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Convolutional Neural Network Based Water Resource Monitoring Using Satellite Images

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Abstract- Perception of surface water is utilitarian necessity for contemplating natural and hydrological processes. Ongoing advances in satellite-based optical remote sensors have advanced the field of detecting surface water to another period. Observing surface water with old-style strategies isn't a simple undertaking. Remote detecting with wide inclusion and different fleeting observing is the best answer for surface water checking. This project exhibits the extraction of water resources from non-water bodies, for example, vegetation, urban regions, and so forth. Using machine learning (ML) algorithms. The data used in the process have been collected from BHUVAN open data archive. This paper also targets measuring the area of a particular water body using GIS. Water bodies have strong absorbability and low radiation in the range from visible to infrared wavelength.CNN speaks of a blueprint for all-round picture handling using neural means. CNN force imperative casing function admirably fit the preparation of spatially or momentarily coursed data. The results display the binary classified output which has been extracted using a neural network and also water body statistics using GIS.

Keywords: Water monitoring, Convolution Neural Network.

I. INTRODUCTION

Surface water insinuates water outwardly of Earth, for instance, conduit, lake, wetland, and the ocean. By and large, the ocean is dismissed in definition since it is so tremendous and because it is salty, anyway more diminutive saline water bodies are ordinarily included. This definition is gotten in this review. Surface water bodies are inessential freshwater resource, for both human and ecological systems.

They are of fundamental centrality in supporting a wide range of lives. Water ensures the biodiversity in riparian or wetland organic frameworks by offering domains to a lot of verdure. It isn't only essential to the organic frameworks as a key piece of the hydrologic cycle yet furthermore contacts each piece of our lives, for instance, drinking water, cultivation, power creation, transportation, and daily needs. Surface water bodies are dynamic as they wither, develop, or change their Appearance or course of the stream with time, inferable from different types and human provoked variables.

Assortments in water bodies influence other trademark resources and HR and further affect the earth. Change in surface water volume regularly causes authentic outcomes. In silly cases, snappy addition of surface water can realize flooding. Thusly, it is basic to capably perceive the nearness of surface water, to remove its degree, to quantify its volume, and to screen its components.

II. LITERATURE SURVEY

1. An Inversion-Based Fusion Method for Inland Water Remote Monitoring:

Although remote sensing technology has been widely used to monitor inland water bodies, the lack of suitable data with high spatial and spectral resolutions has seriously obstructed the practical development of inland water color remote sensing.

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An inversion-based fusion (IBF) algorithm is proposed to fuse water color and high-spatial resolution images. The algorithm was applied to two datasets: The Hyperion simulated dataset (dataset #1) and a pair of Environmental Satellite 1 (HJ1, launched by China in 2009) and medium resolution imaging spectrometer images (dataset #2).

The fusions are quantitatively and qualitatively compared with three widely used algorithms. The results show that the IBF algorithm performs better using both evaluation indexes and visual comparisons.

A discussion of the free parameter window size n and the contribution of the low-resolution image (LRI) to the spatial distribution (wLRI) shows that a larger n will result in both greater model errors and better control of geometric errors, whereas wLRI helps stabilize the algorithm.

Finally, chlorophyll-a concentration maps are developed from the fusions. The significant advantage of the IBF-derived chlorophyll-a concentration map indicates that the IBF algorithm has the potential to advance the monitoring of optical complex inland water.

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2. Index-Based Identification of Surface Water Resources Using Sentinel-2 Satellite Imagery:
Water is a key variable for the sustainability of the world. Surface water resources are of prime importance for all living creatures. Thus, these resources should be monitored for proper water planning. In this study, we aimed to identify which spectral water index will represent water body better when the data of new imaging satellite, namely Sentinel-2, are used. Since these indices were originated from old Land sat missions, it is important to investigate the performances of these indices with other data resources. Catalan and Yedigöze dam reservoirs were considered as the study area. Normalized Difference Water Index (NDWI) and Modified Normalized Difference Water Index (MNDWI) were utilized as spectral indices. The obtained results showed that NDWI presented water body better than MNDWI when using Sentinel-2 data.

As a statistical metric, the kappa values of NDWI and MNDW were obtained as 0.88 and 0.83 respectively. The results have revealed that remote sensing technology and remotely sensed images are important resources for surface water monitoring and management.

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III. MATERIALSANDMETHODS

1. Dataset:
Image-based Water identification includes Training phase, Evaluation phase etc. it requires large amount of data. Hence the source of data is collected from website. The image thus collated is labeled with different categories.Correspondingly, a database compromising of more than 500 images was used for training and around 100 images were used to validate.

2. Process and Label of Images:
Several sets of images were collected from website, which were spread across several formats having varying levels of resolutions and variations in quality. Thus for the purpose of acquiring reasonable feature extraction, the final images are provided as input to the classifier which are then pre-processed to achieve consistency.

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IV. IMPLEMENTATION

1. Data Collection:

The images are collected from the ISRO's geoportal known as Bhuvan, which is a data archive openly available for downloads. Various types of data downloading methodologies are present such as bounding boxes, map sheet, tiles, and interactive drawing. In this paper, map sheet is preferred to download the images. Enter the map sheet id to get the relevant data. Select and download the data according to the requirement. A zip file is downloaded and when extracted images with its metadata are obtained.

2. Data Cleaning:

The fundamental point of data cleaning is to recognize and evacuate blunders and copy information, to make a dependable dataset. This improves the nature of the preparation information for investigation and empowers precise dynamics.

3. Data Normalization:

Data Normalization is a strategy regularly applied as a component of information groundwork for AI. The object of normalizations to change the estimations of numeric sections in the dataset to a typical scale, without controlling contrasts in the scopes of qualities. For AI, each dataset doesn't require normalization.

4. Data Labeling:

Data labeling, with regards to AI, is the way toward identifying and labeling information testes. Marked information features information highlights- or properties, attributes, or arrangements- that can be broken down for designs that help foresee the objective.

5. CNN

CNN's are beneficial for picture courses of action and affirmation taking into account its high precision. Each specific neuron gets different data sources and a short time later takes weighted total over them, where it goes through an order work and responds with a yield. CNN's are very basic level used to arrange pictures, bunch them by similarities, and thereafter perform object affirmation.

6. GIS:

The use of GIS in water is ceaselessly on the climb. GIS applications are presented including surface hydrologic and groundwater illustrating, water deftly and sewer structure showing, nonpoint pollution exhibiting for cultivating domains, and other related application

V. RESULTS

The collected dataset is divided into 70% for the training, 10% for validation and 20% for testing. Different models with different architectures and learning are tested. Trial and error methods are used to select the parameters of the network, the parameters in the architecture are kernel size, filter size, learning parameters etc. The below table depicts the classification results from different models using different architectures.

Table 4: indicates graph of training accuracy versus actual accuracy from the results, we found that colored images is better than gray scale and the segmented images. This shows the color feature is important to extract the features for classifying. The model that provides good classification accuracy contains three convolution layers followed by max pooling layer. The graphs of the training accuracy vs. validation accuracy of the model are shown. It can be seen from the graphs that the model is over fitting. Over fitting happens when the model fits too well to the training set. It then becomes difficult for the model to generalize to new examples that were not in the training set.

Experiments were conducted to see how each model performs. Since the data is too small when compared to the total number of trainable parameters of the model, the first experiment was to increase the training data by rotating, flipping, rescaling of the images. Only the training data is augmented.

VI. CONCLUSION

In this paper, a hybrid of 3-D and 2-D CNN-based network architecture is proposed for satellite images classification. We also propose a strategy (namely, target-pixel orientation (TPO)) to incorporate spatial and spectral information of satellite images. In general, classification accuracy degrades due to mis-classification at the boundary region. Our approach attempts to take care of this limitation by using the orientation of the Target-pixel view. Our architectural design of neural network exploits point-wise 3-D convolutions for band reduction whereas we adopt multi-scale 2-D inception like architecture for feature extraction. We have tested the granular arrangement of multi scale convolutions in inception like architecture in (TPOCNN2).

We find TPO-CNN2 provides better results compared to TPO-CNN1. The experimental results with real satellite images demonstrate the positive impact of including TPO strategy. Also, the proposed work improves the performance of the classification accuracy compared to the state of the art methods even with a smaller number of training samples (For example, 150 samples per class). All the experimental results suggest that the arrangement of multi-scale convolutions in TPO-CNN2 provides more useful features compared to TPOCNN1.

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