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Flood Detection regions Model using Whale-Crow Search Optimization based Deep Convolutional Neural Network

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Abstract : The advancements in satellite images have attracted more attention in the field of flood detection. Flood detection is an important task for planning actions during emergencies, but the major obstacle is to detect the flooded regions using satellite images. This paper design a model named Whale-crow search algorithm based deep convolutional neural network (W-CSA DCNN) model for flood detection. The proposed model undergoes four steps namely pre-processing, segmentation, feature extraction, and classification. At first, a satellite image is given to pre-processing for extracting noise and artifacts from the input image. Then, the pre-processed image is subjected to the feature extraction process for extracting the features based on vegetation indices. The obtained features are then used in the segmentation process, which is done using Kernel Fuzzy Auto regressive (KFAR) model. Once the segments is obtained, then the segments are given to the classification, which is performed using the DCNN, which is trained optimally using the proposed W-CSA that is obtained from the combination of Crow search Algorithm (CSA) and Whale optimization algorithm (WOA) The performance of the proposed method shows superior performance than the existing methods based on accuracy, specificity, and sensitivity with values 0.972, 0.982, and 0.975 respectively.

1.INTRODUCTION: The advancements in satellite imagery has gained many attention thanks to its emerging and advanced functionalities, which may detect the flooding that covers huge geographical areas, and offer plenty of benefits to the in-situ data sources. the data attained from the satellite imagery is a smaller amount spatial and temporal resolutions are expensive to achieve. the standard and also the quantity of the accessible satellite products on the events are significantly improved. The enhancements using satellite images had result in the expansion of automated flood mapping techniques [13]. Additionally, offering the crucial information in emergencies has greatly improved the understanding of flood dynamics. the knowledge is devised from the satellite imagery and may be utilized for standardizing and validating the hydrodynamic models thereby, enhancing the accuracy of prediction [14]. The satellite imagery are categorized into two categories, namely synthetic aperture radar (SAR) and optical sensors and these satellite images will be accessible in spatial resolutions for managing the surface water dynamics. Various land covers demonstrates precise reflective characteristics for every spectral band which will be utilized for identifying the watery areas [15], [16], [17], and [9]. The usage of images tends to supply more suitable outcomes within the existence of decisive circumstances. additionally, the interferometric SAR (InSAR) and also the coherence information are the feasible means to detect the flooded regions as an expansion of existing detection mechanisms. the issues in preparing pairs of SAR acquisitions are inappropriate in SAR. Moreover, the SAR determines the problems in operational scenarios for monitoring the floods. The rehabilitated attention for this problem came up using high-resolution sensors [4]. Thus, the satellite imagery for mapping the floods is applicable within the following sectors: Landsat-7 sensors [24], Moderate Resolution Imaging Spectroradiometer (MODIS), and Advanced Spaceborne emission, Advanced Very High Resolution Radiometer [23], and Reflection Radiometer (ASTER). The Landsat 7 TM images obtained before and after processing are utilized for identifying the watery features for identifying the flooded regions [3].

IMPLEMENTATION : The proposed W-CSA algorithm-based DCNN is adapted for detecting the floods using the satellite images. Assume a database with satellite images and the need for flood detection is to detect the floods using the satellite images. The overall procedure of theproposed technique involves: pre-processing, feature extraction, segmentation, and classification. At first, the satellite images are considered fromthe geographical area, like Kerala floods. Then, the obtained images are subjected to pre-processing in which the noise and artifacts are removed from the image using filtering method. The obtained pre-processed images are subjected to feature extraction phase in which the vegetation indices are extracted from the pre-processed image.

Proposed W-CSA based DCNN: : The proposed W-CSA-based DCNN is used for detecting the floods using the satellite images and W-CSA-based DCNN is that the application of the proposed W-CSA algorithm for training the DCNN. The proposed W-CSA is obtained by modifying the update equation of CSA algorithm using WOA.

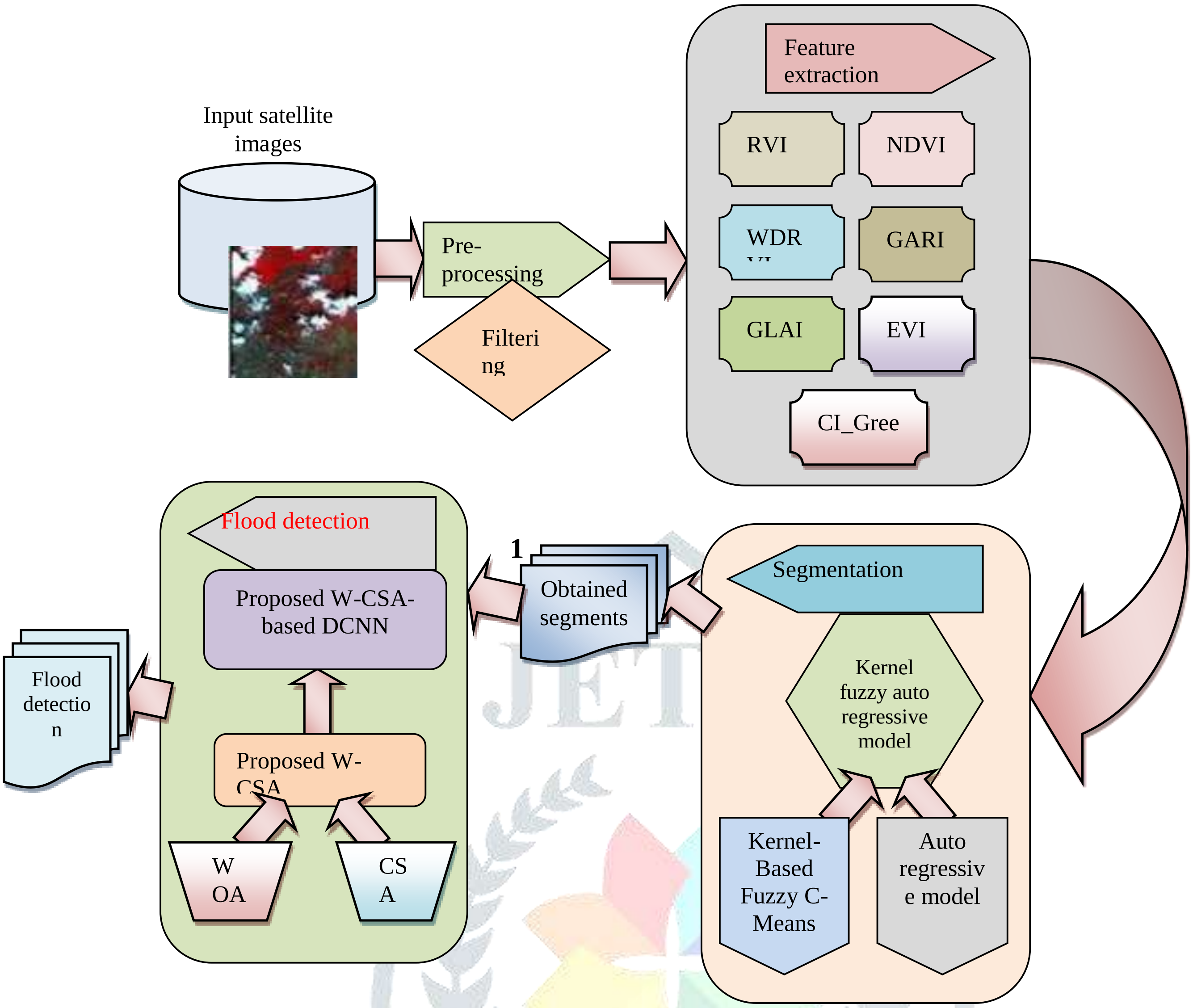


Figure 1. Block diagram of flood detection model using proposed W-CSA-based DCNN

Pre-processing: The importance of pre-processing is to facilitate smooth processing of the input satellite image and it is progressed using the filtering methods.The pre-processing is done to make the image suitable for segmentation.

Feature extraction based on vegetative indices: Once the pre-processed image is obtained, then the feature extraction is initiated in which the significant vegetativeindices are extracted from the input satellite image.

Segmentation: The obtained features aresubjected to the segmentation process for partitioning the image into segments. Here, the segmentation is performed using the KFAR model, which is designed by integrating KFCM [21] and auto regressive model, CAVIAR [29]. The benefit of using CAVIAR is to address the optimization issues concerning the selection of the optimal solution from the set of feasible solutions.

Classification: After obtaining thesegments, the classification process begins using the newly devised classifier, proposed W-CSA-based DCNN. Here, the flood detection using the proposed W-CSA-based DCNN is presented and theclassification is progressed using the

segments of input satellite image. The segments are presented for classificationusing DCNN and the training of the classifier is done using the proposed training algorithm, called W-CSA, whichis the modification of CSA [32] with the WOA [31]. The main aim of the proposedW-CSA-based DCNN is to acquire the segments of the input image and then classify the images for detecting the floodsbased on the features extracted from the input satellite image

.Algorithmic steps of the proposedW-CSA:

a) Initialization

b) Compute the error

c) Computation of the weights

d) Fitness evaluation for the new solutions

e) Terminate

RESULTS AND DISCUSSION:

This section illustrates the result of proposed W-CSA with respect to existing methods in terms of accuracy, specificity, and sensitivity. The analysis is carried out based on K-fold and training data percentages.

Experimental setup

The experimentation of the proposed W-CSA is implemented in MATLABoperating in the PC containing windows10 OS and 2GB RAM.

Competing methods: The analysis is performed on the method, which involves Artificial Neural Network (ANN) [34], Radial Basis Function Network (RBFN)[35], DCNN [36], and proposed W-CSA DCNN based on sensitivity, accuracy, and specificity. The analysis is carried out using training data percentage and K-Fold values.

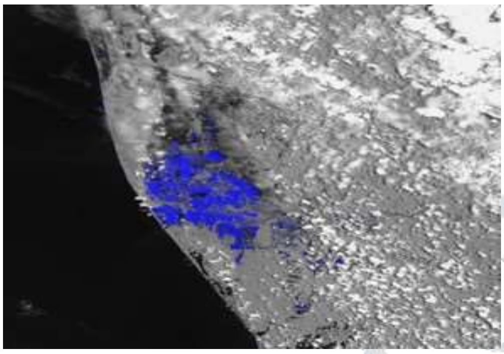
Experimental results

a

(b)

(c)

(d)



(e)

Figure 3 Experimental results of proposed W-CSA using a)Original image, b) Pre-processed image, c) Feature extracted image, d) Segmented image, e) Classified image

4.6 Performance analysis

The analysis of the proposed W-CSA-based DCNN is carried out with different number of epoch values. The performance analysis is carried out by varying the values of training data percentages. values. The performance analysis is carried out by varying the values of training data percentages.

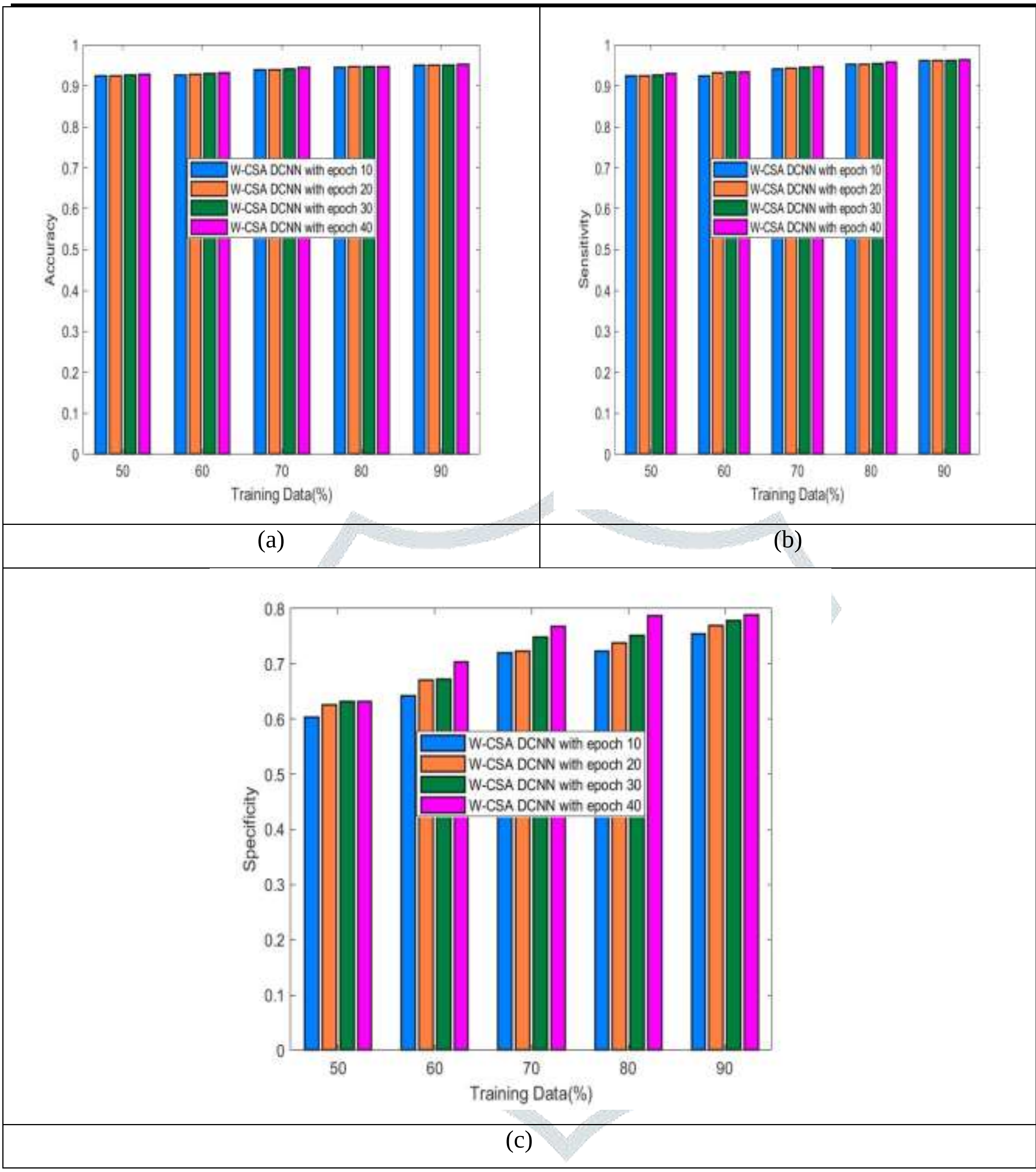


Figure 4 Performance analysis of proposed W-CSA DCNN based on a) Accuracy b) Sensitivity c) Specificity

Figure 4 illustrates the performance analysis of proposed W-CSA-based DCNN in terms of accuracy, sensitivity, and specificity based on varying epoch values. The analysis is carried out using training data percentages which is varied from 50% to 90%. The analysis based on accuracy metric for proposed W-CSA-based DCNN is depicted in figure 4a. When the training data percentage is 50, the corresponding accuracy values measured by W-CSA-based DCNN with epoch 10, W-CSA DCNN with epoch 20, W-CSA DCNN with epoch 30, W-CSA DCNN with epoch 40 are 0.923, 0.925, 0.926, and 0.928 respectively. Similarly, when the training data is 90%, the corresponding accuracy values computed by W-CSA DCNN with epoch 10, W-CSA DCNN with epoch 20, W-CSA DCNN with epoch 30, W-CSA DCNN with epoch 40 are 0.949, 0.951, 0.951, and 0.951 respectively. The analysis in terms of sensitivity metric for proposed W-CSA DCNN is depicted in figure 4b. For 50% training data, the sensitivity values computed by W-CSA DCNN with epoch 10, W-CSA DCNN with epoch 20, W-CSA DCNN with epoch 30, W-CSA DCNN with epoch 40 are 0.923, 0.924, 0.926, and 0.930 respectively. When the training data is 90%, the sensitivity values computed by W-CSA DCNN with epoch 10, W-CSA DCNN with epoch 20, W-CSA DCNN with epoch 30, W-CSA DCNN with epoch 40 are 0.960, 0.961, 0.962, and 0.964 respectively. The analysis based on specificity metric for W-CSA DCNN is depicted in figure 4c. When the training data is 50%, the corresponding specificity values measured by W-CSA DCNN with epoch 10, W-CSA DCNN with epoch 20, W-CSA DCNN with epoch 30, W-CSA DCNN with epoch 40 are 0.602, 0.626, 0.631, and 0.632 respectively. Likewise, for 90% training data, the corresponding specificity values computed by W-CSA DCNN with epoch 10, W-CSA DCNN with epoch 20, W-CSA DCNN with epoch 30, W-CSA DCNN with epoch 40 are 0.754, 0.769, 0.778, and 0.788 respectively.

CONCLUSION: The flood detection is performed using the DCNN, which aims at enhancing the performance of flooddetection using satellite images. The flood detection model undergoes three stages for detecting the flooded regions, which involves pre-processing, feature extraction, segmentation, and classification. At first, the satellite image is subjected to the pre-processing phase in which the noise and artifacts present in the image are removed and then the pre-processed image is further given to feature extraction.

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