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DSAAM-UNet: Flood Detection Based on Lightweight Deep Learning Model and Satellite Imagery

Kavita Bathe* [1,2], Dr. Nita Patil[3]

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Abstract: Flood is the most destructive type of natural disaster on Earth. Mapping the extent of a flood is essential to ascertain the damage and plan for rescue operations. Recently, Deep learning has achieved remarkable performance in remote sensing applications like flood detection. Many variations of the fundamental U-Net segmentation model have been developed and applied in the related studies. In this paper, DSAAM-UNet, an improved version of basic U-Net is proposed. This improvement is achieved by incorporating depth-wise separable convolution blocks and attention blocks in U-Net architecture. Depth-wise separable convolution considerably reduces the number of trainable parameters and training time whereas attention block adaptively focuses on relevant features from satellite imagery. The Ombria dataset is used for performance assessment of proposed model DSAAM-UNet. The proposed segmentation model outperformed the various state-of-the-art methods, such as U-Net, Depth-wise Separable U-Net, and Attention U-Net on the Ombria dataset. The DSAAM-UNet model enhances flood detection from satellite imagery data. The proposed model is beneficial to administrators for flood extent mapping.

Keywords: *Deep Learning, Remote Sensing, Flood detection, Segmentation*

1. Introduction

Floods are most devastating kinds of natural hazards. India is particularly susceptible to this hazard due to its geo-climatic circumstances. Flood leads to major losses of human lives, damage to infrastructure, public utilities, and destruction of crops. In past few years, a sudden increase has been observed in the frequency of floods. According to the Central Water Commission report of India, deaths due to floods increased from 37 in 1953 to 1815 in 2020. During flood events, it is essential to detect flooded areas and immediately plan for rescue operations. Conventional methods of flood detection are time-consuming, labor-intensive, tedious, and can be used for limited areas. Remote sensing due to its large area mapping is a viable solution in such situations. Optical remote sensing and radar remote sensing approaches are generally used. Flooding is mainly caused by heavy precipitation. During the flooding situation, the weather is cloudy. The optical remote sensing-based satellite sensors are unable to acquire satellite data in such situations. Microwave remote sensing-based synthetic aperture radar satellite sensors due to their all-weather capability and data acquisition in day and night are beneficial in flooding situations. Conventional remote sensing-based flood detection methods include Single Band density slicing, spectral indices-based methods, and threshold-based methods like Otsu thresholding. These methods have shown significant performance. However, a remote sensing expert is needed to utilize these methods. In the past few decades, Machine learning has shown remarkable success in earth observation data, particularly flood detection.

[1] *Research Scholar, Datta Meghe College of Engineering, Airoli, Navi Mumbai, Maharashtra, India.*
[2]*Assistant Professor, K.J. Somaiya Institute of Technology, Sion, Mumbai, Maharashtra, India. ORCID ID: 0000-0002-5141-2123*
3 Associate Professor, K. C. College of Engineering and Management Studies and Research, Thane, India.
ORCID ID: 0000-0003-4276-9742
** Corresponding Author Email: kavitag@somaiya.edu*

The related studies show that supervised machine learning-based methods like classification and regression tree [1], Support vector machine [2], and ensemble learning based Random forest [3] are employed for flood detection. Machine learning-based methods have shown notable performance but with their own set of limitations. In recent years, Deep learning in association with computer vision has provided the pathway for addressing the issue of flood detection from satellite imagery. Deep learning due to its automatic feature extraction capability has become a predominate tool in remote sensing applications. It has attracted the attention of remote sensing researchers for handling complex satellite images in particular to Synthetic aperture radar (SAR) data. Various deep-learning methods are utilized for computer vision-based classification and segmentation tasks. Semantic segmentation plays a key role in remote sensing applications like urban mapping, precision agriculture, and flood detection and mapping. The remote sensing image semantic segmentation aims to determine the class of each pixel in the satellite image [4]. Semantic segmentation frameworks like Fully Convolutional Network, UNet, UNet and attention, UNet++, and DeepLabV3 architecture are used in literature for remote sensing tasks. In this article, we propose a hybrid model that utilizes attention mechanism, Depth wise separable convolution with UNet architecture for flood detection from satellite imagery.

Rest of the article is organized as follows. Section 2 describes Related work. Section 3 mentions about method. Section 4 describes Results and Discussion. Lastly Section 5 concludes the paper.

2. Related Work

Satellite-based remote sensing is a way of acquiring information about an object on the Earth's surface. Optical remote sensing-based satellite sensors such as Sentinel-2, LandSAT- 8 and Microwave remote sensing-based satellite sensors like Sentinel-1, RADARSAT provides satellite data. Over the years, researchers have employed various methods such as thresholding-based methods, spectral indices

methods, machine learning algorithms, and deep learning methods for delineating floods from satellite imagery. Various methods are applied on this satellite data for flood detection.

The potential of Otsu's method for automatically deciding the threshold value in image segmentation created a new pathway [5]. Researchers have utilized automatic threshold selection based on the Otsu algorithm and its modified version in various studies. For instance, Sekertekin [6] conducted a study and evaluated the performance of various thresholding methods. The authors have applied aforementioned methods on sentinel-2 satellite imagery to map open water bodies. The spectral indices-based method computes the water index based on mathematical equations. Researchers utilized various indices like Normalized difference water index (NDWI) (McFeeters1996), Linear discriminate analysis water index (LDAWI)(Fisher A 2013), Modified normalized difference water index (MNDWI)(Hanqiu Xu. et al. 2006), Automated Water Extraction Index(AWEInsh) (Gudina L Feyisa 2014), Normalized difference water index NDWI with Spectral bands (MNDWI)(Kshitij Mishra 2015), Enhance Water Index (EWI)(Jason Yang 2017), Proposed Index(PI)(Pallavi Jain 2020), Sentinel-2 water index (SWI), Deep blue normalized difference water index (DBNDWI) (Aroma, R.J. 2023) on satellite data acquired from optical satellite sensors like Sentinel-2 and Landsat-8 for water feature extraction. The aforementioned methods produce accurate results. However, it lacks generalization ability and needs a remote sensing expert. Machine learning has shown great success in flood detection and flood extent mapping. Machine learning methods like Support Vector Machine (SVM), Maximum Likelihood Classifier (MLC), Bayesian Networks (BNs), classification, and Regression Trees (CART) and ensemble bagging method like Random Forest (RF) are utilized for flood detection. For instance, Ireland et al. [7] investigated the potential of SVM in detecting flooded areas from Landsat TM satellite data. Further, Pervez et al. [8] used Landsat 8 OLI data to examine the capability of SVM algorithm for shoreline detection. Shadi Sadat [9] investigated the feasibility of using InSAR and PolSar for flood detection in urban settlements using RF classifiers. Further, Himan Sahabi [10] applied the Bagging–Cubic–KNN ensemble method. The results show that this method outperformed other ensemble methods for flood detection and susceptibility mapping. R. I. Jony [11] used ensemble classifiers to detect water from satellite images. The aforementioned classifier outperforms sophisticated classifiers like SVM. Lamovec Peter [12] applied ML algorithms like Nearest Neighbor, SVM, RF, JRip, and J48 on Rapid Eye satellite images in combination with a digital terrain model and hydrological network for the classification of flooded areas. Though the method provides good results in the plain region, flood mapping in urban and agricultural areas covered with vegetation remains a challenge. Sarah Mazhar [13] implemented flood mapping by leveraging an integrated approach of newly formed MuWI index and ML classifiers like classification and regression tree, SVM, and RF on Landsat 8 and Sentinel 2 satellite imagery. ML algorithms have shown promising results on optical data [13][28]. However, acquiring cloud-free satellite images in flooding situations seems difficult. Recently, deep learning has shown significant performance in flood detection. U-Net, architecture of a CNN, was originally developed for the segmentation of biomedical images [14]. In recent years, several variants of UNet have been proposed. It is now widely adopted and used by researchers and remote sensing experts for floodwater segmentation from satellite imagery. For example, Dong Z et al. [15] assessed the performance of various deep learning models, including ResNet, SegNet, DeepLab V3+, DenseNet, and HRNet, for flood detection. According to the experiment findings, CNN models outperform the conventional techniques [26]. In another study, A hybrid CNN strategy utilizing Inception and U-Net models was used by Lalchhanhima et al. [16]. Only few training samples are required for the aforementioned approach to function successfully. Subsequently, W. Li [17] investigated an additional hybrid approach that combined U-Net with an attention module, yielding impressive results for the detection of flooded areas that were submerged. Further, Bofei [18] proposed Siam-DWENet flood detection method that utilizes an attention mechanism with a multi-scale pyramid structure. The method has demonstrated promising results with a small number of training samples. Building of lightweight deep-learning model is essential. To address this, Alshawi et al. [19] proposed A Depth-Wise Separable U-net architecture in integration with Multiscale Filters to Detect Sinkholes whereas Zabihi 2021 proposed SepUnet for MRI Reconstruction [20]. Though significant work is reported in the literature, building an automatic deep learning model for flood detection remains a challenge.

3. Method

3.1 Dataset

Recently released, multimodal and multi-temporal OMBRIA dataset [21] is utilized for this research work. The dataset is publicly available at https://github.com/geodrak/OMBRIA. [22]. The dataset is composed of SAR Sentinel-1 and optical Sentinel-2 satellite image sequences. Sentinel-1 data is available with VV polarization whereas Sentinel-2 data considers Band-3(Green), Band-8(Near Infrared), and Band-11(SWIR). The authors have utilized both Sentinel-2 and Sentinel-1 satellite images.

Dataset provides before flood, after event and masks images. After flood images and masks are used from the dataset as a subset. This subset of dataset comprises of a total 1250 images. A total of 787 images are used as training samples and 463 images are used as testing samples. The dataset provides satellite image patches of 256 X 256. The images and

corresponding masks are provided in the input. The aim is to segment the flood water from given input images. Fig.1. depicts the images and masks from Sentinel-1 and Sentinel-2.

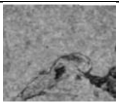			
Sentinel-1 Image	Sentinel-1 Mask	Sentinel-2 Image	Sentinel-2 Mask

Fig. 1. Image samples from the Ombria dataset [21][22]

3.2 Methodology

The proposed method aims to generate the flood segmentation map from remote sensing-based satellite images. The segmentation approach is widely adopted for the aforementioned purpose. The semantic segmentation approach assigns a class label to every pixel in a satellite image. UNet is the most popular and efficient architecture for segmentation tasks. It was introduced by Ronneberger Olaf in 2015 for biomedical image segmentation [14]. It has also shown remarkable performance in the semantic segmentation of satellite images. In recent years, numerous variants of deep learning architecture have been proposed by researchers [23][24][27]. This study, which draws inspiration from UNet [14][17][20], proposes a Hybrid framework DSAAM-UNet to enhance the performance by utilizing Leaky ReLU and by integrating Depth wise separable convolution and attention mechanism in U-Net architecture. The pseudo-code for DSAAM-UNet method is given in Algorithm 1 and the step-by-step procedure is discussed in the subsequent section. The architecture of proposed model is depicted in Fig 2.

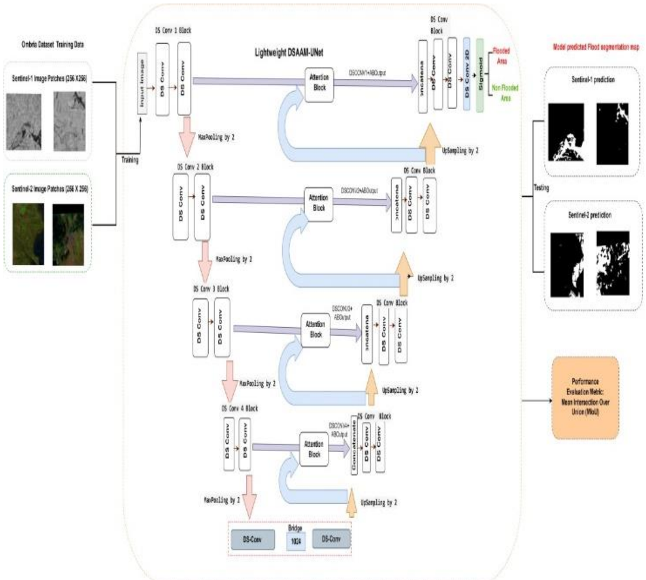

Fig.2. Block diagram of proposed architecture

3.2.1 Pseudocode for proposed method :

Let dataset DS=(X_i,L_i) where X represents the number of images, L represents the class category

L={L1:Flooded,L2:Non-flooded},

Let DS={$DS_{Multispectral}$,DS_{SAR}} DS_{SAR} € Ombrias $_{Sentinel1}$

where $DS_{Multispectral}$€Ombria$_{Sentinel2,}$

The detailed algorithm 1 is explained below.

DSAAM-UNet:Pseudocode for proposed model

```
Input :  Satellite images patches and Masks from dataset DS
Output: Flood segmentation map
BEGIN
Step 1:  Choose dataset  where DS € Ombria_Sentinel2)  OR  DS € Ombria_Sentinel1)
Step 2:  Divide dataset DS into DS_Train ,DS_Validation and DS_Test with split ratio of 70:10:20
Step 4: Construct Depth wise separable Conv block     -DSC block
   DSC block: Add depth wise separable
                    layer with kernel size of 3X3
                    Add Batch Normalization Layer
                    Add Leaky ReLU activation function
Step 5: Construct Encoder Module:
            for i=1 to 4: Add DSC block
                         Add Max Pooling layer
Step 6: Add bridge layer with DSC block
             to generate feature map.
Step 7: Construct Decoder Module: for each block
              Add up sampling with kernel size of 2
              Add Attention layer
              Concatenate output of attention block
               and skip connection
Step 9: Add DSC block
Step10: Add 1X1 Conv with Sigmoid activation function.
Step11: Compute Mean Intersection over Union
Step12: Generate Flood segmentation map for test images.
END
```

3.2.2 *DSAAM-UNet*

The proposed model DSAAM-UNet adopts lightweight encoder–decoder architecture. The proposed architecture consists of a DS-Encoder module, a DS-Bridge or Center block, and a DS-Decoder module. These modules are depicted in Fig.2

Depthwise separable convolution assisted Encoder Module (DS-Encoder module):

The encoder block comprises 4 Depth wise separable convolution (DSC) blocks. In Encoder module, Max pooling layer with a pool size of 2X2 is added after each DSC block. In the proposed model, the DSC block is introduced by employing depth-wise separable convolution, Batch normalization, and the activation function Leaky Rectified Linear Unit (Leaky ReLU). The DSC block consists of Input, followed by depth-wise separable convolution operation with a kernel size of 3X3. Depthwise separable convolution assist to build a model that requires fewer numbers of parameters. The batch normalization layer which makes the training process faster, is added after the depth-wise separable convolution layer. Next, the LeakyRelu activation function

is applied to overcome the dying ReLU problem. Equation

(1) represents the mathematical formula for the Leaky ReLU activation function and Fig 3 depicts the DSC block.

$$LeakyReLU(x) = max(alpha * x, x) \quad (1)$$

Where alpha is small positive constant.

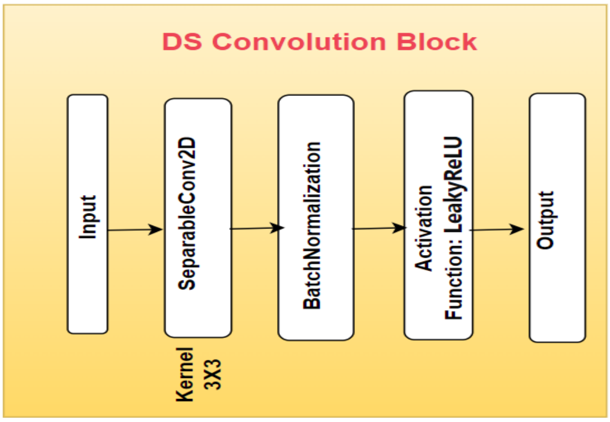

Fig. 3. DS convolution block

DSC block is provided as an input to the max pooling layer. The pool size of 2X2 is utilized for down sampling.

Bridge or bottleneck layer:

A bridge or bottleneck layer is added between the DS-encoder and DS-decoder modules. It comprises two DSC layers followed by batch normalization and Leaky ReLU. This center block generates a feature map.

DS Decoder Module:

The feature map is utilized by the Decoder module to generate a segmentation map with the aid of skip connections. The Decoder module consists of 4 decoder blocks. Each block starts with up sampling by kernel size of 2X2. The output and corresponding skip layer connection from the encoder block are provided as input to the attention block that utilizes Leaky ReLU and Sigmoid activation function. Further, the encoder layer's skip connection and attention block outputs are concatenated. The next steps involve the usage of two depth-wise separable convolution layers followed by batch normalization and Leaky ReLU are used. Flood segmentation considers two classes such as flooded and Nonflooded. Hence, lastly, 1 X 1 convolutions with a sigmoid activation function is added.

3.2.3 Model Training

Dataset plays a vital role in deep learning as it directly impacts the performance. The proposed model is trained on the Ombria dataset (Sentinel-1 data and Sentinel-2 separately). The dataset is split into Training (70%), Validation (10%) and Testing (20%). The dataset consists of 256X256 image patches of flood and non-flood images along with their corresponding masks. The proposed model is trained on this dataset to assess the performance. Adam optimizer is used for optimization. The learning rate of 0.001 is selected. The binary cross entropy is used as a loss function. The model is trained on Ombria training Dataset for 100 epochs. The batch size of 8 is selected for the same. Table 1 depicts the hyper parameters of the proposed architecture.

Table 1. Proposed architecture Hyper parameters

Hyper para meter	Batch Size	Filter Size	Activation Function	Pool size	Optimizer	Learning Rate
Value	8	3X3	Leaky ReLU, Sigmoid	2X2	Adam	0.001

3.2.4 Hyper parameter Tuning

Experiments are conducted with various hyper parameters like batch size, activation functions, and filter size. Various activation functions such as Leaky ReLU and Sigmoid are experimented. The batch size of 8, 16 and 32 are experimented. An experimental result shows that batch size 8 has performed better in comparison to batch size of 16 and 32. Learning rate of 0.001 is used. The best performing hyper parameters are finally selected for proposed architecture.

3.2.5 Performance Evaluation

The performance of a deep learning segmentation model is assessed with metrics such as Intersection Over Union

(IoU) and Mean Intersection Over Union (MIoU).

IoU:

This metric compares the area of overlap between ground truth and the predicted mask to the total number of pixels present across both masks. Generally, IoU ranges from 0 to 1. The 0 value of IoU depicts No overlap whereas value 1 represents the perfect overlap. Equation 2 presents the formula for IoU.

$$IoU = \frac{\text{Area of Intersection}}{\text{Area of Union}} \tag{2}$$

MIoU:

MIoU of semantic segmentation prediction is calculated by computing IoU score of each class separately and then averaging over all classes. Equation 3 represents the mathematical formula for MIoU for multiclass segmentation. The research work considers two classes. Hence, the equation 4 depicts the mathematical formula for two classes as flooded and not flooded.

$$MIoU = \frac{1}{\text{n}}\sum_{i=1}^{n} IoUi \tag{3}$$

$$MIoU = \frac{1}{2}\sum_{i=1}^{n} IoUi \tag{4}$$

4. Results and Discussion

The proposed method is evaluated on the Ombria dataset to assess its performance. All the experiments are performed in the Google cloud platform Google Colab. The experiments are conducted on the Ombria dataset. The optical data samples and SAR data samples available from Sentinel-2 and Sentinel-1 satellite sensors are used respectively. Initially, baseline UNet [14][25] architecture is implemented separately on Sentinel-1 data and Sentinel-2 data.

UNet architecture considers only one input. Hence, only after flood event images are used for training. Next, various hybrid architectures like UNet and attention[17], UNet and Depth-wise separable convolution [20], UNet, Attention, and depth-wise separable convolution architectures are assessed on the datasets for flood segmentation. Batch sizes like 8 and 16 are experimented with. Table 2 depicts the performance evaluation based on training accuracy, validation accuracy, and MIoU for various UNet architectures on Sentinel-1 and Sentinel-2 data. It is observed that using Sentinel-1 data, the highest validation accuracy of 81.27%, highest training accuracy of 97.91%, and highest Mean Intersection over Union 0.630035 is achieved with the proposed hybrid model DSAAM-UNet with a batch size of 8 for 100 epochs. Considering the sentinel-2 data, the highest training accuracy of 98.26%, validation accuracy of 78.37 %, and highest Mean Intersection over Union 0.560702 is achieved with a batch size of 8 for 100 epochs.

Table 2: Sentinel-1 and Sentinel-2 data performance evaluation for 100 epochs

Model	S1Training Accuracy (%)	Validation Accuracy (%)	MIoU	Training Accuracy (%)	Validation Accuracy (%)	MIoU
UNet [14]	72.62	74.61	0.55	73.14	73.68	0.52
UNet+Attention [17]	90.30	78.24	0.58	85.85	71.01	0.49
Unet+Depthwise Separable Conv [20]	85.02	76.3	0.57	82.81	70.97	0.49
Unet+Attention+ Depth wise Sep-arable Conv [**Proposed**]	**97.91**	**81.27**	**0.63**	**98.26**	**78.37**	**0.56**

As shown in Table 2, the accuracy of Sentiel-1 data is better than Sentinel-2. In particular, in Sentinel-1, it is observed that validation accuracy is a little bit more than training accuracy in UNet. In the case of Sentinel-2 flood images training accuracy is found better than validation accuracy.

Table 3 depicts model architecture parameters. DS convolution significantly reduces the parameters in the network. The number of trainable parameters are significantly reduced with depth-wise separable convolution with the proposed model. It helps to build lightweight models. It is observed that Trainable parameters of UNet and depthwise separable convolution are minimal among all architectures. The proposed architecture reduces the training parameters and helps to focus on important features. Fig. 4 and Fig. 5 depict the comparative analysis of Deep learning

model architectures based on accuracy and Mean Intersection over Union respectively.

Table 3: Model architecture parameters

Model	**Total parameters**	**Trainable Parameters**	**Non Trainable Parameters**
UNet [14]	31054145	31042369	11776
UNet +Attention [17]	32457365	32441741	15624
UNet+Depthwise Separable Conv [20]	3576330	3564554	11776
Unet+Attention+ Depthwise Separable Conv [**Proposed**]	4637150	4621526	15624

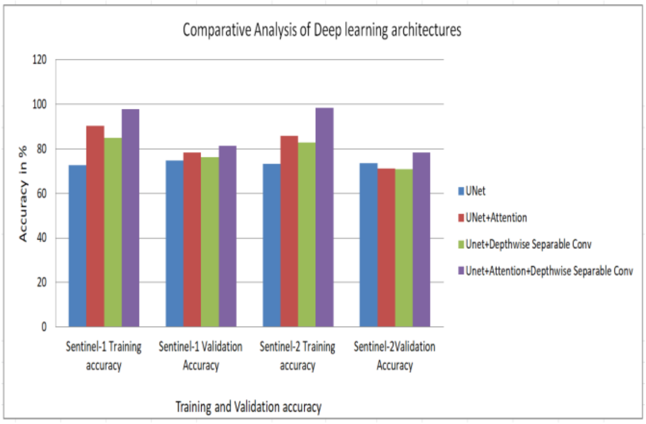

Fig 4. Comparative analysis of Deep learning model architectures based accuracy

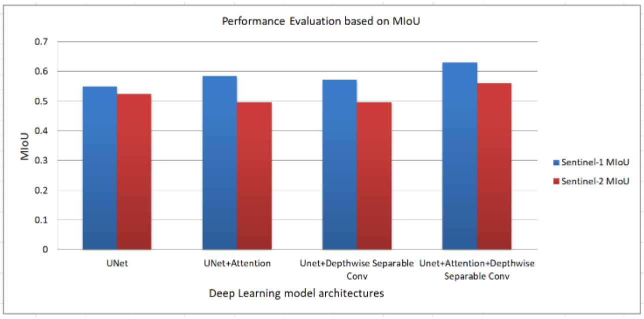

Fig 5. Comparative analysis of architectures based on MIoU

The model is assessed on testing images to check its performance. Fig 6 depicts the Input image, Ground truth and prediction done by Lightweight DSAAM-UNet on Sentinel-1 testing images whereas Fig 7 depicts the Input image, Ground truth and Prediction done by Sentinel-2 testing images. Flood is depicted by white pixels. The proposed model efficiently detects the flood pixels from satellite images.

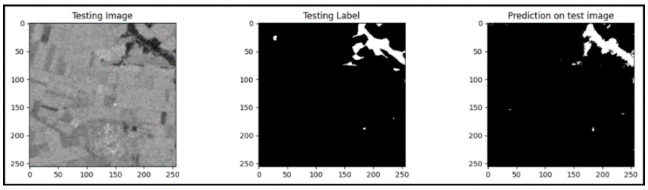

Fig 6. Sentinel-1 predictions made by DSAAM-UNet

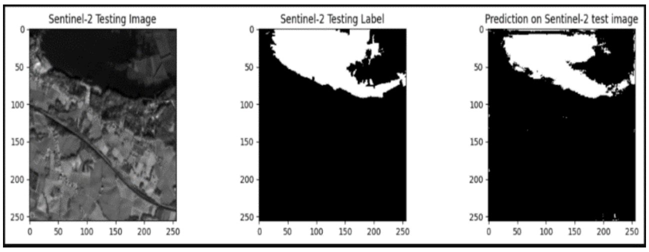

Fig 7. Sentinel-2 predictions made by DSAAM-UNet

5. Conclusion and Future Enhancements

In this paper, the DSAAM-UNet semantic segmentation model is proposed for floodwater segmentation. This model integrates the depth wise separable convolution operation and attention mechanism with UNet. The encoder-decoder structure forms the basis of this model. It defines a depth wise separable block in order to extract spectral features from satellite imagery. The point wise convolution followed by depth wise convolution is used to enhance the model's generalization ability. In order to rebuild the image, the retrieved features are lastly uniformly encoded and sent into the decoding network. The experimental findings demonstrated that, in comparison to currently employed techniques, the DSAAM-UNet model enhanced segmentation accuracy and segmentation effect. The proposed architecture is applied to Sentinel-1 and Sentinel-2 datasets available in the Ombria dataset. The number of trainable parameters was significantly decreased by using depth-wise separable convolution operation. It is observed that the proposed model provides better results on Sentinel-1 data in comparison to Sentinel-2 data. The accuracy of multispectral and SAR images with small samples is effectively improved for flood detection.

Declarations

Author contributions

All authors contributed to the study's conception and design. Kavita Bathe: Material preparation, analysis and writing of the first draft of the manuscript. Nita Patil: Final structure, editing and critical review of the final draft.

Conflict of Interest:

There is no conflict of interests regarding the publication of this article.

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