70]. Flash flood event was estimated which was caused by the severe

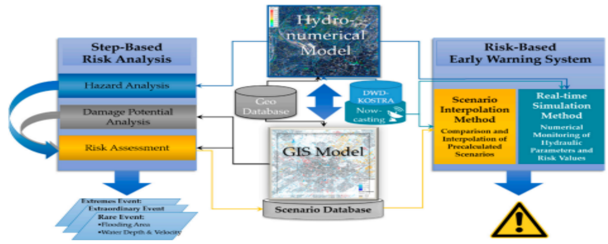

FIGURE 3. Multifunctional Pluvial flood information system [70].

rainfall eighty millimeter per day in northern Morogoro and Tanzania. Flash flood event was caused due to the overflow of Ngerengere river. Automatic weather observations may boost the accuracy in identifying the flood events accurately [71]. There are so many deciding parameters which have been used for the robust estimation of floods like meteorological properties, time duration, precipitation intensity, wind velocity, time variation of rainfall, watershed occupied area such as size, slope, length, soil humidity and vegetation cover [72], [73]. Another fresh case study was conducted in Tanzania which elaborated that mainly flash floods were caused by the severe precipitation patterns [74]. Recent researchers also proved that severe precipitation also depends upon the sea surface temperatures (SSTs) [75]. River density, forest density, soil, geomorphology, landslide density, mean slope of tributes, topographic wetness index and mean annual precipitation index was estimated for the identification of flash floods on early basis. Grading of estimation was divided into five categories. Real time data for the precipitation from iMETOS was also collected. Nine types of maps were utilized to evaluate the floods accurately [76]. Thresholds of flash floods risk assessment vary widely due to the slope and rainfall intensity. Flash floods levels were categorized into four levels in Vietnam. Determination of thresholds level for the accurate measurement of floods are very important [77]–[81]. Rainfall was evaluated for the Netherland earth surfaces, i.e., link-derived rainfall maps, Integrated Multi-Satellite Retrievals for Global Precipitation Measurement (IMERG) Final Run (IMERG-Global Precipitation Measurement mission), Meteosat Second Generation Cloud Physical Properties (CPP) and Nighttime Infrared Precipitation Estimation (NIPE). Precipitation results were compared with gauge-adjusted radar data, considered as the ground truth given its high quality, resolution, and availability [82]. Feed forward propagation was combined with the particle swarm optimization for the development of the predictive model [68]. Researchers have also designed a predictive model in which fuzzy control system was optimized by the genetic algorithm [83].

IV. LITERATURE REVIEW SUMMARY

Fig. 4 illustrates that extensive literature review for flash floods prediction has been categorized into four categories named as a) Sensors and gauges based measurement b) Artificial Intelligence based methods c) Radar and Satellite based observation and d) Modeling and Nowcasting.

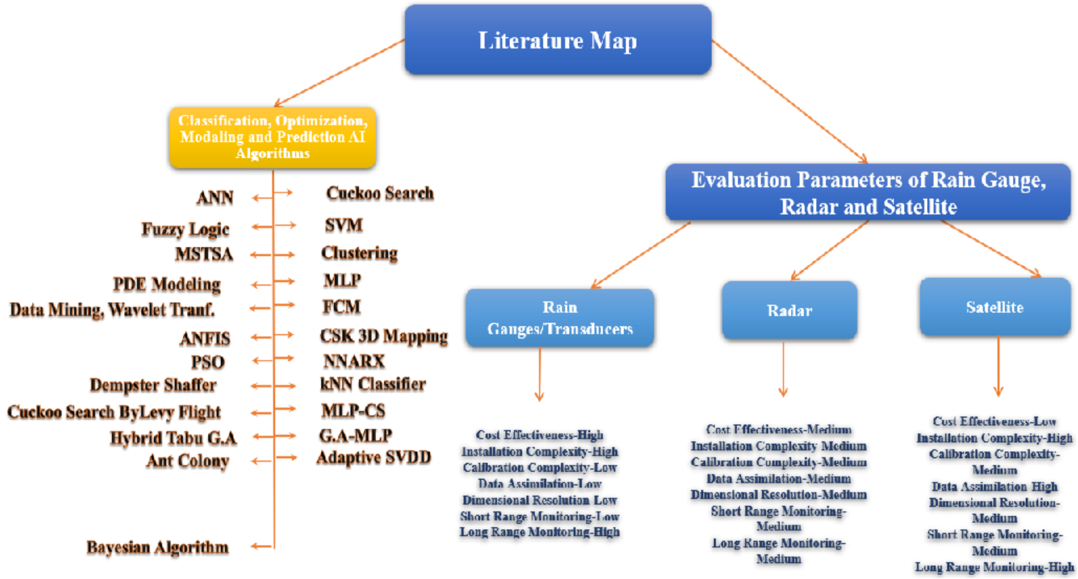

FIGURE 4. Literature Review summary.

TABLE 5. Comparative analysis of various latest AI methods [68].

Performance Indices	ANN	SVM	ANFIS	NNARX	M-PSO
RMSE	0.194	0.390	0.116	0.090	0.0047
Best Fit	73	64	78	80.10	98.7
Results	satisfactory	unsatisfactory	satisfactory	satisfactory	satisfactory
Hourly data	6 hrs	6 hrs	3 hrs	3 hrs	3 hrs
Accuracy	73	64	78	80.16	98.99
Precision	Medium	Low	High	High	High
Reliability	Medium	Low	High	High	High
Power Utilization	Limited	Limited	Limited	Limited	Limited

A flood prediction system was developed using satellite altimeter. The root mean square for the prediction of the flash floods in Bangladesh was found to be 0.75m to 1.5m [84]. Flash floods were also identified using satellite synthetic aperture radar(SAR). Data was collected of pre and post floods from Japan Aerospace Exploration Agency's Advanced Land Observing Satellite-2. Greater spatial resolution was achieved from Satellite-2. The differences were correlated between the pre and post flood [85]. Digital Basin Technology was adopted to reduce the flash floods disaster in Yellow river floods [86]. Flood scene ontology [FSO] was designed to determine the topological and direction information to mitigate the flood disasters [87]. Mathematical equations depending on multiple factors were designed for the modeling of the system [88]. River maps, soil moisture, water levels, precipitation intensity and volume data was processed using cellular automata algorithm. The output results produced 2-dimensional image for the prediction of the flash floods [89]. NNARX-EKF (Neural network auto regression with exogenous Input-Extended Kalman Filter) results were compared with the NNARX. Results showed that NNARX-EKF performed better for the prediction of run-offs. Flood inundation level (FIL) model was designed using spatial factors to reduce the floods [90]. MODIS satellite observations were utilized to detect the floods [91]. The images which were captured from the SMOS satellite were processed to classify the wetlands and waterlogged areas [92]. Results using Bitemporal TerraSAR-X StripMap data set from South West England during and after a large-scale flooding in 2007 confirmed the performance capability of the proposed identification approach [93].

V. COMPARATIVE ANALYSIS

Table no. 5 elaborated the comparative analysis of new Artificial intelligence methods of Artificial Neural network, Support Vector Machine, Adaptive Neural Fuzzy Inference System, Neural network auto regression structure and hybrid algorithm based on ANN and particle swarm optimization in terms of root mean square error (RMSE), fitness, accuracy, precision, reliability and power utilization. This comparative analysis is beneficial for the researchers and scientists for the further research work.

VI. CONCLUSION

Authors have tried their best to demonstrate and explain all the fresh, novel and robust techniques that have been developed for the identification of flash floods in this research paper. Researchers and scientists may be benefited with this research paper in terms of comparison of different flash flood analysis. All the major Artificial intelligence based algorithms, sensors based and modeling-based observations have been discussed for the flash flood identification accurately and precisely. Results have been presented in this research paper. On the basis of the reviews, critics, results and rigorous analysis a new researcher can be benefited in the research area of flash flood prediction. This comparative analysis is beneficial for the researchers and scientists for the further research work. Modified Particle swarm optimization has the better tendency to optimize the weights of neural networks having multiple perceptron's or fuzzy logic can also be optimized by genetic algorithms According to the survey firefly and particle swarm optimization have better results for the optimization of the weights for the prediction of the flash floods.

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