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ORIGINAL RESEARCH PAPER

Hybrid deep learning approach for pre-flood and post-flood classification of remote sensed data

Amit Maru[1*], Dhaval Vyas[2]

Abstract

Satellite images are the best way to identify flood pretentious areas. Once we identify flood pretentious regions, then it is possible to identify the portion of vegetation area, residential area, water area, etc. But satellite images are very complex images from which data extraction is a very crucial task and it is also very difficult to identify pre-flood and post-flood images from large sets of data. So many techniques are used, but accuracy is still a major constraint. Thus, in this paper, the proposed nature-inspired algorithm is explained, which is inspired by the foraging technique of zebra animals and deep learning classification. Major focus on three phases of the proposed model: data processing, feature extraction and classification. Various comparison matrices are used to prove that the proposed algorithm is better than the existing algorithms.

Keywords: Satellite images, Pre-flood, Post-flood, Remote sensed data, Feature extraction, Image classification.

Introduction

There are different types of disasters and floods are one of them, which distresses the properties and humankind largely. It is a major global problem and also, in India, every year, we face flood occurrence in different regions. The North Indian Flood occurred in 1954 and affected Bihar and Uttar Pradesh largely. The estimated deaths of this flood were more than 1000 human lives. The Assam Flood in 1970 affected Assam state and estimated deaths were more than 700 people. In 1978, Floods occurred in Bihar and West Bengal and we lost more than 1000 lives. The Bihar Flood in 1987 was a most dangerous flood and we lost more than 1390 people, their homes and properties. In 1998 flood occurred in Gujarat and the estimated deaths was more than 1000 people. The flood that occurred in 2005 in Mumbai affected different regions of Maharashtra and we lost more than 1094 people. A very dangerous flood occurred in 2013 in Uttarakhand and Himachal Pradesh, where we lost more than 5700 people and lots of properties. Similarly, in 2018, in the Kerela Flood, we lost 483+ human lives. In 2021 flood occurred on the Rishi and Dhauli Ganga River Uttarakhand lost 80 people (Singh, Aryan, & Mayank, 2022). In 2021 in Uttarakhand and 2022 in Assam again, we lost more than 200 lives. Recently, in 2023, in Himachal Pradesh, we lost more than 227 human lives.

We cannot stop natural disasters, but if we identify flood-affected areas with high accuracy, then we can take necessary remedy actions immediately. There is so much research done and also much research going on to find accurate results in pre-flood and post-flood classification.

Different Techniques Used for Image Classification

There are different approaches such as thresholding, segmentation, visual interpretation, textural analysis, and Normalized Difference Water Index (NDWI) were used. These all are the classic techniques that have some limitations in detecting floods in complex environments. To solve this problem, Machine Learning is the best choice. In Machin Learning there are so many algorithms like artificial neural networks (Kia *et al*., 2012), K-nearest neighbor, and logistic regression and decision trees (Peng, Meng, Huang, & Wang, 2019) are used. Some nature-inspired algorithms use a hybrid approach, like the foraging technique of Manta Rays (Rai, Mandal, Singh, & Bonafilia, 2023) (Gayathri *et al*., 2023).

[1]Ph.D Research Scholar, Department of Computer Engineering, Gokul Global University, Sidhpur, Gujarat, India.

[2]Faculty of Computer Science, Gokul Global University, Sidhpur, Gujarat, India.

***Corresponding Author:** Amit Maru, Ph.D Research Scholar, Department of Computer Engineering, Gokul Global University, Sidhpur, Gujarat, India., E-Mail: amitmaru009@gmail.com

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Machine Learning itself also has some limitations, like some ML techniques are time-consuming and feature-dependent. To overcome this limitation nowadays, deep learning can be used.

Now the question is, "Why do we use Remote Sensed Data?". Sometimes, it is difficult to visit flood-affected areas physically. So, mapping floods is possible through remote sensing data (Bonafilia *et al.*, 2020). Especially for water-treated hazards, remote sensing data is very important (Abdi, Kolo, & Shahabi, 2023). To identify, determine, and assess the flood, remote sensing data definitely plays a very important role (Aslam *et al.*, 2024).

Actions taken immediately before, during, or after a flood event are known as Emergency measures. In similar situations, the ability to implement countermeasures requires real-time knowledge about the flood's size and the locations that are in danger. Rather, the goal of preventive measures is to lessen the likelihood that a particular location will flood. Maps that show the risk of flooding or the possible features of an event can be used to determine those.

Problem Definition

Pre-flood and Post-flood classification and further classification such as vegetation area, water area, and residential area can be applied to remotely sensed data. Remote sensed data is available without physical contact with flood affected area. It is a very crucial task to accurately recognize flood-affected areas and further classification with classic techniques. Morden techniques, such as Machine Learning and Deep Learning algorithms (Jacinth Jennifer *et al.*, 2020), are used to solve this problem nowadays. Still, the accuracy of the result is a very challenging task.

Here in this paper proposed approach discussed is nature nature-inspired approach inspired by the Zebra Foraging technique. Hybridge approach is designed for better classification of remotely sensed images.

Proposed Approach

There are different phases in the proposed model. Our Satellite Images will pass through different phases, such as data preparation, data processing, feature extraction, image classification and the final phase, which is analysis (figure 1).

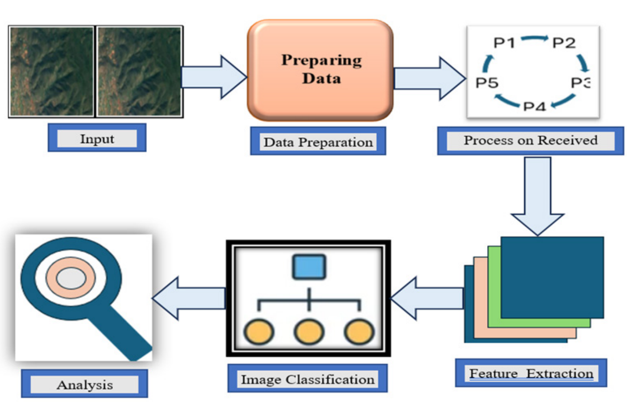

Figure 1: Different Phae of Propoed Model

Input

Satellite Images are used as input to the proposed model. The images are the images captured from flood-affected areas.

Data Preparation

Data Preparation is a set of processes that gathers images, removes noise, and converts in to accurate data for better prediction (Geudtner *et al.*, 2014).

Process of Received Data

Received data from the previous step pass to the next step for further process and improvement of images.

Data Extraction

Normalized Difference Water Index is used for feature extraction on data received from step four (Figure 2).

$$NDWI = \frac{Green - NIR}{Green + NIR}$$

NDWI index provide water information of images.

```
Proposed_Nature_Inspired_Algo

{     Input ()        // Collect Satellite Images as input)

      Data_Preparation ()

      Processing ()         // Process to improve quality of Satellite Images

      Extracting ()

      {

            NDWI = (Green – NIR) / Green + NIR)

            // NIR indicates Near Infrared

      }

      Classfication1 ()     // Classification Pre-Flood and Post-Flood

      {

            If (X == 0)

                  Pre-flood Images

            else

                  Post-flood Images

      }

      Classification2 () // Further Classification (Vegetation, Forest, Residential, Water Area

}
```

Figure 2: Proposed algorithm (with different phases)

Image Classification

Image Classification is different algorithms to classify images into different parts like pre-flood and post-flood. After the identification of pre-flood and post-flood images next step is to further classify into residential areas, water areas, vegetation areas, etc.

Analysis

Different latest classification algorithms are compared with the proposed technique and verified results with different parameters and matrices to prove proposed algorithm is far better than the existing algorithm

Proposed Algorithm and Flowchart

Proposed Algorithm

Image Classification is different algorithms to classify images into different parts like pre-flood and post-flood. After the identification of pre-flood and post-flood images, the next step is to further classify into the residential area, water area, vegetation area, etc.

Flowchart of Proposed Algorithm

The detailed flow of the proposed algorithm is illustrated in Figure 3.

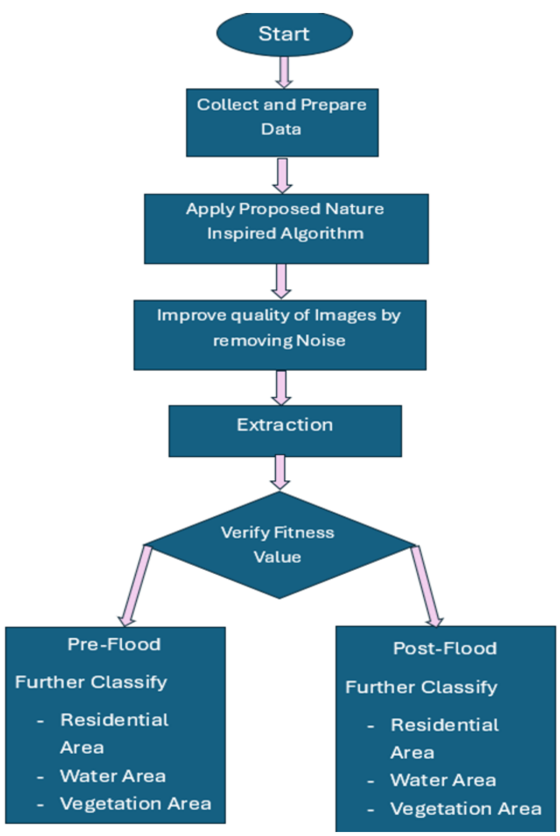

Figure 3: Proposed Flowchart

Implementation

As per the proposed model and flowchart, first, give Satellite Images as input. This input will be passed to Pre-processing to improve the quality of images. feature extraction

As per Figure 4 Algorithm is implemented in Python programming. The first image shows input images, the second image shows Feature extraction, and the last images are output as per our need, that is, pre-flood, post-flood classification into, forest area, building area, water area, vegetation area, etc., along with a comparison of precision and recall values is visualized in Figure 8.

The loss of data across 100 epochs is demonstrated in Table 1.

Comparative Analysis with Precision and Recall Matrices

This comparative analysis is a comparison of the result of standard existing algorithms with the proposed algorithm.

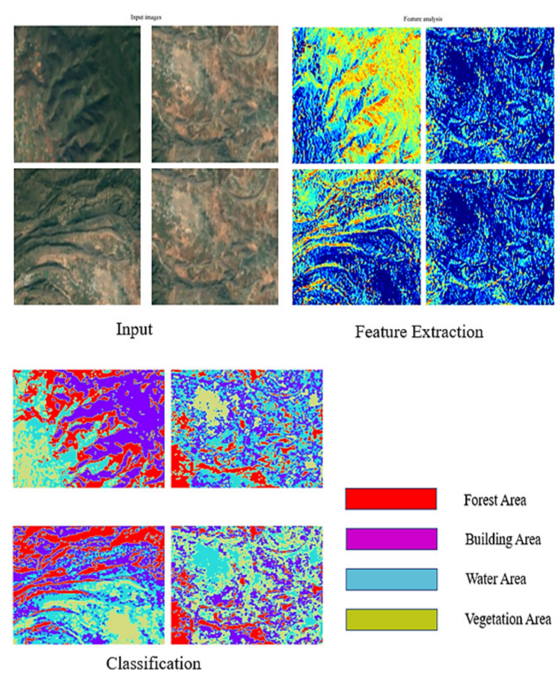

Figure 4: Implementation Result (Classification into Forest, Vegetation, Water Area, etc

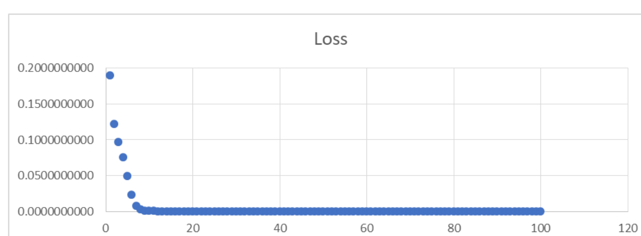

Figure 5: Loss Diagram with 100 epoch

Table 1: Epoch and Loss data for verification

Epoch	Loss	Epoch	Loss	Epoch	Loss	Epoch	Loss
1	0.1892000000	16	0.0001170400	31	0.0000432910	46	0.0000214800
2	0.1219000000	17	0.0001064800	32	0.0000409500	47	0.0000206720
3	0.0964000000	18	0.0000976280	33	0.0000388010	48	0.0000199060
4	0.0753000000	19	0.0000900620	34	0.0000368700	49	0.0000191700
5	0.0487000000	20	0.0000832940	35	0.0000350070	50	0.0000184770
6	0.0231000000	21	0.0000770070	36	0.0000332620	51	0.0000178210
7	0.0078000000	22	0.0000715810	37	0.0000317140	52	0.0000172010
8	0.0022000000	23	0.0000668290	38	0.0000302780	53	0.0000166160
9	0.0008156800	24	0.0000624080	39	0.0000289120	54	0.0000160600
10	0.0004164100	25	0.0000584190	40	0.0000276390	55	0.0000155220
11	0.0002716200	26	0.0000548090	41	0.0000264270	56	0.0000150190
12	0.0002043300	27	0.0000515000	42	0.0000253220	57	0.0000145490
13	0.0001689800	28	0.0000484440	43	0.0000242610	58	0.0000140760
14	0.0001457800	29	0.0000432910	44	0.0000232860	59	0.0000136470
15	0.0001300200	30	0.0000432910	45	0.0000223690	60	0.0000132280

Table 2: Epoch and Loss data for verification

Epoch	Loss	Epoch	Loss	Epoch	Loss
61	0.0000128380	76	0.0000085122	91	0.0000060550
62	0.0000124490	77	0.0000083068	92	0.0000059308
63	0.0000120860	78	0.0000081065	93	0.0000058078
64	0.0000117440	79	0.0000079166	94	0.0000056899
65	0.0000114110	80	0.0000077265	95	0.0000055765
66	0.0000110830	81	0.0000075489	96	0.0000054676
67	0.0000107810	82	0.0000073762	97	0.0000053587
68	0.0000104870	83	0.0000072050	98	0.0000052569
69	0.0000102110	84	0.0000070468	99	0.0000051537
70	0.0000099319	85	0.0000068906	100	0.0000050572
71	0.0000096727	86	0.0000067411		
72	0.0000094244	87	0.0000065921		
73	0.0000091847	88	0.0000064511		
74	0.0000089544	89	0.0000063131		
75	0.0000087305	90	0.0000061814		

Table 3: Comparative analysis (Precision)

Methods	*Precision (%)*
DeepLabv3+	90.87
PSPNet	90.87
OCRNet	89.84
CMCDNet	93.16
Proposed	98.77

Table 4: Comparative analysis (Recall)

Methods	*Recall (%)*
DeepLabv3+	95.84
PSPNet	95.6
OCRNet	95.51
CMCDNet	95.98
Proposed	98.75

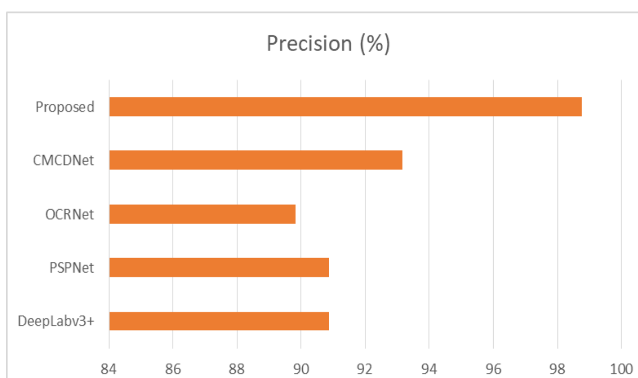

Figure 6: Precision matrix chart

The below table shows that the proposed algorithm is far better than the existing algorithm (He *et al.*, 2023). One existing algorithm, such as PSPNet, is the Pyramid Scene

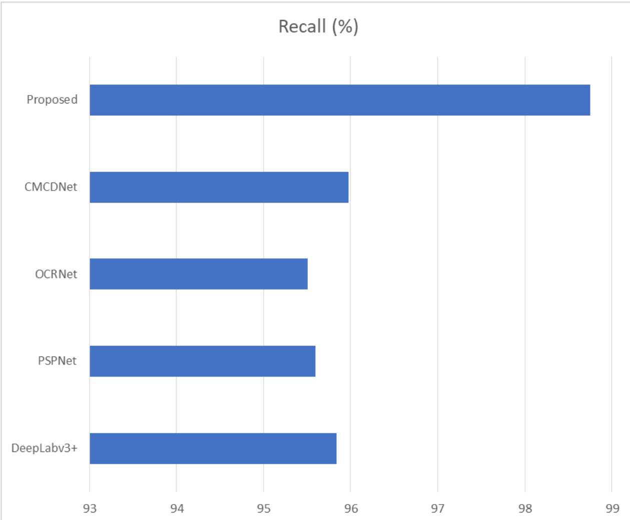

Figure 7: Recall matrix chart

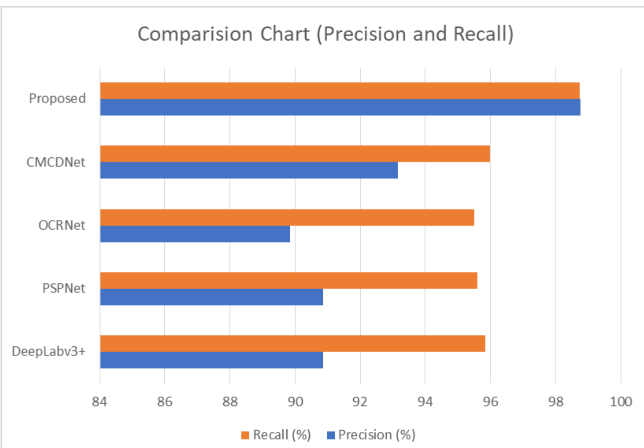

Figure 8: Comparison chart with precision and recall

Parsing Network, which uses a deep learning approach for segmentation and classification (Yu & Zhang, 2021). DeepLab was improved with a new concept, which is DeepLabv3+ has good accuracy (Chen *et al.*, 2017). Same way, OCRNet (Gupta, Gupta, Arora, & Garg, 2021) and CMCDNet (He *et al.*, 2023) used the deep learning concept for Image Classification. A detailed comparative analysis of precision among various algorithms is shown in Table 2.

Precision = True Positive / (True Positive + False Positive), and the precision matrix chart is shown in Figure 6.

Recall = True Positive / (True Positive + False Negative) , and the recall values are represented in Figure 7.

The recall values for each method are provided in Table 3 for comparison.

Conclusion

This paper presented different approaches for pre-flood and post-flood classification. Also discussed were further classifications like vegetation area, water area, residential area, etc. For the comparison of various existing approaches, we can consider different factors such as accuracy, recall, precision, F1 factor, etc. But for deep concentration, we have used recall, precision, and IoU matrices, which are very important for classification approaches for machine learning and deep learning. The result shows that the proposed approach is far better approach as compared to other existing modern approaches.

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Conflict of Interest Statement

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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