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Flood Mapping Using Satellite Images- A Review

Prakhar Dixit[1], Dr. Bhola Nath Roy[2]

[1,2]Maulana Azad National Institute of Technology Bhopal/Madhya Pradesh/India
[1] prakhar.dixit29@gmail.com [2]bholanathroy@manit.ac.in

***Abstract*—This review paper investigates the application of deep learning and machine learning techniques for mapping floods using remote sensing data. The application of machine and deep learning algorithms has shown promising results in improving the accuracy and efficiency of flood mapping, which is a crucial task in disaster management and response. The processing of remote sensing data using various methodologies and techniques, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and support vector machines (SVMs), is covered in this study. It also encompasses several remote sensing data sets, including radar and optical imaging, that are utilised for flood mapping. The review paper goes on to explore the difficulties and limits of these approaches, such as the demand for a significant amount of labelled data and the effects of changing environmental factors. Overall, the report emphasises opportunities for additional research and improvement while offering insightful information on how flood mapping is currently being done utilising machine and deep learning techniques.**

Keywords: Machine learning, Deep learning

I. INTRODUCTION

Flood mapping is a crucial activity in disaster management and response because it provides significant data for organising emergency operations, rescue missions, and post-flood rehabilitation efforts. Satellite imagery is becoming a viable source of data for flood mapping due to the expansion of the remote sensing data market. However, due to the complexity of the data and environmental factors, reliably and efficiently mapping floods from satellite photos remains a difficult undertaking. Flood mapping from satellite pictures has demonstrated remarkable improvements in accuracy and efficiency thanks to machine learning and deep learning techniques. These techniques make it possible to automatically extract intricate features and patterns from the data, enabling more accurate flood mapping. In addition to providing new opportunities for real-time flood monitoring and prediction, the use of machine learning and deep learning techniques in flood mapping can help enhance flood management and response. n this review article, we investigate the application of deep learning and machine learning techniques to flood mapping with satellite imagery. We describe a number of methods and algorithms, such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and support vector machines (SVMs), that are used to interpret remote sensing data for flood mapping. We also discuss the difficulties and limitations of using optical and radar pictures, two forms of satellite imagery, for flood mapping. The current state of flood mapping utilising machine learning and deep learning techniques is discussed in this work, along with areas that could use additional study and improvement. A more automated and precise method of mapping floods is provided by machine learning

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and deep learning algorithms, which offer an alternative to conventional flood mapping approaches. These techniques can accurately predict and map floods by learning from big datasets and automatically extracting features and patterns from satellite photos. The application of machine learning and deep learning techniques for flood mapping has increased recently, with an emphasis on creating more precise and effective algorithms.In-depth information about flood mapping utilising satellite photos employing machine learning and deep learning techniques is provided in this review study. It covers the numerous remote sensing data processing methods and algorithms, the kinds of satellite images used for flood mapping, and the difficulties and drawbacks of these approaches. The paper also summarises some of the most current advances and uses of machine learning and deep learning in flood mapping, offering insightful information for academics and professionals working in this area.

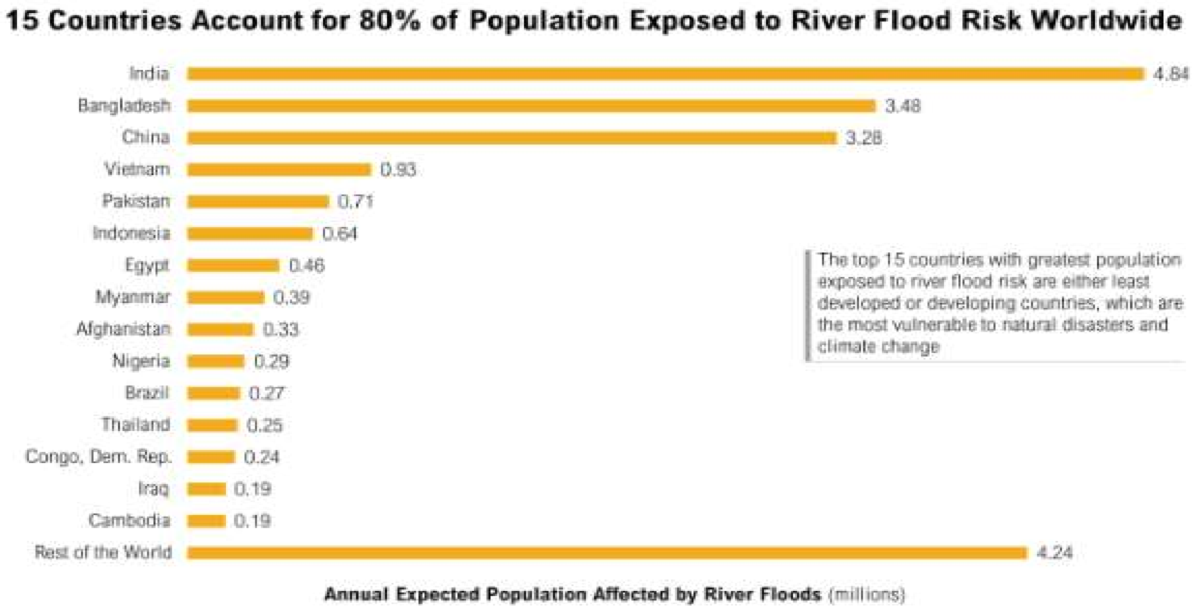

Fig.1 Flood affected population in world[40]

II. LITERATURE REVIEW

A. Machine Learning Methods

Flood mapping is done in San Diego, in southern California. There is a significant risk of tsunamis, flash flooding, and other natural disasters in Southern California. They have employed both supervised and unsupervised approaches. The European Space Agency Sentinel Application Platform (ESA SNAP) was used to perform the first picture preprocessing in order to acquire the models. Radiometric and geometric correction, speckle reduction, and multilooking were preprocessing stages. The following stage involves the use of the supervised methods Support vector machine (SVM)[1], Random Forest (RF)[2], and Maximum Likelihood Classifier (MLC)[3]. These photos distinguish between pixels that are water and those that are not, but there needs to be a critical threshold value to distinguish between the two classes of pixels. Therefore, in their analysis, unsupervised algorithms performed better. Their method uses an unsupervised change detection algorithm with fuzzy classification and Otsu threshold[4, 5]. After performing fuzzy classification, they employed iso-clustering to categorise the pixels. The result is that unsupervised algorithms offered superior accuracy, and choosing a key threshold value for both classes proved to be a difficult challenge. In supervised models, the accuracy was 0.69, 0.87, and 0.83, respectively.Accuracy in the unsupervised model was 0.87. [6] discussed about a method, This scheme investigates a traffic-light-based intelligent routing strategy for the satellite network, which can adjust the pre-calculated route according to the real-time congestion status of the satellite constellation. In a satellite, a traffic light is deployed at each direction to indicate the congestion situation, and is set to a relevant color, by considering both the queue occupancy rate at a direction and the total queue occupancy rate of the next hop. The existing scheme uses TLR based routing mechanism based on two concepts are DVTR Dynamic Virtual Topology Routing (DVTR) and Virtual Node (VN). In DVTR, the system period is divided into a series of time intervals. On-off operations of ISLs are supposed to be performed only at the beginning of each interval and the whole topology keeps unchanged during each interval. But it has delay due to waiting stage at buffer. So, this method introduces an effective multi-hop scheduling routing scheme that considers the mobility of nodes which are clustered in one group is confined within a specified area, and multiple groups move uniformly across the network.

The Ganges, Brahmaputra, and Meghna river basins make Bangladesh one of the most flood-prone regions in the world[7]. 20,000 flood-related fatalities have been recorded in Bangladesh between 1995 and 2015. Prior flood maps and quick safety measures are required before the flood event. For mapping the extent of the flood, the authors employed Sentinel-1 and Landsat-8 imagery. The preprocessing procedures involve geometric calibration, which is similar to radiometric calibration[8], followed by speckle filtering and noise removal. [9] proposed a system, in which a predicate is defined for measuring the evidence for a boundary between two regions using Geodesic Graph-based representation of the image. The algorithm is applied to image segmentation using two different kinds of local neighborhoods in constructing the graph. Liver and hepatic tumor segmentation can be automatically processed by the Geodesic graph-cut based method. This system has concentrated on finding a fast and interactive segmentation method for liver and tumor segmentation. In the preprocessing stage, the CT image process is carried over with mean shift filter and statistical thresholding method for reducing processing area with improving detections rate. Second stage is liver segmentation; the liver region has been segmented using the algorithm of the proposed method. The next stage tumor segmentation also followed the same steps. Finally the liver and tumor regions are separately segmented from the computer tomography image. Following that, authors of raw images employed RGB clustering thematic raster values. A RGB image[10,11] is constricted to turn theme class values into individually numbered "polygons" after the thematic map has been created. These polygons are nothing more than two distinct bands of backscattered VH or VV values. These backscattered values from two distinct bands are utilised as the input for categorising the pixels in the image as being either water or non-water. The categorization accuracy under expert guidance was 96.44%.

Using Sentinel-1 ground range photos, a novel method for quick flood mapping is examined. The process uses two different ways. The first technique uses a Sentinel-GRD product image with a 10-m spatial resolution. It is subjected to the spatial multilooking for speckle reduction. After that, histogram trimming is carried out to make locations with low backscatter more reflective. Haralick dissimilarity texture[12] and the reflectivity map are used to feed a fuzzy system, which assigns flood and non-flood pixels to the designated area in the image. Due to the use of multilooking, the output image of the flood map has a 30 m spatial resolution.[13] This approach is completely unsupervised and devoid of thresholds. The second method uses two Sentinel-1 ground range images with a 10-m spatial resolution that have been calibrated and co-registered (pre-event and post-event). After the pictures have been cross-calibrated and despeckled, a variable amplitude-level equalisation technique is used[14]. Cross-calibrated images are subjected to a change index system before being fed into a fuzzy classification system, which classifies them according to their semantic attributes (low and high). The low and high areas denote the flooded and unflooded areas, respectively. In the final step, an object-based picture analysis is performed to eliminate regions with a threshold that has been set by the user[15]. A map with a 10-m spatial resolution is the final product. With an accuracy of 95.4%, the first approach exceeds K-means, SVM, NN, and ML, which have respective accuracy of 83.8%, 82.8%, 57.2%, and 51.8%. With an accuracy of 92.9%, the second technique exceeds K-means, SVM, NN, and ML, which have respective accuracy of 73%, 73.4%, 76.6%, and 70.2%.

The Krishna River Basin flood assessment utilising unsupervised approaches is provided. Multi-temporal MODIS satellite photos were used. Two techniques are compared for the automatic detection and extraction of water pixels, including the mean shift algorithm and the artificial neural network technique self-organizing maps. Using MODIS satellite photos, the flooded and non-flooded areas are divided. Meanshift method[16] is the first approach, which chooses random sites in space and then converges to the local maximum density. By employing the weighted average, the mean iteratively converges to pixels with equal densities. Otsu thresholding is used to divide the pixels into distinct classes after utilising the Mean Shift technique. Self-Organizing maps[17] with ISO thresholding[18] are the second technique utilised. As training samples, SOM uses random samples of images[19]. These are sent for similarity matching, after which the identical pixels are grouped together. By using Receiving of Characteristics (ROC) and Root Mean Square Error (RMSE), these approaches' performance is assessed.

An innovative flood mapping method using Bayesian inference is examined[39]. pictures from Sentinel-1 satellite pictures make up the dataset. These are distributed pixel-by-pixel in comparison to the local and water distributions. We can determine whether an image is part of a local or water distribution using Bayesian posterior probability. SAR is very beneficial for regional mapping of flood surface because it is highly sensitive to water content. In general, single-image scenario maps with water surfaces like tarmac, sand, salt ponds, and sparse, dry vegetation might produce false positive results. A change detection approach is used to improve these impacts because it produces fewer false positives and directly identifies flood zones as opposed to water areas.

Flood susceptibility (FS) mapping is done in the eastern Indian region of the Koiya River Basin. This method uses the hyperpipes[20–22] and support vector regression machine learning methods. By combining these two in a creative way, a superior outcome can be achieved. By utilising hyperpipes and support vector regression (SVM), we create flood susceptibility maps. This approach yielded accuracy of 84.9% and 85.8%. Accuracy is 92.8% when these two approaches are combined

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B. Drawbacks of Machine learning Methods

Though they have some limits, machine learning techniques have showed promise in enhancing flood mapping using satellite imagery. Large quantities of labelled data are required, but obtaining them during a flood event might be challenging. Their sensitivity to environmental factors like cloud cover and shadowing, which can cause mistakes in flood mapping data, is another drawback. Furthermore, machine learning models are frequently referred to as "black box" models, which makes it difficult to comprehend the logic underlying the model's predictions. It may be difficult to confirm the model's outputs because to its lack of interpretability, which is important for applications like flood mapping. Machine learning techniques might not be able to manage every facet of flood mapping's dynamic and complicated nature. For instance, alterations in the weather or unanticipated occurrences may affect the algorithm's accuracy and necessitate human intervention for correction.Despite these drawbacks, machine learning techniques are still a viable way to increase the accuracy of flood mapping. When developing and putting into use machine learning algorithms for flood mapping applications, researchers and practitioners must take these restrictions into account. These limitations are the subject of ongoing research, which includes creating fresh methods for data augmentation, addressing the interpretability of models, and incorporating real-time data into machine learning algorithms for better flood prediction and mapping. Overall, machine learning techniques have the power to revolutionise flood mapping and enhance disaster management and response efforts, but it is crucial to recognise and work around their shortcomings.

C. Deep learning methods

Using two photos from the Sentinel dataset obtained before and after, a novel research of flood mapping is carried out in the Iranian city of Pol-e-Dokhtar, in the Lorestan region. The use of SRTM DEM[23] data increases the amount of input features. In this paper, the 2D CNN convolution technique is examined. Prior to performing any image normalisation or preprocessing, radiometric and geometric calibration is done. The following step involves classification and change detection[24]. In this method, a multi-layer perceptron with two hidden layers is coupled to a classifier network with two convolutional layers[25]. Three by three two-dimensional filters are present in each convolutional layer. ReLU function is employed as an activation function in every layer of the network. Two classification maps that are trained with change detection to produce precise mapping are obtained. By switching the training size between 1D and 2D, an accuracy difference of 91.03%–93.57% and 94.90%–98.5% is attained in CNN[26]

At Xinxiang, Henan, China, a deep learning approach to flood detection is described. The study includes position attention mechanisms based on U-Net and channel attention mechanisms[29]. This improves the classification of water's efficiency and accuracy. Additionally, this disregards the unimportant information provided by the weight learning mechanism and directs information towards water. The suggested process consists of both encoding and decoding steps. The U-Net component, which extracts depth features from water bodies, is present in the encoding part.[30] With regard to channel attention, the decoding portion is embedded. The recall of the procedure is up to 94.2% and the OA is up to 95.9%.

In Seoul, South Korea, a new study is being done to map floods using deep learning. For flood mapping, the study uses two models: a convolutional neural network (NNETC)[27] and a recurrent neural network (NNETR). The training variable was a collection of flood inundation locations (295 flooded sites), while the

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predictor variables were 10 flood-affecting parameters. These are then divided in a ratio of 70:30 for the development of flood models and for process validation.The techniques receiving operating characteristic curve (AUC) and root mean square error (RMSE) are used to test the models [28]. The study's advantage is that the NNETC model's prediction ability was superior to the NNETR model's (AUC = 82%, RMSE = 0.186). The drawback is that the model's relative inaccuracy (based on AUC) was up to 20%.

UNET[31], LinkNet[32], and SegNet[33] are deep learning models used in a new study for flood mapping. Pre-event and post-event flood photos from the Sentinel dataset are evaluated in this work, and several classification techniques are used to identify the disaster area. These images go through initial preprocessing stages like calibration, Doppler image correction, speckle filtering, and orbit file acquisition to produce filtered images known as masks. After that, the image is classified using the image segmentation technique, which classifies each pixel displayed in the image. In this paper three segmentation methods UNET , LinkNet and SegNet were used. The dataset was fragmented into 80% , 10% and 10% train , validation and test set before applying the model. The accuracy obtained for UNET and LinkNet are same which is 87% and for SegNet is 79%.
The aforementioned systems are used in a different study for flood mapping. This study primarily focuses on metropolitan areas that have experienced flooding. Temporal-ensembling active self-learning CNN is the algorithm in use[34]. It is built on a two-step process that involves first training the temporal-ensembling[35] deep CNN and then updating informatively unlabelled samples within pseudo-labels to the training dataset. A deep CNN model, which we refer to as the student model, is initially trained using labelled training data. The parameters of the student model are then combined to create the instructor model[36]. By training just one model, this approach produces two (or more) models. It was believed that a multi scale spatial constraint would label and filter the chosen samples if they were from the same class and were physically adjacent.

In Spain's upper basin of the Adaja River, research is being done to determine the flood risk. For flood mapping, a novel model called F-CNN is utilised. F-CNN[37] model is used to detect floods more precisely than SVM classification model, according to a comparison of the models. Pixel-wise classification method and rule-based classification method are the two types of thresholding techniques that are employed. These techniques use a threshold base classification to distinguish between water and non-water pixels. This method discusses the contextual pixel information for pixel-by-pixel categorization of floods or semantic segmentation[38]. This classification divides areas into dry ground, temporary or flood water bodies, and permanent water bodies. Compared to the 45.27 percent accuracy of SVM classification, the F-CNN model has an accuracy rate of 76.7%.

III. Proposed Approach

The suggested method for mapping floods makes use of convolutional neural networks (CNNs) to accurately map flood extent by extracting characteristics from satellite images. It uses U-Net and channel, multi-head, and position attention techniques. An encoder network and a decoder network coupled by a series of skip links make up the U-Net design, a form of CNN. This architecture enables the network to efficiently extract features from various scales and resolutions, allowing it to collect both local and global data. The suggested method also includes attention mechanisms such as channel, multi-head, and location attention in order to enhance the performance of the U-Net. By concentrating on the relationships between the channels in the feature maps, channel attention enables the network to selectively enhance or suppress particular channels based on their significance for flood mapping. The

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network can focus on many locations on the feature maps thanks to multi-head attention, which makes it possible to record intricate spatial patterns. Contrarily, location attention concentrates on the connections between various points within the feature maps, allowing the network to detect long-distance dependencies.

IV. CONCLUSION

As a potent tool for precise and timely assessment of flood threats in many parts of the world, flood mapping utilising satellite pictures has evolved. Early warning and efficient response plans are made possible by the swift detection and monitoring of flood events made possible by the use of remote sensing technologies and satellite data. Flood extent, water depth, and frequency may be precisely calculated from satellite photos, which is helpful for assessing flood risk, managing floodplains, and managing disasters. This strategy aids in lowering the costs and duration of more conventional flood mapping techniques, which may require fieldwork, hydrological modelling, and ground-based observations. With the development of technology and the accessibility of satellite data, flood management and mitigation activities are increasingly relying on satellite-based flood mapping.

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