

Automatic Detection of Flood Extent and Volume Estimation from Sentinel-2 Satellite Images using Deep Learning Techniques in India

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Abstract:

Floods are unexpected natural disasters that can have a major impact on human life, soil along bank erosion, damage vital infrastructure, road closures, economy standard, and society of various affected regions. An initial step of proper assessment is necessary for flood damage along with accurate measurements to easily restore essential damage of infrastructure, relief, and mitigation as quickly as possible. Nowadays, the rapid development of remote sensing images using deep learning as a most positive tool for accurately estimating the extent of overall flood detection surfaces. The monitoring of flood detections from remote sensing images still extends a few issues due to mostly varying from different weather changes conditions, cloud coverage areas that can have a limit to use of level of visible remote sensing satellite collected data. Moreover, Remote Sensing Satellite based observations may not always be mapped to the distribution's flood point peak, also it is very essential for both the flood extent and flood volume estimation. To overcome this challenge, we have presented a new remote sensing technology that integrates with a high resolution multi-spectral satellite data/information by using an advanced Deep Learning to accurately analyze remote sensing based observations. In our experiment, we use the European Space Agency (ESA) launched Sentinel type-1, Sentinel type-2 data and Digital Elevation Model (DEM) to accurately measure flood monitoring results. In our study, we reviewed a real example of the flood situation that happened in 2019 in Kolhapur. In our results, we evaluated a flood volume estimation at 0.0010 km³ in Kolhapur district. Finally, the proposed methodology provides an effective way to accurately monitoring floods using low-cost satellite data and deep learning approaches. This project has the potential to improve the more accurate flood detection and mapping which can prevent an exactly timely response and immediate recovery efforts for flood surrounding affected areas.

Keywords: Flood, Disaster Management, Satellite Imagery, Sentinel, Remote based Sensing.

1. Introduction

Inundation is a very dangerous type of natural category of hazard that occurs worldwide, that are mainly affecting human life, negative effect on wildlife, disease proliferation, habitat destruction and causing significant damage to both economic standard and overall environmental damage. The common methodologies of floodwater monitoring are mostly floodwater ground-based various surveys, manual reports and collection of aerial images, which can be generally costly, a lot of time consuming along with high-risk tasks [1]. In many cases, there is no possibility of monitoring flood extent and volume estimation in larger flood areas. To overcome drawbacks of these Traditional methodologies in accurate flood monitoring of large areas. The remote sensing-based satellite data (RS) and machine learning algorithms can provide an efficient, high speed and low-cost option for an automatic flood monitoring in large areas [2]. For example, Floods in western Maharashtra's Kolhapur district in India August 2019, affected nearly 51,000 peoples, 200 villages, 342 bridges have gone under flood, the highest flood in the last 100 years. Overall, economic losses due an expected flood in both Kolhapur and Sangli Maharashtra Districts ₹700 cr. (\$94,280,000), Electricity based infrastructure worth ₹1,200 cr. (\$16, 16, 41,000) has been damaged, while damage to many national highways, many roads and public bridges is overall ₹1,500 cr. (\$202,051,000) and Crops across 339,000 hectares have been damaged due a flood in western region of Maharashtra and Konkan region of India. Remote sensing-based satellite imagery can easily provide detailed information of the flooded coverage area, it is possible to accurately monitor the flood extent and volume estimation in large areas. For instance, in [3] Liis Sipelgas showed the mapping of Open- surface Water Flooding (OWF) and Flooding Under level of Vegetation (FUV). Jianzhong Lu used the Normalized Difference based Water Index (NDWI), Modified based Normalized Difference Water Index (MNDWI), and Water Ratio level Index (WRI) using advanced supervised maximum likelihood algorithm [4] that authors are being mainly carried out in area of the Chenab Basin, country- Pakistan with highest accuracy of 89%. In [5], Rizwan Sadiq also proposed an advanced deep learning models for mainly flood detection based on remote sensing through satellite imagery. Kaixin Yang [6], proposed the Deep Learning advanced Models (DLM) to automated accurate detection of flood affected buildings construction with Unmanned Aerial Vehicles (UAVs) aerial imagery in Kangshan levee of Poyang Lake. Although Unmanned Aerial Vehicles (UAVs) are based on the measurements, they provide a complete detailed information of flood affected areas. Such various observations do not always acquire more valuable information such as flood depth and destroyed degree of the buildings due to factors of poor illuminations, in complete light time or bad weather conditions. Remote sensing satellites are more satisfactory in mostly particular cases. Matias Bonansea [7], Various satellite (European Space Research) missions are most commonly used for flood detection such as Landsat-8 OLI- (L1 and L2), Sentinel-1, Sentinel-2A and 2 B, MODIS, MERIS, SPOT, QuickBird and Ikonos. In [8], Asmamaw Gebrehiwot utilized various image classification techniques including mainly SVM (Support based Vector Machine) that have been primarily used for an automatic flood extent mapping. There has been the most significant improvement in remote sensing based image classification using advanced Convolutional based Neural Networks (CNNs). Convolutional Neural Networks (CNN_s) have a very high excellent performance in image classification and segmentation. Lianchong Zhang [9] has proposed the Chinese Satellite categories of Datasets including the 1) Gaofen (GF) series and 2)

Zhuhai-1 hyper spectra during the year of 2020 china summer period of the floods monitoring. Microwave remote based sensing flood inundation for flood assessment based on synthetic aperture radar (SAR) [10]. In [11], Afshin Akram has proposed a framework to accurate evaluate the flood water extent and volume mapping by used advanced MODIS and NDWI techniques (MODIS combined with NDWI-16 Days) for a cumulative based flood risk map for the period of 10 years (Year:2010 to 2020) in Mianwali region. In [12], Qiuyang Chen has proposed the solutions for detection of flood situations from remote based sensed satellite collected images, they have a worldwide serious problem due to cloud cover flood scenes, different weather conditions, leading to fragmented and degraded flood data collections. To overcome these challenges, the author proposed a framework based on Advanced U-Net architecture and collection of dataset of flood situations in cloudy cover regions by collecting all information mainly from the ESA-Sentinel series-1 and Sentinel series-2 categories of the satellites. Shangjia Dong [13], demonstrates the predictive watershed flood monitoring of Harris County using an advanced deep learning technique based on the level of physical sensor and second level of social sensor data. In [14], Bonafilia et al has introduced the Sen1 Floods 11-a row imagery water data set from Sentinel-1. The Sen1 Floods is used for both the train and test available dataset as well as test FCNN (Fully Convolutional Neural Networks) to accurate segments of flood water. B. Ghosh shows, in [15], two deep learning approaches: 1) U-Net Architecture and 2) Second, FPN (Feature Pyramid Network). The different dataset primarily covers all flood situations from various countries such as North Alabama, Nebraska, Red River North, Bangladesh and the city of Florence. Both deep learning approaches U-Net and FPN were easily evaluated with three sets 1) Training sets, 2) Testing sets and 3) Validation sets. During the testing sets, the model of U-Net achieved the score of meanIoU-75.07% and the FPN deep learning approach achieved the score of meanIoU-75.77 %. In [16], Rudner has implemented a new approach for accurate segmentation of buildings in flood areas by using three satellite imagery such as Multisensory, Multi-resolution and Multi-temporal based satellite imagery in a Convolutional Neural Network-CNN. However, the proposed system has significantly expedited the flood maps based on satellite imagery, critical for first stage responders and all local administration in the before time stages of flooding. In addition, monitoring the flood water extent unattended may not be sufficient for accurate flood detection. The estimate of both the extent of flood and flood volume of estimation of the flood surfaces. Quinn [17] has highlighted the importance of depth estimation of flood covered areas. In [18], Weikai Tan used remote sensing as a very powerful tool for accurate monitoring of floods. The Digital (advanced) Elevation Models (DEM'S) are very essential for flood inundation information estimation towards a proper flood mapping in urban areas. Most of the time High-Resolution (HR)- advanced DEMs are mostly inaccessible due to the very high acquisition costs of HR-DEMs. The proposed system has been designed as a framework consisting of three important components: 1) Novel DEM up scaling based Network 2) High Speed of flood segmentation network, and 3) GIS-Geographical collected Information System tool mainly for accurate mapping of flood extent and volume estimation. A similar approach is explored in [19], Kepeng Xu, Jiayi Fang has introduced a problem that is extremely acute in small size, flat coastal cities in the entire world. It is very necessary to find the various differences of the advanced DEMs and possibly reduce maximum anomalous errors of the DEMs method. The author has experimented on urban areas flood simulation in a coastal city of Shanghai-Huangpu River by utilizing Two-Dimensional Hydrodynamic based Model (LISFLOOD-FP) mainly designed to

estimate flood water inundation over complex topography and used six DEMs open access such as 1) SRTM, 2) MERIT, 3) Coastal-DEM, 4) GDEM, 5) NASA-DEM, and 6) AW-3D30m, and simply analyzed the differences in the various results of automated flood inundation level of simulations. In [20], Ahmed M. AL-Areeq has used the Global level of Digital Elevation Models (G-DEMs) to assess automatic risk of flooding in Jeddah, Saudi Arabia. This study, author compared the overall performance of all five Global level of Digital Elevation Models (G-DEMs) namely: 1) 30-m based SRTM, 2) 30-m based ASTER, 3) 90-m based MERIT, 4) 10 m Sentinel type-1 satellite DEM, and 5) 12.5 m based ALOS PALSAR - in estimating the flood inundation extent level and volume of watersheds in Jeddah including all three dams. The quality with resolution of Digital based Elevation Models (DEMs) has mainly focused on urban hydrology research . Manoranjan Muthusamy [21] focused on all primary impact root causes of DEM based resolution and quality on urban category of fluvial flood monitoring results simply using Digital Elevation Models (DEMs) with a high grid resolution ranging between 1m to maximum 50m. HEC-RAS two-dimensional model was used for all the simulations. The results show that there is an approximately 30% increase in flood extent from 58.8 ha to 78.0 ha and a 151% increase in mean level of flood depth volume from 1.75 m to 4.31 m when the resolution reduces mainly from 1 m grid to maximum 50 m grid.

In our proposed research methodology, we evaluated experiments by using three Neural Network based architectures: 1) Nested U-Net (U-Net++), 2) MA-Net, and 3) DeepLabV3+. We used all real time cases of flood events that mostly occurred in Kolhapur, India-2019.

The major contributions of our proposed work are mentioned:

- 1) We designed an automatic flood volume estimation by using remote sensing Sentinel type-1 and Sentinel type-2 satellite data / information that easily utilizes NN-Neural concept Network Technologies.
- 2) In our experiments, we took real time limitations such as limited availability of satellite data and cloud shadows or cloud area coverage during real time flood events.
- 3) Also, we utilized various advanced deep learning methodologies to achieve our approach.
- 4) Lastly, we designed an advanced method for mainly flood water volume accurate estimation that used both DEM methods and expected flood water extent.

2. Resources and Approaches

2.1. Data-Record

2.1.1. Flood Monitoring Data Explanation

In our proposed system, the original set of data includes only possible raw images of Sentinel type-1. The preprocessed data are collected from Sentinel-1 and Sentinel-2. Both training and testing datasets are called as labels taken from the Sen1 Floods 11 [22] open datasets. The datasets are collected from various continents and cover different areas with climate changes, topographical influencing factors and natural causes of floods. The dataset covered the flood that occurred in 2019 in Maharashtra state. The labels are classified into three different categories: 1) Water Areas 2) No water Areas, and 3) Clouds coverage areas. The overall area of flood water is “66.82 km²” of Kolhapur district of which

only 10 km² flood areas are hand operated and manually identified. Remaining rest of areas, based on indices images that are captured from multiband images. It was observed that the Indices based Sen1 Floods 11 dataset is not strongly accurate. Hence, we commonly used accurate manual annotation in our present research work.

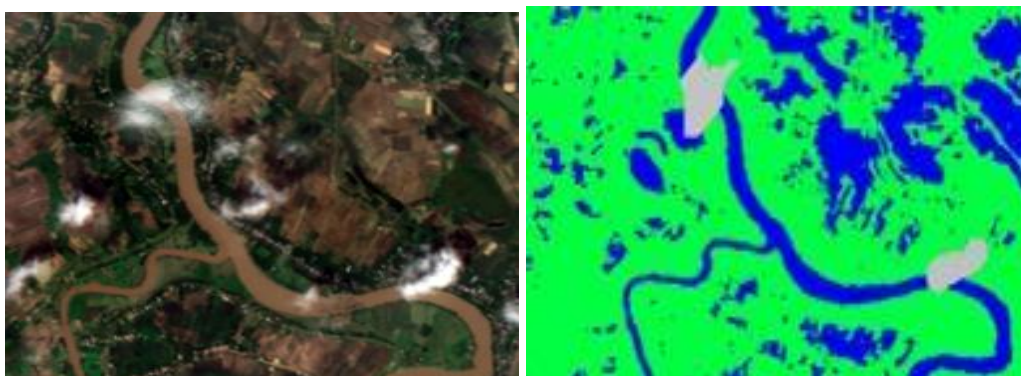


Figure 1. Example of Flood is taken from Open Sen1-Floods 11 [22] set of data records and three RGB channels of the Sentinel type-2 data a) Real Image of flood from Sentinel type-2 satellite with cloud mask b) Shows [Blue] water areas, c) [Green] background and d) [Gray] Cloud areas.

Table 1: The dataset statistics are presented.

	Area (km ²)	Total number of Images
Train Flood Area	6 km ²	95 Images
Test Flood Area	4 km ²	42 Images
Validation Area	4 km ²	42 Images

2.1.2 Satellite based Image Processing:

The Copernicus Open Access Hub (Formerly known as Scientific Data/ Information Hub) was used to download, free and open access images to Sentinel-1 and Sentinel-2 products starting from the In-Orbit Commissioning Review-IOCR which provides continuous all three weather, full day and night latest collection of imagery for land monitoring. Both the Satellites, Sentinel type-1 and Sentinel type-2 provides up-to-date up-to-date information of land, mostly revisit time might change for various areas of land territories, but satellite Sentinel type-1 revisit frequency is up to next 3 days. The Sentinel type-2 with two satellites (Sentinel type- 2A and Sentinel type-2B) to take 5 days revisiting time over land area and surface. The Sentinel-2 Multispectral Instrument (MSI) has 13 spectral bands for measure the earth's reflected radiance from Visible along with Near Infrared (V-NIR) to Short Wave based Infrared (S-WIR) with 10 m, 20m and 58-60 m spatial (pixel)resolution depending on the wavelength.

The Sentinel type-1 Ground Range Detected (GRD) is focused on satellite data/ information that has been accurate detected, multi-looked and projected to various ground range by simply using an advanced Earth-Ellipsoid Model (EEM).The Sentinel-1 preprocessing system is consists of 7 steps to mainly reduce propagation of error in subsequent processes: 1) Apply Orbit File: The operator to apply precise orbit (po) available in Sentinel Application Platform (SNAP) that allows to automatically

download the accurate state vectors of each satellite images in its metadata of product information with accurate position of satellite and information of velocity 2) Removal of Thermal Noise: The thermal noise removal is mainly reducing noise effects in the texture, normalizing the signal of backscatter within the complete sentinel type-1 image. The Thermal noise removal operator present in the SNAP for Sentinel-1 data can reintroduce the noise signal 3) Border Noise Removal: The algorithm of Border noise based removal is present in the SNAP to remove all low level intensity of noise and also remove the false data on image edges. 4) Calibration: The Calibration that mainly converts all digital pixel values to calibrated satellite backscatter. 5) Speckle Filtering: Speckle is appearing in satellite images/data as granular type of noise, The Speckle filtering removes the speckle and increases the quality of image. 6) Range Doppler Terrain Correction: The Range doppler terrain correction (RDTC) operator is present in the SNAP to mainly used in causes of topography in correction of geometric distortions. 7) Conversion to dB: This is a final step of sentinel-1 preprocessing workflow, we used a logarithmic transformation to convert the unit less backscatter into dB. For Sentinel type-2 images, we extract all 13 spectral (bands) channels excluding B-10 band and reflectance multiplied by 10^5 is considered as units for all spectral channels.

Furthermore, we calculated three water level of indices based on Sentinel type-2 on 13 multi-spectral channels:

1) N-DWI: Normalized based Difference Water Index is mainly appropriate for mapping of water bodies and N-DWI can enhance the information of water effectively [23].

$$NDWI = \frac{GREEN - NIR}{GREEN + NIR} \quad (1)$$

2) MNDWI: Modified Normalized Difference Water Index uses both green and SWIR bands for the enhancement of open water information [24].

$$MNDWI = \frac{GREEN - SWIR}{GREEN + SWIR} \quad (2)$$

3) SWI: Standardized based Water-Level Index. It mainly estimates the contents of soil moisture by simply analyzing the difference between the method of Near-infrared (NIR) and Shortwave infrared (SWIR) reflectance [25].

$$SWI = \frac{NIR - SWIR}{NIR + SWIR} \quad (3)$$

2.1.3. External Data Test:

In the external data test , we covered an area of Kolhapur District (Maharashtra, India). The heavy flood occurred there during the months of July & August 2019. We collected 3 days of data in three available categories such as before flood, after flood and during flood.

Table 2. Remote Sensing satellite images were collected of the flood events in Kolhapur District according to various dates .

Date of Satellite Images (August 2019)	Manual Markup	Flood Position
20/05/2019	Yes	Before Flood
07/08/2019	No	During Flood
12/08/2019	Yes	During Flood
25/08/2019	No	After Flood

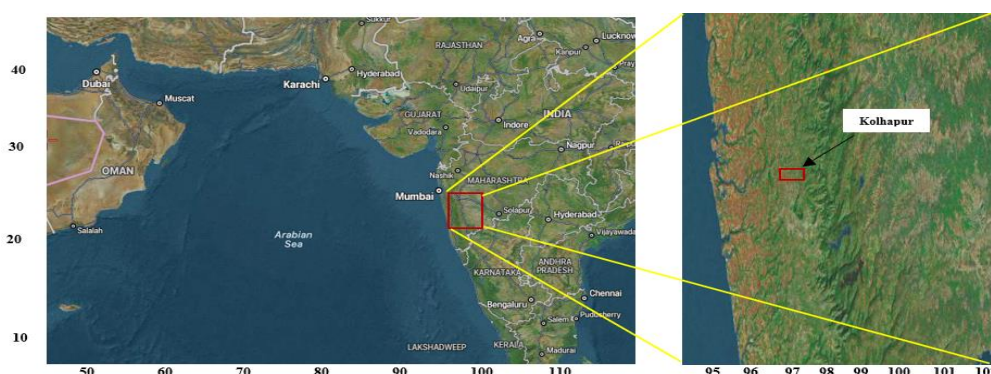


Figure: 2 Geography of External test area of land, Kolhapur district, Maharashtra, India.

2.2. Flood Approaches

2.2.1. Flood Water Extent

The proposed system is illustrated in figure 03. Cloud and other atmospheric interference can have an important impact on overall accuracy and usability of satellite observation data. They can hide the extraction of useful information from the satellite images and complicate data analysis. For this reason, we employ Usable Data Mask (UDM 2.1 Latest version) from raw image data of sentinel type-1 and sentinel type-2 to extract the availability of Surface Water Mask (SWM) for Synthetic Aperture Radar (S-AR) satellite data along with Multi-spectral (MS) data. In addition, cloud masking is an essential step in our proposed work. We utilize s2 cloudless (s2cloudless algorithm) to improve cloud and cloud shadow masking with probabilities in sentinel type-2 imagery which is generated by using the Sentinel-2 cloudless (S2) processor. These three masks are generally processed concurrently to create (SWM_S-AR) mask, (SWM_S-AR+MS) mask and (MS) mask. These all masks are mostly utilized to describe a specific land region where these specific models should be successfully applied. In this, each of the three various data configurations as well as we train two unique combinations of input channels. Furthermore, we used the per-channel technique of Min-Max normalization (also called Min-Max scaling) technique to calculate global minimum (global-min[i]) and global maximum (global-max[i]) data values based on availability of data per channel.

$$\begin{aligned} & MIN_MAX(s(i)) \\ &= \frac{s[i] - global-min[i]}{global-max[i] - global-min[i]} \end{aligned} \quad (4)$$

Where, $s[i]$ show i -th channels, $global-min[i]$ indicate the minimum value in per channel, $global-max[i]$ indicate the maximum value in per channel.

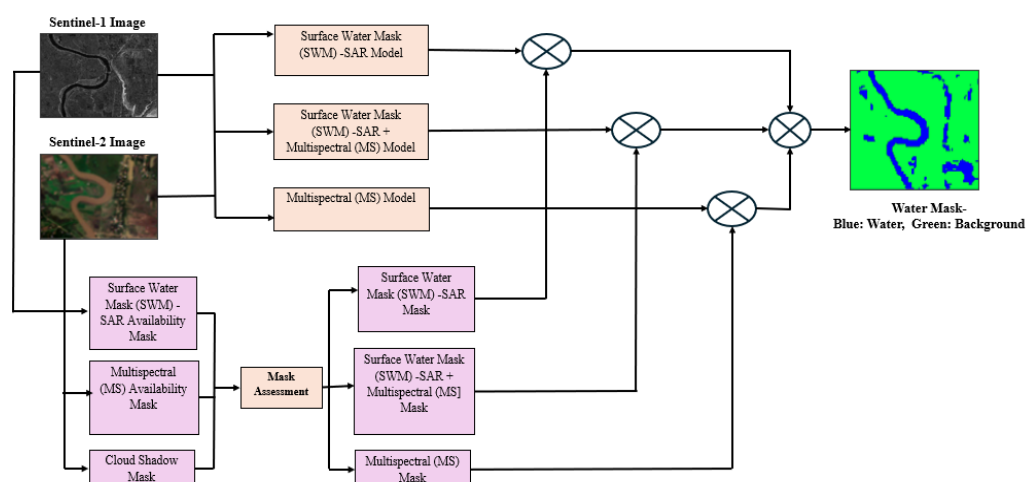


Figure 3: The proposed method for identifying water level bodies primarily based on Sentinel-1 and Sentinel-2 imagery.

In our result, we conducted various experiments by using three Neural advanced Network Architectures: Nested U-Net (U-Net++) [26], MA-Net_s [27] and DeepLabV3+ [28] in both the remote sensing and segmentation tasks.

The A Nested U-Net (U-Net++) is an advanced deep learning model mainly based on transfer learning concept to solve the semantic level of segmentation problem of high pixel resolution on remote sensing-based satellite imagery. The U-Net++ model is consist of encoder-decoder framework, the sensing device encoder part of U-Net++ model that simply captures high level of relevant features from the input image through a series of convolutional layer and pooling layer where the decoder part of U-Net++ up-samples features of these input image to product a dense based segmentation advance map. After complementing the U-Net++, we include the MA-Net_s used to extract the detailed features of low spatial resolution based on the remote sensing satellite images at multi scales. This capability of MA-Net_s permits it to efficiently account for the changeable scales present in the remote sensing satellite imagery to accurately capture all large level geographical features to small level geographical features. Additionally, both the U-Net++ and MA-Net_s, we utilized an advanced DeepLabV3+ lightweight neural network based on the sensing device of encoder and decoder structure, where the DeepLabV3+ encoder is also responsible for extracting shallow as well as high-level detailed information. The DeepLabV3+ decoder is responsible for combining both the low level and high-level information to improve high level of accuracy of remote sensing segmentation across various boundaries and accurately categorize detailed information of various pixels. To enhance flexibility and robustness of our proposed models, we used the VAE-Variational Auto-encoder into our system architecture of each image from different time series and utilized a distance metric to detect any changes between two sentinel-2 images. Nowadays, there is a huge demand for remote sensing-based image classification in many applications. Inputting the feature map into the CNN-convolutional neural network can obtain more accurate abstract features from the input feature map. Thus all features of the input feature map can be applied to remote sensing-based image classification. Therefore, we used MobileNetV3 as a simple network applied CNN- convolutional neural network can obtain more features of the input map, and these features can be applied on CNN- convolutional neural network to

remote sensing image classification. Similarly, ResNet50 is CNN- convolutional neural network that belongs to ResNet-Residual Networks family, the ResNet50 consists of 16 residual blocks and each block of residual consisting of several convolutional based layers with residual connections. The ResNet50 also includes 3 layers such as pooling layers, softmax output layer and fully connected layers for remote sensing image classification. In the CNN model, the input data of CNN model is available in a 3D Three-Dimensional Array with a simple combination of pre-processed channels of various multispectral images, also calculated remote sensing indices. The set of these input features differs depending on the new various experimental setup. In our experimental output, we took a 2D Two-Dimensional Array primary consisting of values “0” and “1”. Where, “0” pixel value indicates the surface level without water objects; “1” pixel value indicates surface with water level objects. Additionally, cloud levels are masked for post-processing as a new class of these multispectral images and these models are trained to operate over 150 epochs and the same batch size is consistent across all these models.

2.2.2. Flood Water Volume

New Digital Elevation Model (DEM) plays an important part in Flood monitoring. The mapping of flood water is extremely dependent on accuracy of DEM. Most of the time, DEM-Copernicus products with a resolution between [10-30 m], that defines the level of altitude, cannot be used easily for estimating level of water including both before flood as well as after flood events to lower the temporal resolution. Cohen et al. proposed [29], to estimate the depth of water surface during the flood time by using the DEM for collection of general information of the surface. In our proposed work, we used one new method for flood volume estimation which is based on prediction of flood water surface from remote sensing derived information and single-DEM that defines territory. The basic information of territory, represents the territory before the flood occur, the calculation of levels of water from different points of territory boils down to primary estimating the Absolute Level of Surface water floods (ALSWFs) during flood event. Recognizing where floods are occurred, along with the baseline territory, we can exactly calculate the Absolute Level of Surface water floods (ALSWFs) at flood boundary, other than internal areas of interpolating (ALSWFs) presents a more difficult due to probably complex territory. In this method, we obtained (ALSWFs) the complete flooded area, along with the baseline level. We can accurately calculate the various water levels in all points of flood events by using a simple subtraction method. After recognizing the water level in all points of the flooded surface, the volume of flood can be estimated using the products of the flood area and level of water for all points of flood event.

2.3. Metrics of Flood Evaluation:

To accurately evaluate and overall performance of flood water segmentation methods, we used two different metrics: 1) Intersection over Union (Io_U) called “Jaccard index” 2) F1_Score (F1) called “Dice Score”. Equation of Intersection over Union (IoU) and F1_Score are the following:

$$Io_U = \frac{T_P}{T_P + F_P + F_N} \quad (5)$$

$$Precision_P = \frac{T_P}{T_P + F_P} \quad (6)$$

$$Recall_R = \frac{T_P}{T_P + F_N} \quad (7)$$

$$F1_Score = 2 * \frac{Precision_P * Recall_R}{Precision_P + Recall_R} \quad (8)$$

The F1_Score ranges between (“0” and “1”) where F1_range is 1 shows the highest accuracy and F1_Range is 0 shows lowest accuracy. True Positive T_P is number of all pixels accurately classified in the target class, False Positive F_P is number of all pixels inaccurately classified in the target class, as well as False Negative F_N is number of pixels of target class that were incorrectly classified as one more class.

3. Results

3.1. Practically Results on Dataset of Sen1_Floods_11 Surface Water

We conducted various practicals on different combinations of multiple input channels. The tables 3-5 are shown the outputs for the test set of Sen1_Flood_11 dataset. The best result of the Sen-1_Floods_11 dataset was obtained from combining all Sentinel type-2 multispectral based channels and all of Sentinel type-1 radar channels. In this MA-Net_s model, the F1-Score on test set is 0.94 and Io_U score is 0.853. Overall, the result is based on both multi-spectral data and available radar data separately. Even with only the availability of multi-spectral data, it is more easy to achieve very high outcomes by using all spectral channels of Sentinel type-2. In the U-Net++ model, the accuracy of F1- score on the test set is 0.919. The radar measurements show lower results of F1_Score is 0.795 and Io_U score is 0.659. In [30,31], it was experimented that many input channels have not provided the best outcomes, along with use of dedicated indices can yield poorer results than a complete application of all accessible channels.

Table 3. Results of Nested U-Net (U-Net++) model with various configurations of input data.

Combination of Various Features	MobileNetV3		ResNet-50	
	F1_Score	Io_U	F1_Score	Io_U
SWR- SAR	0.779	0.638	0.783	0.643
SWR- SAR+NDWI	0.876	0.778	0.889	0.799
SWR- SAR+MNDWI	0.895	0.809	0.895	0.809
SWR- SAR+SWI	0.874	0.774	0.869	0.767

MS+ SWR-SAR	0.919	0.847	0.916	0.844
MS	0.919	0.849	0.915	0.86
SWR-SAR + All Indices	0.900	0.816	0.895	0.809
MS+ SWR-SAR+ All Indices	0.903	0.819	0.904	0.823
MS+ All Indices	0.905	0.826	0.897	0.811

MS (0.919 and 0.849) shows the best combination of features and type of encoder type with highest metric.

Table 4. Results of MA-Net_s model with various configurations of input data.

Combination of Various Features	MobileNetV3		ResNet-50	
	F1_Score	Io_U	F1_Score	Io_U
SWR- SAR	0.794	0.657	0.794	0.657
SWR- SAR+NDWI	0.884	0.81	0.91	0.804
SWR- SAR+MNDWI	0.895	0.809	0.898	0.813
SWR- SAR+SWI	0.89	0.79	0.875	0.776
MS+ SWR-SAR	0.94	0.853	0.917	0.845
MS	0.917	0.845	0.911	0.835
SWR-SAR + All Indices	0.905	0.825	0.897	0.811
MS+ SWR-SAR+ All Indices	0.901	0.818	0.903	0.821
MS+ All Indices	0.898	0.813	0.899	0.815

MS+ SWR-SAR (0.94 and 0.853) shows the best combination of features and type of encoder type with highest metric.

Table 5. Results of DeepLabV3+ model with various configurations of input data.

Combination of Various Features	MobileNetV3		ResNet-50	
	F1_Score	Io_U	F1Score	IoU
SWR- SAR	0.783	0.643	0.795	0.659
SWR- SAR+NDWI	0.850	0.738	0.89	0.755
SWR- SAR+MNDWI	0.876	0.778	0.876	0.779
SWR- SAR+SWI	0.855	0.746	0.845	0.730
MS+ SWR-SAR	0.893	0.805	0.890	0.801
MS	0.889	0.799	0.888	0.798
SWR-SAR + All Indices	0.875	0.776	0.880	0.784
MS+ SWR-SAR+ All Indices	0.884	0.791	0.885	0.81
MS+ All Indices	0.881	0.786	0.91	0.788

MS+ SWR-SAR (**0.893 and 0.805**) shows the best combination of features and type of encoder type with highest metric.

3.2. Experimental Results on Availabilities of External Data

3.2.1.Real of Flood Water Extent

Figure 4 and Figure 5 shows the Forecasts for Kolhapur District beyond flood event (BF) and Kolhapur District during flood event (DF) areas. The F1_Scores shows 0.708 and 1.01 for Kolhapur BF event and Kolhapur DF event respectively. Thus, the overall average value is 0.850. In water surface segmentation, the difference in metrics before flood and during flood can be explained easily as follows. Mostly, the segmentation based models are difficult to find to differentiate areas along with a limited number of pixels except the boundaries of surfaces are apparently detectable. In our study, the river is somewhat thin, and all models have some inaccuracies i.e. F1_Score is 0.708. Particularly, in the situation of flood, the level of water area has a very larger, more unceasing and additional more dissimilar area which allows the segmentation model to accurately segment the surface water body i.e. F1_Score of 1.01.

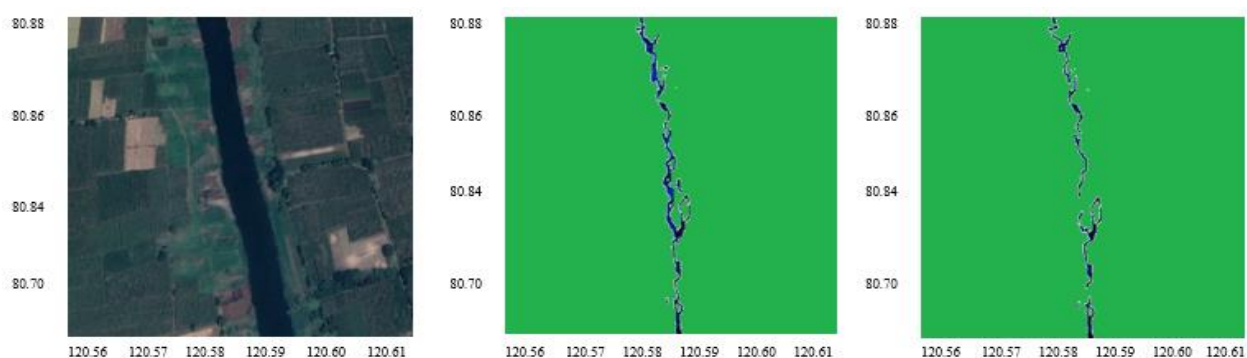


Figure 04. Test area: Kolhapur (Before Flood) Observation date: 20 May 2019. a) Before Flood Image (RGB), b) Result of Manual Markup, c) Result of Model prediction.

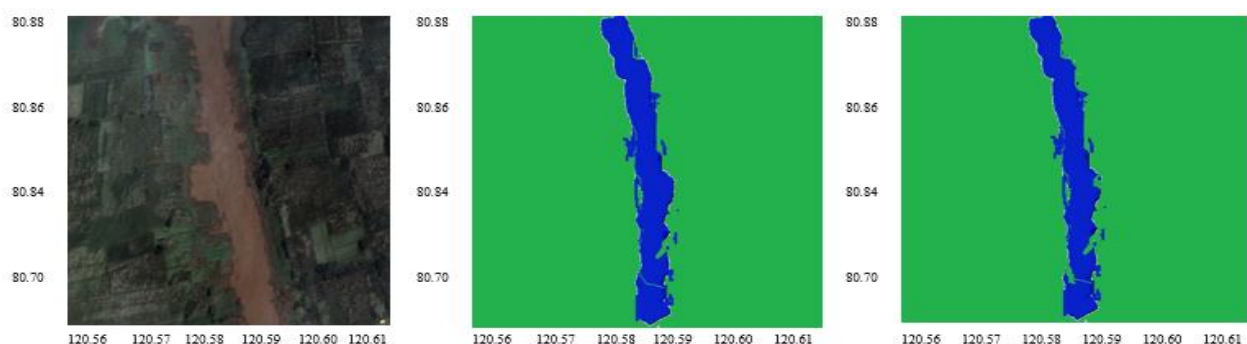


Figure 05. Test area: Kolhapur (During Flood) Observation date: 12 August 2019. a) During Flood Image (RGB), b) Result of Manual Markup, c) Result of Model prediction.

For permanent surface water measurements, Yang Liu [33] provides an advanced Global annual surface water cover frequency based dataset (GLOBMAP_SWF) at the level of global scale from the MODIS. Yang Liu [33]: GLOBMAP_SWF: an advanced Global annual surface water cover frequency based dataset during the year of 2000–2020. To complete analysis of infrastructure objects along with

also natural objects, Open_Street_Map+ (OSM+) [32] dataset is most often commonly used. Mostly, emergencies during flood events, all these datasets can only be used to primarily compare a huge flooded water area with primary areas of water level bodies. In figure 6-Kolhapur test area, simply shows a difference of mask predicated by model as well as mask provided with Sentinel type-2 data. The main advantages of the proposed method to water level body detection is combination of both the multi-spectral data and radar based data. In the figure 6, a dissimilar type mask provided with Sentinel type-2 data, the same mask predicted by the model correctly processes flood areas coverage covered by heavy clouds and cloud shadows.

The advanced algorithm always allows for a very effective mapping of rivers during a wide flood event. Figure 7 shows a real example of a river flood event that occurred in July 2019 in Kolhapur with overall calculated water surface area (WSA).

3.2.2. Volume of Flood Water

To estimate the level of flood extent along with the level of flood volume, we successfully applied our proposed method described rapidly. In our figure 5 to 7, we used original images (RGB colors) in our study area during the flood event along with after flood event, respectively.

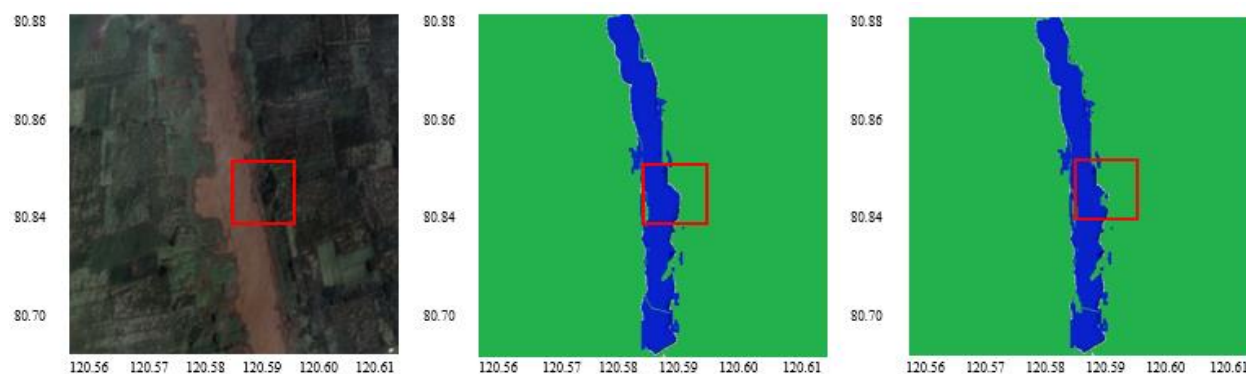


Figure 06. Kolhapur Test Area. Observation date: 12 August 2019 a) During Flood Image (RGB), B) Result of Model Prediction, c) Mask of Sentinel-2. Examples of a) and b) Where the result of model prediction superior to sentinel-2 mask are red spotlighted.

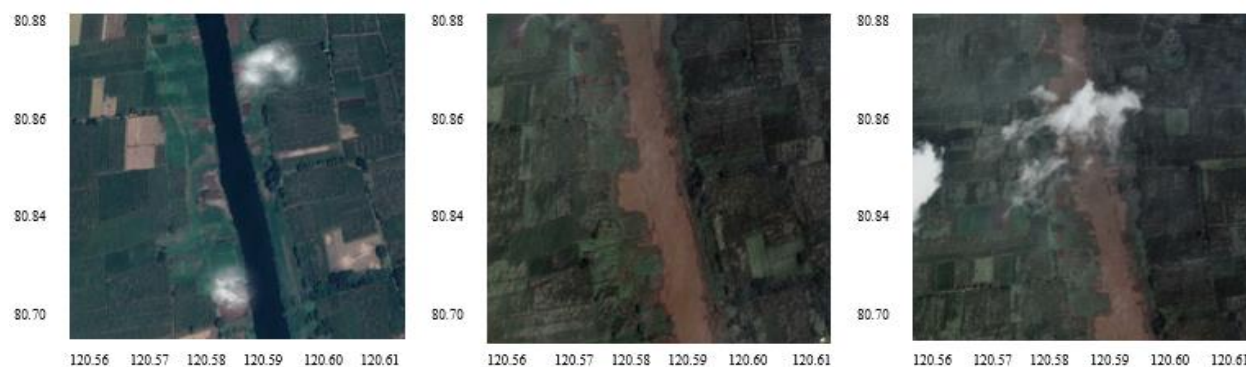


Figure: 07 Continued.

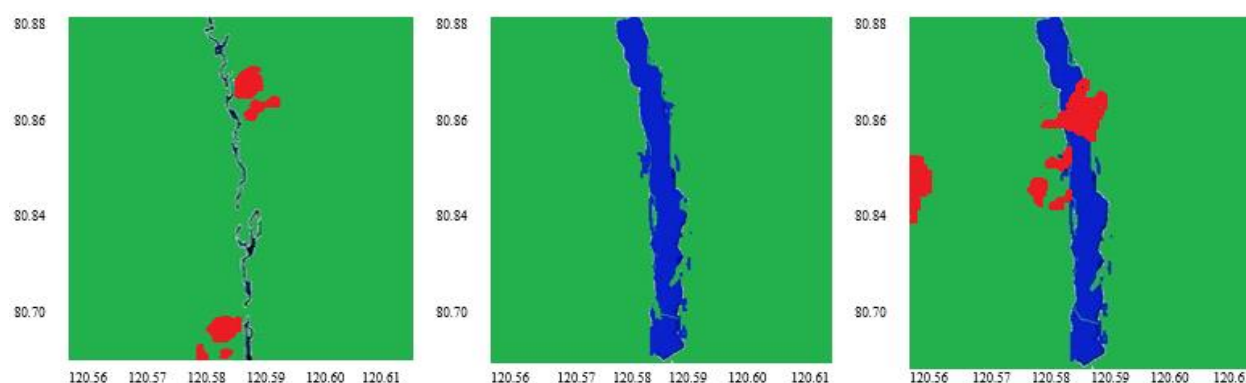


Figure: 07 Flood event monitoring in Kolhapur with sequences of available images: RGB color image and predicted based mask on 7 August 2019 a) RGB image, estimated water level of surface area-8.3 km² and predicted mask on 12 August 2019; b) RGB image, estimated water surface area-5.0 km² and predicted based mask on 25 August 2019; c) Estimated a complete surface area-4.1 km². Legend: Water (Blue), Green (Background), and Red (Clouds).

4. Discussion on Flood Analysis

In our research study, we designed an unique methodology for accurately estimating both the flood water extent and flood volume level by simply employing a popular remote sensing-based satellite data/ imagery from both Sentinel type-1 and Sentinel type-2. In this study, we used multi-spectral data and radar based data by utilizing various advanced deep learning algorithms to accurately process along with analyzing both of these data. In our result, we created an effective tool for flood water monitoring, reliable and also added many multispectral images and indices levels that leads to accurate outcomes in our case study of the 2019 flood event that occurred in Kolhapur district of India. Therefore, a more constant estimate is proposed where indices level can not work correctly either, sometimes it requires additional levels of decision rules. The proposed system has advantages from addition of advanced machine learning algorithms, mainly the type of both learning based algorithms or zero-shot learning based techniques. Both algorithms can effectively help to accurately uncover the patterns of visual data sets. Additionally, we saw an accurate estimate of the volume of floods. Such a method, combined with hydro-meteorological models, will simply allow a complete examination of dynamics of developing emergency situations. Many researchers have previously defined approaches for both flood extent and volume estimation based on advanced DEM methods. The main issues are availability of those data and their spatial pixel resolution of water level bodies map. The Landsat-5 satellite can be primarily used for mapping these water level bodies with only 30 m spatial pixel resolution per pixel. So, our work, we focus on flood level analysis with 10 to 30 m per pixel spatial resolution using both Sentinel type-1 and Sentinel type-2 observations. In the previous research studies, often Liis Sipelgas [3], showed the mapping of both OpenWater_Flooding (OW_F) and Flooding Under_Vegetation (FU_V) which might lead to inaccurate accuracy in predictions. Quinn [17] has highlighted the significance of a complete depth estimation of flood covered surfaces. The research authors mentioned all challenges of such level of value estimation due to mostly similar type of reflectance of other surfaces. In [18], Weikai Tan used remote sensing as a very powerful tool for mainly flood monitoring. The Digital Elevation based Models (DEM'S) are compulsory for flood inundation information for accurate estimation towards a real flood mapping in urban areas; sometimes

High-Resolution-DEMs techniques are mostly inaccessible due to a very high acquisition cost of HR-DEMs. Our method is developed to simply mapping the flood areas using advanced convolutional based neural networks (CNN) that are easily capable of extraction of spatial features. Also, our proposed method has been added with previous research on flood water mapping. In addition, our research methodology could be simply expanded to other types of data and various modeling such as hydrological models could help to predict the temporal based analysis of flood events, same as the more detailed information of topographical collected data [34] could increase an accurate estimation of wide flood extent and flood volumes. We can expand our methodologies with other regions and different types of flood events. Kaixin Yang [6], proposed the Deep Learning various models (DLM) to automated based detection of flood affected houses with Unmanned Aerial Vehicles (UAVs) aerial images in Kangshan levee of Poyang Lake. Although Unmanned Aerial Vehicles (UAVs) based on measurements simply provide the detailed information of flood affected regions. Such types of observations do not always acquire more related information namely flood depth and destroyed degree of buildings due to factors of poor illuminations, in complete light time or bad weather conditions. Our research approach could be improved to flood study in urban coverage areas. It is possible to integrate with other types of neural network techniques, mainly solutions for construction / building recognition in flood for further a huge damage evaluation [35]. There is possibility to estimate the level of water in the number of flooded coverage floors in houses and structures. In proposed work, we focus mainly on remote sensing-based Sentinel type-1 and Sentinel type-2 satellite imagery. All those data are freely available and its high temporal resolution. The Sentinel-2 satellite has 13 multispectral bands for measuring the earth's reflected form from VNIR to SWIR with 10 m, 20m and 60 m spatial resolution depending on the wavelength that enable us to easily compute more indice levels to improve the overall performance of the model. Our method, we added super resolution techniques [36]. The main advantages of our proposed method is the possibility to combine many sensors and simply apply these corresponding models in a single (ROI) region of interest, completely depending on the possibility of imagery information for that area along with the current climate situations.

Additionally, we experimented with the flood event in Sangli district (India) on 9 August 2019. In figure 9 the level of water body before the flood event is accurately segmented by using multi-spectral images as well as figure 10 illustrates the level of flood water body with a cloud mask where the complete study of flood area is covered by cloud as well as cannot be useful for a proper flood monitoring based on various visual level of bands.

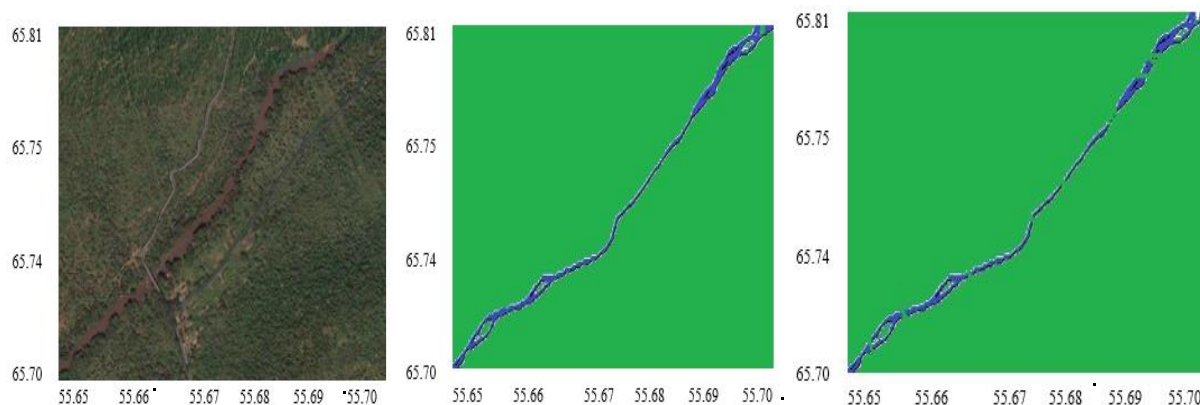


Figure 8. Test area (Before Flood): Sangli District. Observation Date: 1 August 2021. a) Before flood image (RGB), b) Result of Manual markup, c) Result of model prediction.

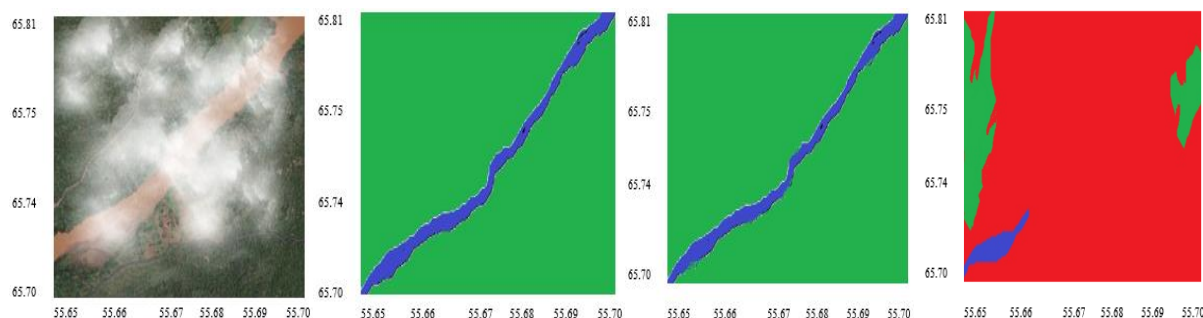


Figure 9. Test area (During Flood): Sangli District. Observation Date: 9 August 2021. a) During flood (RGB) composite, b) Result of manual markup, c) result of (SWM-SAR+MS and SWM-SAR), d) Result of MS prediction Legend: Water (Blue), Green (Background), and Red (Clouds).

The proposed methodology introduces an effective tool mainly for the event of flood water monitoring by using advanced remote sensing satellite data/ images along with advanced deep neural network technologies. Further research work should focus on improving a high level of accuracy and high speed of automatic flood damage identification and assessments. In the flood monitoring, it will expressively be important to the accurate timely flood monitoring response and these all recovery shows in flood affected covered regions, finally best to superior flood events risk management and decrease approaches.

Conclusion:

In our proposed work, we have implemented a unique method for automatic assessing flood extent and volume estimation of flooding in real time using remote sensing sentinel type-1 and sentinel type-2 data with deep learning models. Our flood monitoring method produced the F1-score of 0.893, in the flood event in Kolhapur in 2019. This F1 score shows a capability to effectively predict the depth level of flood and calculate its level of volume during a flood as well as after a flood. In our result, we evaluated the level of flood volume at 0.0010 km^3 . In our proposed approach, we used both the sentinel type-1 and sentinel type-2 and an advanced Digital Elevation Model (DEM) that provided exact along with consistent in our flood monitoring results. It has improved a high accuracy with speed of accurate estimation of flood damage assessments. The advantage of the proposed work, it is possible for an extended of time response, to assess the flood peak and recovery efforts in flood affected areas regardless of different weather conditions and cloud coverage. Finally, the proposed system must perform an effective tool for flood monitoring and management which is important in the real time flooded impacted regions. In our future work, we would like to improve our approaches to have better accuracy and high speed of flood water mapping in the affected regions.

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