After the Flood: A Novel Application of Image Processing and Machine Learning for Post-Flood Disaster Management

Hafiz Suliman Munawar[1], Ahmad Hammad[1], Fahim Ullah[1], Prof. Dr. Tuaha Hussain Ali[2]

[1]*Faculty of Built Environment UNSW, Sydney,*
[2]*Mehran UET-Jamshoro, Sindh, Pakistan*

Abstract: **Floods are natural disasters and pose a threat to the lives, property, and infrastructure of an urban area. Though their risk cannot be fully eliminated, several methods can be used to manage floods, once they occur. This includes identification of flood-prone areas, timely detection of the affected areas, mapping rescue routes and arranging logistics to carry out the rescue as soon as possible. The use of advanced innovative technologies for flood management such as image detection and machine learning can assist in effective flood management. This paper presents a novel approach through the integration of image processing and machine learning to detect flood-affected areas using a set of images. The three-step approach proposed in this study is based on landmark detection from images, training of a machine learning algorithm and classifying images from an area as flooded or non-flooded. The results based show an accuracy level of 90% depicting the significance of the proposed model for image-based flood detection.**

Keywords: **Flood Detection, SVM, Machine Learning, Edge Detection, Landmarks Detection, Disaster Management.**

I. INTRODUCTION

The increased meddling of mankind with nature and climate change are the factors contributing to an increased risk of natural disasters throughout the world [1]. Earthquakes and floods are among the most commonly occurring disasters, which have been pondered upon for a long time by geologists and disaster managers with the main aim of predicting these calamities before their occurrence [2]. However, in many cases, these forecasts are not accurate and fail to determine the occurrence or the exact location, time and duration of these disasters [6]. Thus, the best solution would be to take effective measures to prepare for them to minimize the destruction caused in case of occurrence. Similarly, once they occur, many barriers exist in carrying out the post-flood activities because the communication networks, transport routes, and vehicles get damaged and are mostly unavailable at this critical time. Technologies like the internet, WiFi signals, and mobile networks are mostly inaccessible. This makes the rescue process more complicated and difficult due to the inability of detecting the flood-affected regions. Many human lives are at risk and may be lost due to untimely identification of the occurrence of floods and pertinent delay in the rescue works. Owing to this life-threating risk, the current study focuses on managing floods through the use of innovative technologies such as image processing and machine learning with the aims of accelerating the detection of flood in the affected area so that the rescue activities could be started as soon as a disaster strikes.

Image processing has been used extensively for detecting floods, landmarks and rescue routes within the flood-affected regions [3]. However, the image processing techniques used independently have proven to be less accurate as there exist many factors that affect the quality of images. These factors include cloud barriers, noise due to pollution, brightness, and contrast. Also, image processing techniques have several limitations due to which consistent results cannot be obtained with each test image. An algorithm working fine for some images may not bring good results for another set of images due to the inherent inconsistencies that may be fuel due to the afore-mentioned barriers. To overcome these issues, machine learning is increasingly adopted and utilised in addition to the image processing [4]. This involves using large datasets for training a prediction model that can adopt the intelligence based on the training modules resulting in higher accuracy and reliability. According to the reviewed literature and pilot surveys, multiple technologies involving image processing and machine learning have been used to carry out flood management individually, however, very few are focused on using both to formulate a holistic approach for tackling post-disaster flood management.

In this paper, a novel approach to identifying floods based on machine-based scrutiny of images is presented. This model incorporates techniques from both image processing and machine learning, combined in a holistic approach for effective post-flood management. The resultant model has demonstrated improved accuracy and less training time than previous used methodologies. The goal of this research is to develop a computationally efficient model to speed up the training process as well as produce improved results in classifying flooded and non-flooded images for timely rescue response to flood affected areas. For this purpose, a holistic sequential multi-step approach based on image processing and training the model for image examination has been developed. The improved images are then supplied to the classifier for training the model and machine on detections and updating the core algorithms. Results have shown increased accuracy and reduced training time. The following section discusses various methods used in both image processing and machine learning for flood management in the past decade followed by the proposed methodology. The last two sections discuss the experimental results and the conclusion and future direction for building upon current work and expanding the horizons.

II. LITERATURE REVIEW

Floods being one of the most destructive natural disasters are not only dangerous to human lives but also affect the infrastructure of the country. Pakistan is prone to floods every summer which along with being a threat to human lives and having catastrophic results on infrastructure, destroys the economy as well. The following sections provide an overview of the UpToDate innovate techniques used for image processing and machine learning.

A. Flood management using Image Processing

Image processing is a growing area of research having special inputs and exploitation in the areas of disaster analysis and management. Previously, image processing has been used extensively for biological analysis, however, modern approaches have extended its applications to other fields as well and hence it has a diversified outlook in modern world [7]. Specifically, it has been extensively utilised by different countries that have a radar system for capturing satellite images and processing the results. An application based on such remotely sensed and captured images and data is that of flood monitoring, analyses and management. Table 1 summarises the most recent methods in image processing that are being used for flood management.

Table 1: A review of flood management techniques using image processing

SR	Technique	Method	Limitation	Authors
1	Object Extraction	Target recognition of landmarks like bridges using image segmentation.	Results highly depend on image segmentation results	Munawar et al., 201
2	Edge Detection	Applying edge detection to determine water surface levels of a region.	Manually choosing parameters for edge detectors; not good results for low contrast regions in images	Akbar, Musafa, & Riyanto., 2017
3	Image acquisition through UAVs	Using UAVs to capture high resolution spatial images in complex landscapes and transmitting to the servers.	Limited tracking time as UAVs are battery operated	Abdelkader et al., 2013, Coveney & Roberts., 2017; Șerban et al., 2016
4	Pixel based Threshold on SAR images	Capturing images through SAR and applying threshold on pixels to classify flooded and non-flooded regions.	Less classification accuracy for hyper-spatial data	Anusha & Bharthhi 2019

Edge detection has been used to detect a horizontal water line or the height of a dam. This helps in separating water images from other objects in the surrounding as the water surface level of any region can be calculated by processing the captured image [8]. Detecting roads, runways and bridges are necessary for identifying routes that could be used for reaching areas prone to disasters or disaster-affected areas once the disaster has struck. The detection of linear objects like bridges could greatly enhance object detection within the aerial images from the disaster-prone areas [5][9]. Similarly, the Unmanned Aerial Vehicles (UAVs) have been shown to have potential as efficient tools for data collection in the face of calamities. These UAVs can replace traditional data capturing tools such as satellite imaging and GPS based monitoring in the future. Further, these UAVs have the edge of being quick in gaining image data and transmitting it to their respective servers in real time [12]. Using their advanced Synthetic Aperture Radar (SAR), UAVs can capture high-resolution spatial images of the target area. A pixel-based threshold can be applied to identify flood in these high-quality images [13].

B. Flood management using Machine Learning

Machine learning methods have the advantage of being quick, cheap, high performing and easy to validate. In the last couple of years, machine learning methods have proven to be highly suitable for flood predictions and outperformed many of the conventional prediction methods. Table 2 summarizes some of these novel and innovative machine learning methods. The Artificial Neural Network (ANN) models have been regarded as the best tool for developing flood risk prediction models [15]. It has been used to simulate flows at a certain location in the river reach, based on flow at upstream locations [16]. Studies have shown that ANNs have higher speed and accuracy than many of the conventional models and tools used previously [17]. Among the different classes of ANNs, the backpropagation ANN (BPNN) is the quickest and most powerful tool for predicting floods [19]. Similarly, The Multilayer Perceptron (MLP) uses the backpropagation for the training of the multi-layered network [32]. The back-percolation algorithm is used for analysing and removing errors, making MLP a popular and powerful tool for hydrologists [20]. MLP has been used to predict floods using rainfall time series data and water levels in a weir [21].

Another tool i.e. the Adaptive Neuro Fuzzy Interface System (ANFIS) is a combination of ANN and fuzzy interfaces. Fuzzy logic-based systems are also quite popular and have been used for forecasting river water levels [23]. Rainfall-runoff water modelling has been carried out using the fuzzy interface system (FIS) [24]. Short term rainfall predictions and flood identifications are possible using a slightly modern FIS approach, known as the adaptive neuro FIS (ANFIS), that combines ANN and FIS for creating a more robust model for flood predictions [25]. Similarly, the Wavelet Neural Network (WNN) is a combination of the Wavelet Transformation (WT), wavelet regression models and the feed-forward neural network (FFNN) methods. The WNN has proven to be useful in accurate flood modelling due to the potential of enhanced time-series data [26]. This helps in analysing data related to river flow, flash floods and rainfall-runoff [28]. Finally, Support Vector Machine (SVM) is a method that is based on statistical learning and risk minimization rule [29]. Support Vector Regression (SVR) has been used for boosting the learning algorithm of machines to build a flood prediction model [30].

Table 2: Flood Detection using Machine Learning

Model	Technique	Outcome	Authors
Artificial Neural Network (ANN)	ANN model used for simulation of water flows at various locations in the river.	A reliable model to predict flood hazards in the rivers.	Sulafa HagElsafi., 2014
	Used ANN-BPNN for flood predictions.	Quicker, more accurate than simple ANN	Valipour et al., 2013
Adaptive Neuro Fuzzy Interface System (ANFIS)	Training of model using genfis2 and genfis3	ANFIS gives better results than ANN for runoff forecasting (daily and hourly behaviour)	Rezaianzadeh et al.,2013
	Fuzzy logic-based system used for forecasting river water levels.		Lohani et al., 2012
	Used adaptive neuro FIS (ANFIS) which combines ANN and FIS for creating a more robust model for flood predictions.		Ashrafi et al., 2017
Support Vector Machine (SVM)	Support Vector Regression	Non-linear mapping capabilities for SVM are higher than ANN	Li et al.,2016
Wavelet Neural Network (WNN)	Levenberg-Marquardt method (LM) Combined wavelet analysis with ANN	More accurate forecasts were recorded by WNN than by the original signals	Krishna et al.,2010
	Enhanced time-series data used for analysing data related to river flow, flash floods and rainfall-runoff		Supratid et al., 2017, Guimarães Santo & Silva., 2014
Multilayer Perceptron (MLP)	Use of MLP for water elevation level prediction	3.64% error generated by the system	Widiasari et al., 2017

III. PROPOSED METHODOLOGY

The current study presents a novel technique to detect floods from images using most fitting methods from image processing and machine learning. The idea is to improve the image quality and reduce processing time spent in training to get the best results out of the prediction model. An abstract level diagram of this method is shown in Fig 1(a) and (b).

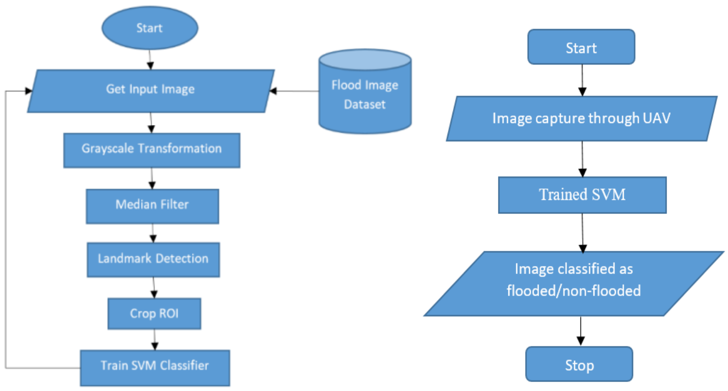

Fig 1: (a) Training of Classifier

Fig 1: (b) Identification of flooded areas using trained model

Fig 1(a) illustrates the image processing and training steps using images captured from UAVs. Ideally, a UAV can be used to capture images of the target area, as it is a battery-operated aerial vehicle, which can be used to capture high-quality spatial images of the affected area quickly. This will be particularly helpful in post-flood circumstances where technologies like Global Positioning System (GPS), WiFi and internet are not available. After acquisition of images, each image is transformed into grayscale to reduce the image size. Edge detection technique is used to detect and separate landmarks from these images. In this study, these landmarks include houses, buildings, and bridges as shown in Fig 2. The Region of interest comprising of selected landmarks is cropped as they indicate populated areas in the image. Next, a median filter is applied to reduce noise from these images. After these image processing steps, the SVM classifier is trained using the resultant set of images. The testing method used is shown in Fig 1(b), where an image acquired by UAV is given as input to the trained SVM classifier. The classifier labels this image as “flooded” or “non-flooded” as its output.

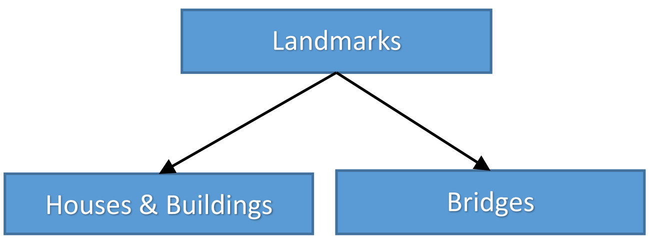

Fig 2: Target landmarks to be detected

A. Pre-processing

Pre-processing is the first step in any image processing task that is conducted to improve overall image quality and reduce noise. First, the images are converted to grayscale to discard information that is not required for the analysis. In the proposed model, the pixel's color information is not used for classification. Hence, images are transformed into grayscale to save memory and processing time. After this, a noise filter is applied to reduce noise and get a smooth image using a median filter which is particularly useful for removing "salt and pepper" noise from images. It is a non-linear filter that removes noise while preserving the edges and reducing the deformation and is deemed suitable for the proposed model. It sorts all pixels present in a window according to their numerical value, then replaces the pixel being considered with the median pixel value. In the case of windows of even size, the filter takes an average of two middle values after sorting giving the output "*O*" using equation 1.

$$O = \frac{i^{th} classified\ value + (i+1)^{th} classified\ value}{2} \qquad (1)$$

B. Landmarks Detection

The target landmarks in the proposed method include buildings, houses, and bridges since these objects point towards populated areas in images which are crucial for flood analysis. Hence, these regions are cropped and retained for training the proposed machine learning algorithm. The detection and cropping of landmarks result in increased classification accuracy, as the model is trained using the most relevant set of images. Further, providing a learning model with irrelevant and noise affected images results in more false detections and less accurate results as well as increased training time thus it is ensured that only relevant materials are fed to the system.

Houses and Buildings: To detect houses and buildings, Harris Stephen's algorithm, which is a combined edge and corner detector, is used. It finds the difference in intensity for a displacement of (p,q) in all directions as shown in equation 2.

$$E(p,q) = \sum_{a,b} w(a,b)[I(a+p, b+q) - I(a,b)]^2 \qquad (2)$$

Fig 3 (a) shows a pre-flood test image of the target area wheras Fig 3 (b) shows a post-flood test image. Fig 4 (a) and (b) show landmark detection using the edge detection algorithm. It is evident from the images that the landmarks like buildings and houses are highlighted indicating populated areas in this region.

Fig 3: (a) Pre-flood image Fig 3(b) Post-flood image

Bridges: Bridge detection was done by using a knowledge-based approach presented by Munawar et al [10], that exploits the spatial arrangement of bridges and their respective surroundings using a five-step approach. Aerial images, captured by UAVs, are analyzed to determine patterns for mining of bridge regions as shown in Fig 5. The landmarks are cropped using the Region of Interest (ROI) function. The detection of landmarks is an important milestone in this research, as it will help in the detection of populated areas from the aerial view of the land. This will help in locating and reaching the flood-affected people and mapping the rescue routes.

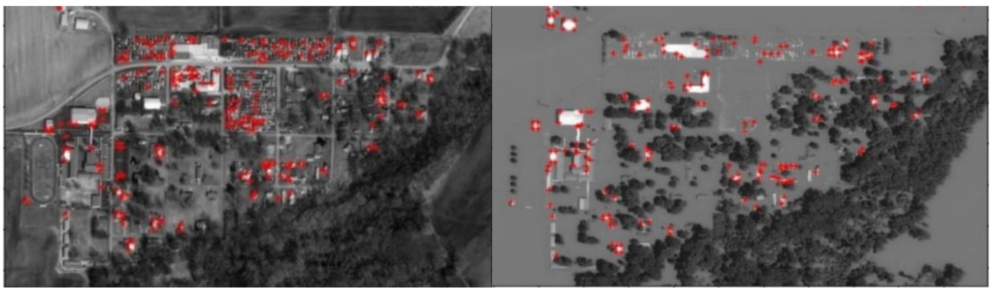

Fig 4: (a) Landmark detection in pre-flood image Fig 4: (b) Landmark detection in post-flood image

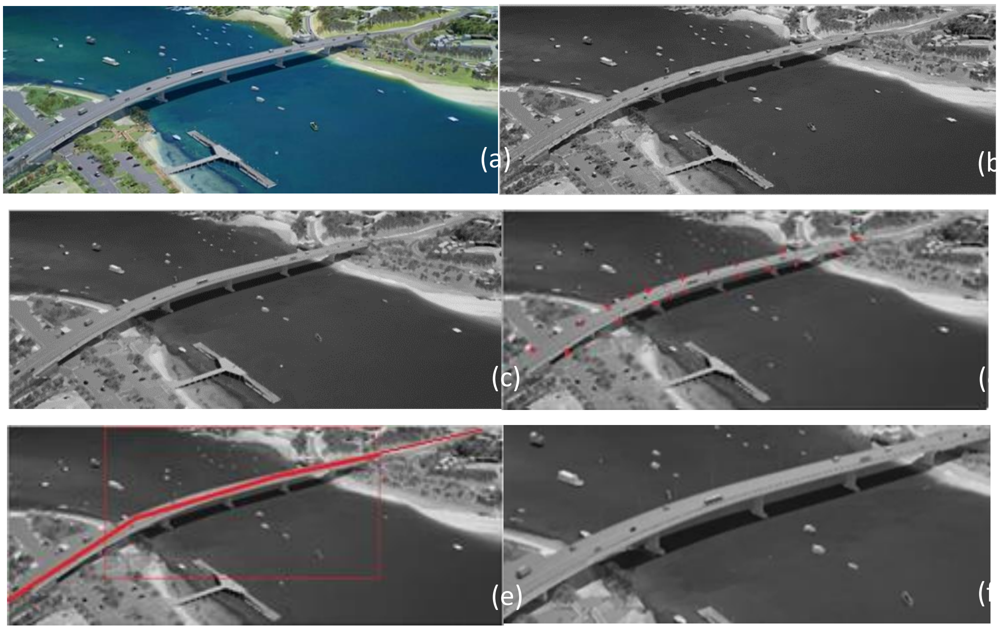

Fig 5: (a) Input Image (b) Grayscale Conversion (c) Noise Reduction (d) Edge Detection (e) Highlighted Bridge (f) Cropped Bridge

C. Training

After the detection of landmarks, the next step is to determine the occurrence of flood in these regions, so that the rescue activities can proceed. The pre-processed and cropped images from previous steps are used to train the classifier including the extensive step of labelling of image data. According to the survey conducted for this study and previous research, SVM has delivered better results than many other classifiers like Naïve Bayes, K-Nearest Neighbour, and ANN.

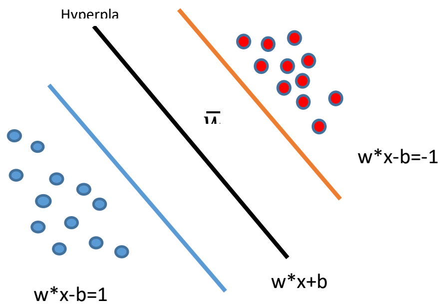

Fig 6: SVM Hyperplane

The SVM training models assign binary linear classifiers that reduce classification errors to a minimum while maximizing geometric margin through an inverse method of problem-solving. A high dimensional space is created by the training data that is divided into positive and negative instances by a hyperplane. To classify new instances, their location, in this space concerning the hyperplane, is determined as shown in Fig 6.

IV. EXPERIMENTAL RESULTS

A. The European Flood Dataset

The dataset used for training is based on flood-affected images from countries based in Europe as discussed and used for experiments by Barz et al [31]. These images were captured during the floods of 2013 and the majority are from dated from May to June 2013. This dataset was used to conduct experiments in current study, as it contains the most recent images of the affected areas and presents the current picture of flood-related destructions. It contains a total of 3710 high-quality images. These images range from aerial views to close-ups of the target areas. The input images are adjusted to 227x227 resolution while preserving their aspect ratio.

B. Experimental Set up

To test the proposed model, the 10-folds cross-validation method has been used. A 90/10 analogy was used to split the dataset into training and testing sets meaning that the input dataset is first divided into 10 parts and from these 10 subsets, 9 are used for training and 1 for testing. This process is repeated 10 times each time taking a different part for testing. An average of results is calculated to get the final performance measure. It is a more comprehensive and reliable evaluation process, as compared to conducting a single experiment. Fig 7 shows the method of 10-fold cross-validation.

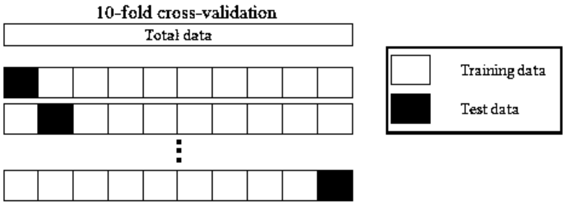

Fig 7: Ten-Fold Cross Validation

C. Results

The model was tested using both pre- and post-flood images of the same area. Results showed an accuracy of 90% in detecting flooded and non-flooded images. The model was tested using varying numbers of images in the dataset. It was observed that the accuracy increased linearly with increasing the number of images in the dataset. The highest accuracy achieved for the experiment was that of 90% at 3300 images in the dataset. After that, there was no noticeable increase in the accuracy of the images. A graph showing the accuracy of the SVM classifier with several images in the training dataset has been shown in Fig 8 and the sample output on a test image is shown in Fig 9, where the image is successfully classified as flooded.

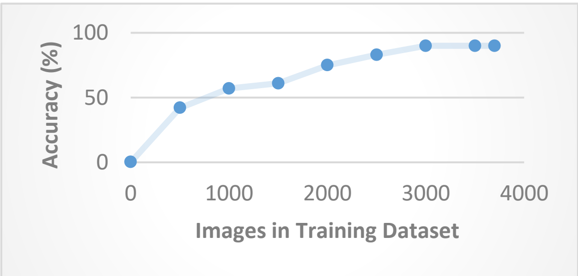

Fig 8: Graph Showing Accuracy vs Training Dataset Size

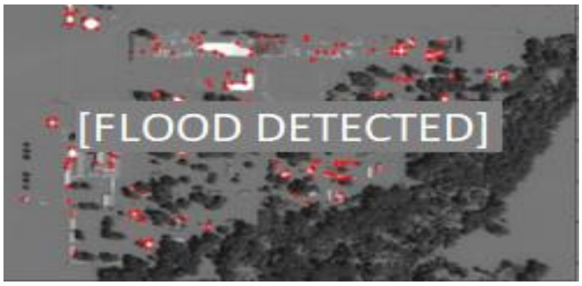

Fig 9: Output of Flood Detected in Image

V. CONCLUSION AND FUTURE WORK

Flood based destruction can be managed through the timely use of state-of-the-art technologies. To deal with the flood-related crisis, the first step will be to identify the occurrence of a flood. In this paper, flood detection methods have been discussed that are used in image processing and machine learning and a novel holistic model has been proposed for the classification of images as flooded/non-flooded. The model aims at increasing the efficiency of the training process while improving accuracy and speeding up the detection process for timely rescue response. To achieve this objective, some image processing steps are applied to the input images to improve their readability and pertinent quality. These steps include grayscale transformation, noise removal, landmark detection and image cropping using ROI. Landmark detection can be particularly useful for the identification of populated areas from the aerial images so that proper aid could be provided to the stranded people. Next, these landmark images were used to train the classifier proposed in current study. The proposed method speeds up the training of SVMs for flood detection with a significant gain in performance. The experimental results have demonstrated an accuracy of 90% with faster processing speed. A comparison to the previous research conducted in the domain of flood detection showed better and improved results thus the proposed approach is expected to serve as a fast and efficient relief tool in accelerating the flood-mitigation and rescue missions.In the future, the proposed model can be tested on more datasets to assess its performance and tested on images captured by UAVs in real-time. Further research will improve this model by detection of water-based landmarks like rivers and oceans and other significant objects such vehicles and movable objects. Additional objects can be detected to identify the populated areas in the images to improve the prediction model and yield better classification results.

REFERENCES

[1]. Najibi, N., & Devineni, N. (2018). Recent trends in the frequency and duration of global floods.
[2]. Hirabayashi, Y., Kanae, S., Emori, S., Oki, T., & Kimoto, M. (2008). Global projections of changing risks of floods and droughts in a changing climate. Hydrological Sciences Journal, 53(4), 754-772.
[3]. Alfieri, L., Velasco, D., & Thielen, J. (2011). Flash flood detection through a multi-stage probabilistic warning system for heavy precipitation events. Advances in Geosciences,29, 69-75. doi:10.5194/adgeo-29-69-2011.
[4]. McCallum, I., Liu, W., See, L., Mechler, R., Keating, A., Hochrainer-Stigler, S & Szoenyi, M. (2016). Technologies to support community flood disaster risk reduction. International Journal of Disaster Risk Science, 7(2), 198-204.
[5]. HS Munawar, Automatic Detection and Rule Based Verification of Strategic Targets from Multispectral Aerial Images, 2016. RCMS NUST
[6]. Dunning, C. M., Black, E., & Allan, R. P. (2018). Later wet seasons with more intense rainfall over Africa under future climate change. Journal of Climate, 31(23), 9719-9738.
[7]. Popescu, D., Ichim, L., & Caramihale, T. (2015, October). Flood areas detection based on the UAV surveillance system. In 2015 19th International Conference on System Theory, Control and Computing (ICSTCC) (pp. 753-758). IEEE.

[8]. Akbar, Y. M., Musafa, A., & Riyanto, I. (2017). Image Processing-based Flood Detection for Online Flood Early Warning System. doi:10.31227/osf.io/ayn2c
[9]. Munawar, H. S., Maqsood, A., & Mustansar, Z. (2017). Isotropic surround suppression and Hough transform-based target recognition from aerial images. International Journal Of Advanced And Applied Sciences, 4(8), 37-42.
[10]. Munawar, H. S., Zhang, J., Li, H., Mo, D., & Chang, L. (2019, April). Mining Multispectral Aerial Images for Automatic Detection of Strategic Bridge Locations for Disaster Relief Missions. In Pacific-Asia Conference on Knowledge Discovery and Data Mining (pp. 189-200). Springer, Cham.
[11]. HS Munawar, U Khalid, R Jilani, A Maqsood. (2017), Version Management by Time Based Approach in Modern Era, International Journal of Education and Management Engineering, 2017, 4, 13-20
[12]. Abdelkader, M., Shaqura, M., Claudel, C. G., & Gueaieb, W. (2013, May). A UAV based system for real-time flashes flood monitoring in desert environments using Lagrangian microsensors. In 2013 International Conference on Unmanned Aircraft Systems (ICUAS) (pp. 25-34). IEEE.
[13]. Anusha, N & Bharathi, B. (2019, February). Flood detection and flood mapping using multi-temporal synthetic aperture radar and optical data. In The Egyptian Journal of Remote Sensing and Space Science https://doi.org/10.1016/j.ejrs.2019.01.001. Science Direct.
[14]. HS Munawar, U Khalid, A Maqsood, Fire detection through Image Processing; A brief overview.
[15]. Sulaiman, J., & Wahab, S. H. (2018). Heavy rainfall forecasting model using artificial neural network for the flood-prone area. In IT Convergence and Security 2017 (pp. 68-76). Springer, Singapore.
[16]. Sulafa, E., (2014). Artificial Neural Networks (ANNs) for flood forecasting at Dongola Station in the River Nile, Sudan. In Alexandria Engineering Journal Volume 53, Issue 3, September 2014, Pages 655-662. Science Direct.
[17]. Abbot, J., & Marohasy, J. (2014). Input selection and optimisation for monthly rainfall forecasting in Queensland, Australia, using artificial neural networks. Atmospheric Research, 138, 166-178.
[18]. HS Munawar, J Zhang, H Li, D Mo, L Chang. Mining Multispectral Aerial Images for Automatic Detection of Strategic Bridge Locations for Disaster Relief Missions. Pacific-Asia Conference on Knowledge Discovery and Data Mining, 2019. Springer, Cham.
[19]. Valipour, M., Banihabib, M. E., & Behbahani, S. M. R. (2013). Comparison of the ARMA, ARIMA, and the autoregressive artificial neural network models in forecasting the monthly inflow of Dez dam reservoir. Journal of Hydrology, 476, 433-441.
[20]. Senthil Kumar, A. R., Sudheer, K. P., Jain, S. K., & Agarwal, P. K. (2005). Rainfall-runoff modeling using artificial neural networks: comparison of network types. Hydrological Processes: An International Journal, 19(6), 1277-1291
[21]. Widiasari, Indrastanti & Nugroho, Lukito & Widyawan, Widyawan. (2017). Deep learning multilayer perceptron (MLP) for flood prediction model using wireless sensor network based hydrology time series data mining. 2017 International Conference on Innovative and Creative Information Technology (ICITech) 1-5. 10.1109/INNOCIT.2017.8319150.
[22]. HS Munawar, AA AAwan, U Khalid, S Munawar. Revolutionizing Telemedicine by Instilling H. 265. International Journal of Image, Graphics & Signal Processing. 2017
[23]. Lohani, A. K., Kumar, R., & Singh, R. D. (2012). Hydrological time series modeling: A comparison between adaptive neuro-fuzzy, neural network and autoregressive techniques. Journal of Hydrology, 442, 23-35.
[24]. Shu, C., & Ouarda, T. B. M. J. (2008). Regional flood frequency analysis at ungauged sites using the adaptive neuro-fuzzy inference system. Journal of Hydrology, 349(1-2), 31-43.
[25]. Ashrafi, M., Chua, L. H. C., Quek, C., & Qin, X. (2017). A fully-online Neuro-Fuzzy model for flow forecasting in basins with limited data. Journal of Hydrology, 545, 424-435.
[26]. Guimarães Santos, C. A., & Silva, G. B. L. D. (2014). Daily streamflow forecasting using a wavelet transform and artificial neural network hybrid models. Hydrological Sciences Journal, 59(2), 312-324.
[27]. HS Munawar, A Maqsood, Z Mustansar. Isotropic Surround Suppression and Hough Transform Based Target Recognition from Aerial Images. (2017). International Journal of Advanced and Applied Sciences, 2017. Inst Advanced Science Extension.
[28]. Supratid, S., Aribarg, T., & Supharatid, S. (2017). An integration of stationary wavelet transform and nonlinear autoregressive neural network with exogenous input for baseline and future forecasting of reservoir inflow. Water resources management, 31(12), 4023-4043.
[29]. Vapnik, V., & Mukherjee, S. (2000). Support vector method for multivariate density estimation. In Advances in neural information processing systems (pp. 659-665).
[30]. Li, S., Ma, K., Jin, Z., & Zhu, Y. (2016, July). A new flood forecasting model based on SVM and boosting learning algorithms. In 2016 IEEE Congress on Evolutionary Computation (CEC) (pp. 1343-1348). IEEE.
[31]. Björn Barz, Kai Schröter, Moritz Münch, Bin Yang, Andrea Unger, Doris Dransch, and Joachim Denzler ."Enhancing Flood Impact Analysis using Interactive Image Retrieval of Social Media Images." arXiv:1908.03361, 2019.
[32]. S.Riad, J.Mania, L.Bouchaou, Y.Najjar. (2004). Mathematical and Computer Modelling. Volume 40, Issues 7–8, October 2004, Pages 839-846.