International Journal of Current Advanced Research
ISSN: O: 2319-6475, ISSN: P: 2319-6505, Impact Factor: 6.614
Available Online at www.journalijcar.org
Volume 11; Issue 04 (B); April 2022; Page No.676-678
DOI: http://dx.doi.org/10.24327/ijcar.2022.678.0152

Research Article

FLOOD DETECTION REGIONS MODEL USING WHALE-CROW SEARCH OPTIMIZATION BASED DEEP CONVOLUTIONAL NEURAL NETWORK

Sharayu S. More*, Salokhe B. T and Mali A.S

Dept. of Eln.Engg, TatyasahebKoreInsti. of Engg. & Tech. Warananagar.
Affiliated to Shivaji University Kolhapur. Maharashtra

A R T I C L E I N F O

Article History:
Received 06th January, 2022
Received in revised form 14th February, 2022
Accepted 23rd March, 2022
Published online 28th April, 2022

Key words:

Flood detection is an important task

A B S T R A C T

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).

INTRODUCTION

The flood is the calamitous innate disasters, which usually arises in various humid nations, like Malaysia [18]. The response activities are required for controlling and preventing the disaster. The detection of flood and mapping are the important steps for managing the risk reduction programs and flood disasters [19]. Flood records are described using the map, which elaborates location of the flooded regions in a specific time and a specific region. Fieldworks are carried out for mapping and monitoring the floods with limited time and weather conditions [20]. The technical progress in geospatial sensors and remote sensing offers advanced mechanisms and tools for detecting the floods and mapping [2]. Flood is generally occurred due to extreme and continues rainfall with more river discharge causing huge damages. The flooding causes devastation of ecological resources, massive economic losses, shortage of foods, and starvation. Hence, the major distress of different countries is to observe flooding so as to reduce the possessions of floods. In satellites, the sensing of remote data is utilized for recognition, evaluation, and managing the flood disaster [21]. The classification systems are exhaustive, separable, and informative [10]. The classification of satellite image contains many tasks for preprocessing, which involves removal of noise, extraction of features using image segmentation, and contrast enhancement [12]. The suitable numbers are selected and the training samples types are considered for the classifying the image [10]. Thus, before designing the classification model, it is crucial for selecting the proper remote sensing data as dissimilar sensors gives images with dissimilar temporal resolutions, radiometric and spatial [3].

Relevance

The flood is the calamitous innate disasters, which usually arises in various humid nations, like Malaysia [2]. The response activities are required for controlling and preventing the disaster. The detection of flood and mapping are the important steps for managing the risk reduction programs and flood disasters. Flood records are described using the map, which elaborates location of the flooded regions in a specific time and a specific region. Fieldworks are carried out for mapping and monitoring the floods with limited time and weather conditions. The technical progress in geospatial sensors and remote sensing offers advanced mechanisms and tools for detecting the floods and mapping [3]. Flood is generally occurred due to extreme and continues rainfall with more river discharge causing huge damages. The flooding causes devastation of ecological resources, massive economic losses, shortage of foods, and starvation. Hence, the major distress of different countries is to observe flooding so as to reduce the possessions of floods. In satellites, the sensing of remote data is utilized for recognition, evaluation, and managing the flood disaster. The classification systems are exhaustive, separable, and informative [4]. The classification

Corresponding author:* **Sharayu S. More

of satellite image contains many tasks for preprocessing, which involves removal of noise, extraction of features using image segmentation, and contrast enhancement [5]. The suitable numbers are selected and the training samples types are considered for the classifying the image [4]. Thus, before designing the classification model, it is crucial for selecting the proper remote sensing data as dissimilar sensors gives images with dissimilar temporal resolutions, radiometric and spatial [6].

Numerous classification methods are devised on the basis of neuro-fuzzy techniques, artificial neural networks, expert systems, fuzzy sets, and decision trees are adapted for classifying the image for performing flood detection [6].

Implementation: The primary intension of the proposed system is to model a technique that detects the flood using the satellite images. The proposed technique is processed in four steps, such as pre-processing, feature extraction, segmentation, and classification.

- At first, the input image is pre-processed using the filtering method such that the input is made effective capable for feature extraction by eliminating the noise and artifacts from the image.
- In the feature extraction process, vegetation indices, like Ratio Vegetation index (RVI), Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), Wide Dynamic Range Vegetation Index (WDRVI), Green Atmospherically Resistant Vegetation Index (GARI), Green Chlorophyll Index (CI_Green), and Green Leaf Area Index (GLAI) are extracted and given to classification module for detecting the floods.
- Once the features are extracted, the features are subjected to the segmentation process, which is performed by KFAR model.
- Then, the obtained segments are given to the classification module in which the classification is progressed using the DCNN, which is trained using the proposed W-CSA algorithm that is the integration of the CSA and WOA. Thus, the proposed W-CSA-based DCNN can be adapted for detecting the floods.

The major contribution of the research is

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.

Architecture of DCNN

The basic architecture of the DCNN [33][27] is illustrated during this section using figure 2. DCNN contains convolutional (conv) layers, pooling (POOL) layers, and Fully Connected (FC) layers, where each layer is chargeable for performing a novel task. The goal of conv layers is to create the feature maps using the segmented image and therefore the feature maps are further sampled all the way down to obtain the pool layers, which is that the second layer in DCNN. Lastly, the FC layer performs the classification. Each of the layers are chargeable for performing specific functions, like forming feature vectors in conv layers, sampling feature maps in pool layers and at last, classification is completed using fully connected layers. The classification accuracy is improved employing a sizable amount of conv layers in DCNN. The DCNN is taken into account as a vital classifier for analyzing the pictures to supply better classification outcomes.

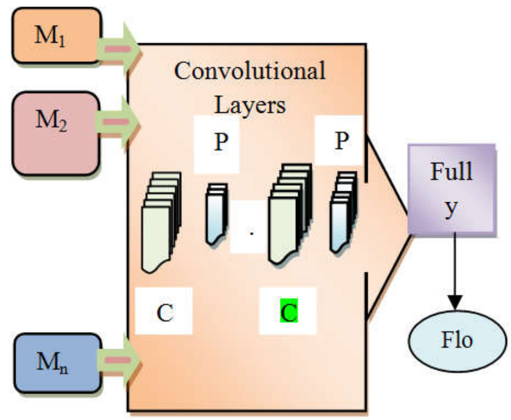

Figure 2 Architecture of DCNN

The function of conv layers, POOL layers, and FC layers are answerable for the classification to detect the flood from the satellite images.

Conv layers: The conv layer is created by interconnecting number of neurons to make the fields, by connecting the neurons of consecutive layers using the trainable weights and therefore the results of the convolution is shipped to the non-linear activation function. The input to the convolution layer is that the segments obtained from the input satellite image.

POOL layer: The pool layers are adapted for undergoing a set operation and its features are given to the fully connected layers and therefore the image is transformed to a vector and it classifies the image. The activation function is tailored to make sure effectiveness and ease and to process faster while addressing large networks.

Fully connected layers: The patterns generated using the pool and therefore the conv layers form the input to the fully connected layers that are subjected to high-level reasoning.

CONCLUSION

The flood detection is performed using the DCNN, which aims at enhancing the performance of flood detection 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 innovate which the noise and artifacts present within the image are removed then the pre-processed image is further given to feature extraction. In feature extraction, the features like RVI, NDVI, EVI, WDRVI, GARI, CI_Green, and GLAI are extracted. the subsequent step is segmentation during which the KFAR model is applied to get the segments. The segmented result's given to the classification phase, which is dispensed using the DCNN that's trained optimally using the proposed W-CSA, where W-CSA is obtained from the mixture of WOA and CSA.

References

1. BiswajeetPradhan, MahyatShafapourTehrany, and Mustafa NeamahJebur, "A New Semiautomated Detection Mapping of Flood Extent From TerraSAR-X Satellite Image Using Rule-Based Classification and

Taguchi Optimization Techniques", IEEE Transactions On Geoscience And Remote SENSING, vol.54, no.7, pp. 4331 - 4342, July 2016.
2. BiswajeetPradhan,Maher Ibrahim Sameen, and BaharehKalantar, "Optimized Rule-Based Flood Mapping Technique Using Multitemporal RADARSAT-2 Images in the Tropical Region", IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol.10 , no.7, pp.3190 - 3199, July 2017.
3. Akansha Singh, and Krishna Kant Singh, "Satellite image classification using Genetic Algorithm trained radial basis function neural network, application to the detection of flooded areas", Journal of Visual Communication and Image Representation,vol. 42, pp.173–182,2017.
4. AnnaritaD'Addabbo, Alberto Refice, Guido Pasquariello, Francesco P. Lovergine, DomenicoCapolongo, and Salvatore Manfreda, "A Bayesian Network for Flood Detection Combining SAR Imagery and Ancillary Data", IEEE Transactions on Geoscience and Remote Sensing, vol.54 , no.6 , pp.3612 - 3625, June 2016.
5. Yu Li, Sandro Martinis, Simon Plank, and Ralf Ludwig, "An automatic change detection approach for rapid flood mapping in Sentinel-1 SAR data", International Journal of Applied Earth Observation and Geoinformation, vol.73, pp.123-135, 2018.
6. Yan Wang, LanDu,andHui Dai, "Unsupervised SAR Image Change Detection Based on SIFT Keypoints and Region Information", IEEE Geoscience and Remote Sensing Letters, vol.13, no.7, pp.931 - 935, July 2016.
7. Sanmei Li, Donglian Sun, Mitchell D. Goldberg, Bill Sjobergb, David Santek, Jay P. Hoffman, Scott Lindsey, and Eric Holloway, "Automatic near real-time flood detection using Suomi-NPP/VIIRS data", Remote Sensing of Environment, vol.204, pp.672–689, 2018.

How to cite this article:

Sharayu S. More *et al* (2022) 'Flood Detection Regions Model Using Whale-Crow Search Optimization Based Deep Convolutional Neural Network', *International Journal of Current Advanced Research,* 11(04), pp. 676-678.
DOI: http://dx.doi.org/10.24327/ijcar.2022.678.0152

****