Third Review Document

Extraction of Water Bodies from SAR Images Using Deep Learning

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1. Introduction

1.1. Theoretical Background

There are regional limitations in ancient strategies of water body extraction. for various terrain, all the methods believe heavily on rigorously hand-engineered feature choice and enormous amounts of previous knowledge. because of the issue and highcost in acquiring, the tagged information of remote sensing is comparatively small. Thus, there exist some challenges within the classification of huge quantity of high dimension remote sensing data. Deep Learning encompasses a sensible capability of hierarchic feature learning from unlabeled data. Stacked distributed autoencoder (SSAE), one deep learning method, is wide investigated for image recognition.Therefore the proposed model was tested on three different terrains,i.e, desert, urban and hilly areas.

1.2. Motivation

Water body extraction is still confronted with a long-standing challenge in removing various shadows (including shadows of mountains, buildings and clouds, etc.) and eliminating noise within water. To figure out that, proposed a model for water body extraction.

1.3. Aim of the proposed Work

The aim of this paper is to extract the best possible results while extracting water bodies from SAR images using advanced deep learning techniques along with finding the best suitable algorithm for image extraction.

Our secondary aim is to implement a model based on one of the features(MNDWI in our case) to show working of an example model.

1.4. Objective(s) of the proposed Work

The main objective of this paper is to use highly efficient deep learning techniques such as Stacked Sparsed Autoencoders along with a newly proposed “Feature Expansion Algorithm” to tune precise details/boundaries while extracting features from the SAR images.

Our other objective is to implement a mini working model using Python and Sentinel-2 Landsat datasets.

2. Literature Survey

Title	Authors	Key Points	Conclusion
1. **A novel deep learning instance segmentation model for automated marine oil spill**	Shamsudeen Temitope Yekeen , Abdul-Lateef Balogun , Khamaruzaman B. Wan Yusof	• Machine learning and deep learning for oil spill detection and discrimination Conceptual architecture of Mask Region-based Convolutional Neural Network (Mask R-CNN) deep learning model • Different from the conventional machine	• the RPN loss, which gives information on how well the background is separated from the objects; ROI loss indicating how well the region of interest is detected; and overall model loss which measures the model’s performance in segmenting the objects of interest, taking into consideration the different components contained in MaskRCNN. • This study developed a novel deep learning model for oil spill detection and

detection		learning models like SVM, RF, and ANN, deep learning object detection, reorganization and instance segmentation is a computer vision technology for processing images. • Mask R-CNN modelling of oil spill detection and segmentation. The modelling was done in three stages. • The first stage was the input of the already annotated SAR images. 2530 images were tagged as training and validation with a percentage distribution of 70% (1771) training images and 30% (759) validation images respectively for feature extraction and generation of ROI. • The second stage involved feeding the output from the features' extraction into the Regional Proposal Network (RPN) which is a lightweight CNN that	segmentation using Mask R-CNN in a two sectional methodological approach which is advanced and different from other methods as it uses pixel value for inference.

		enables the creation of boundary box on the different elements of interest ● In the third stage, the region of interest (ROI) was aligned with the anchors produced by the RPN to enable the fully connected (FC) layer and the fully convolutional network (FCN) predict the class of the elements.	
2. Fusion of SAR, Optical Imagery and Airborne LiDAR for Surface Water Detection	Katherine Irwin 1,*,Danielle Beaulne 1,2,Alexander Braun 1 and Georgia Fotopoulos 1	● Synthetic Aperture Radar (SAR) systems are helpful in this way for wetland resources because their data can be used to map and monitor changes in surface water extent, saturated soils, flooded vegetation, and changes in wetland vegetation cover. ● We use the Curvelet-based change detection and the Wishart-Chernoff Distance approaches to show how they substantially improve mapping of flooded vegetation and flagging areas of change, respectively.	● Analysis of Synthetic Aperture Radar Imagery data is an excellent approach for mapping and monitoring changes within a wetland. The ability of SAR data to be acquired at night and in a variety of weather conditions makes it a reliable and consistent source of information. Past studies have demonstrated that grey-level thresholding is an effective way to map surface water. Finally, the Wishart-Chernoff Distance change detection approach could be used to flag areas of change prior to implementing polarimetric decompositions to characterize these changes. To be able to monitor the status of wetlands on a frequent basis and capture the dynamic changes both seasonally and annually we recommend SAR as the primary source of imagery, supported by other data sources such as lidar, thermal, and

		• a Curvelet-based approach for detecting changes in flooded vegetation has been used . This technique was developed by Schmitt et al and can be used to map changes between SAR images while at the same time suppressing speckle noise, which can be problematic in SAR imagery.	optical imagery, where feasible.
3. **A Collection of SAR Methodologies for Monitoring Wetlands**	Lori White ,Brian Brisco, Mohammed Dabboor, Andreas Schmitt and Andrew Pratt	• The detection and monitoring of surface water and its extent are critical for understanding floodwater hazards. Flooding and undermining caused by surface water flow can result in damage to critical infrastructure and changes in ecosystems. • However, fewer studies discuss the ability to integrate all three. A number of studies assess the ability of an integrated model to detect wetlands, e.g., the focus is on prairie grasslands and LiDAR	• A fused model was developed by exploiting the strengths of three unique remote sensing techniques. Five different fused water models were created, representing the timeline during which the SAR scenes were acquired. • Pixels at which all sensors disagree, principally along shorelines and over wetlands, increase through time which relates to the increase in tree canopy causing a shadow and layover error. Optical disagreement lessens while LiDAR disagreement increases and SAR disagreement remains stable. Finally, LiDAR only increases as the number of commission error of water increases from the growing tree canopy throughout the season.

		is used to correct terrain effects in the SAR models. • Airborne LiDAR scanning (ALS) surveys use laser pulses to collect both positional and intensity information for each reflector. • Much progress has been made in using LiDAR intensity data to classify land cover from the first proof of concept study performed by [28]. This study uses a pixel-based decision tree classification system which incorporates parameters derived from both the positional and intensity data to identify bodies of water [2,29]. Both intensity and positional data were used as inputs to the model to capitalize on the wealth of data provided by LiDAR surveys.	
4. DEEP LEARNING FOR EXTRA	Liu Yang, Shengwei Tian, Long Yu, Feiyue Ye, Jin	• To extract water more precisely, pattern recognition methods have been widely used	• In this paper, a new water body extraction model based on SSAE is established. At first, current useful features (NDWI, NDVI, NDBI and so

	CTING WATER BODY FROM LANDSAT IMAGERY(2015)	Qian and Yurong Qian	in classification of Landsat Imagery. The most commonly adopted methods of pattern recognition are Support Vector Machines (SVM) and traditional neural networks (NN). ● A new water body extraction model based on SSAE is established ● Stacked sparse autoencoder- An autoencoder neural network is an unsupervised learning algorithm which utilizes back-propagation algorithm, letting the target values equal to the inputs, such as y (i) = x (i) ● An autoencoder can learn a low-dimensional representation of data which is exactly similar to PCAs (principal component analysis)	forth) are collected to construct unique feature matrix for each pixel. Next, a Feature Expansion Algorithm (FEA) is designed by taking account of the influence of neighboring pixels to expand feature matrixes. Setting the expansion features as inputs, SSAE is trained to extract water body.
5.	**Object detection from sar images based on**	Mrs. Devi Devapal, Mrs. Hashna N., Ms. Aparna V. P., Ms. Bhavyasree	● The speckle noise is random noise which is multiplicative in nature. This speckle noise is formed as a	● SAR data is increasingly being used in the field of remote sensing applications due to its all-weather day and night imaging capabilities. Due to the coherent processing, SAR images are

curvlet despeckling Speckle-SAR	C., Ms. Jeena Mathai, Ms. Sangeetha Soman K.	result of the random interference between the coherent returns from active imaging sensors such as LASER, SAR etc. Radar pulses are transmitted coherently and depending on the exact distance travelled, the returning wave may be in phase or out of phase. ● When the returning waves are in phase, the intensity of the resulting signal will be amplified resulting in constructive interference (bright spots). When the returning waves are out of phase, they tend to cancel each other reducing the intensity of the signal resulting in destructive interference (dark spots). This constructive and destructive interference of signal produces speckle noise. It appears as granular patterns in the image and make the	corrupted by speckle noise which needs different ways of filtering. Speckle being signal dependent, multiplicative random noise it is difficult to remove. ● Different multi-resolution schemes are compared for removing speckle noise. Several parameters such as ENL, PSNR, SSIM etc. are used for evaluating the despeckling accuracy of various techniques like Wavelet, Contourlet and Curvelet. Based on the results a method for despeckling SAR images based on curvelet transforms is being proposed. ● Object detection is done on the despeckled Curvelet image using CFAR. After the process of Despeckling and Object Detection a high resolution image is obtained as output where the objects are being clearly identified. Curvelet based despeckling technique is time consuming and further research can be carried out to reduce the time taken for this despeckling process.

		interpretation of image difficult. Speckle occurs when object illuminated by coherent radiation have rough surface. ● The incoming radar waves are reflected by most of the man-made objects, from background which clutters the detection of these objects. Due to the bright spots induced by the interference of reflected coherent waves, the SAR image interpretation is difficult . By thresholding the output of the receiver, a target is detected from the radar signals. If the output is greater than a fixed threshold, it is considered as a target presence otherwise a target absence.	
6. Semi-Automated Surface Water Detection with	Amir Behnamian, Sarah Banks, Lori White, Brian Brisco, Koreen Millard, Jon Pasher,	● A new method for semi-automated SWD using SAR data has been described and evaluated. The approach focuses on automatically defining	● The accuracy of water bodies extracted after the thresholding/segmentation step is affected by two types of errors: false positives and overestimation (or underestimation). The suggested cleanup process was used to improve accuracy by removing false positives. The overall

Synthetic Aperture Radar Data: A Wetland Case Study	Zhaohua Chen, Jason Duffe, Laura Bourgeau-Chavez and Michael Battaglia	threshold values, identifying water bodies and edge features on a per-object basis, and implementing an automated cleanup procedure which has been demonstrated to improve accuracy compared to thresholding only. This approach is adaptive to images acquired at different incidence angles and dates, removing the need for human intervention on a scene-by-scene basis. • Smooth features such as roads, as well as areas that are affected by shadow, tend to exhibit low backscattering returns, and thus are potentially falsely identified as water via simple thresholding processes.	effects of different (variance) thresholds on the removal of false positives have been evaluated and quantified in terms of the percentage of false positives that were detected versus losses of correctly-identified water bodies.

7.	**Deep Learning for SAR Image Despeckling**	Francesco Lattari, Borja Gonzalez Leon, Francesco Asaro, Alessio Rucci, Claudio Prati and Matteo Matteucci	• Speckle filtering is an unavoidable step when dealing with applications that involve amplitude or intensity images acquired by coherent systems, such as Synthetic Aperture Radar (SAR). Speckle is a target-dependent phenomenon; thus, its estimation and reduction require the individuation of specific properties of the image features. Speckle filtering is one of the most prominent topics in the SAR image processing research community, who has first tackled this issue using handcrafted feature-based filters. • The Supervised Learning (SL) paradigm, that is the task of learning a mapping between pairs of inputs and the corresponding targets (ground truth). This is done in a data-driven fashion by feeding the	• An adaptation of the U-Net convolutional neural network, originally conceived for semantic segmentation, for the problem of speckle removal in single look SAR images. Its encoder–decoder architecture allowed us to address the problem following the principles of denoising autoencoders. We built an online procedure for synthetic speckle generation, coupled with a well-designed data augmentation pipeline, and we extensively ran experiments to validate the performance of the proposed approach. We built two datasets to first pre-train the network on aerial images and then to fine-tune the model on the real SAR domain.

		algorithm with examples coming from a well-designed training set and minimising the error between the network predictions and the expected outputs.	
8. **Automatic Segmentation of River and Land in SAR Images: A Deep Learning Approach**	Manohara Pai M. M, Vaibhav Mehrotra, Shreyas Aiyar, Ujjwal Verma, Radhika M. Pai	• Possibility of false positives, that is the model may identify water in regions of relatively low intensity ,there would be an extension of this model for multi-class classification and introduce information from panchromatic satellite imagery for verification • The advent of very deep neural-networks in the past few years along with off-the-shelf libraries for learning algorithms has enabled easy building of end-to-end models to perform common computer vision tasks such as image recognition, object detection and image segmentation. • To reduce the effect of	• A robust methodology is proposed for an efficient and highly precise segmentation of surface river water and land. In addition, two different implementation of U-Net architecture is studied on SAR images, one in which U-net is trained from scracth (Vanilla U-Net) and other in which pretrained weights are used (Transfer U-Net). • Experimental results show that the both architectures gave similar performance in terms of F1 score, pixel accuracy and mean IoU. However, transfer U-Net is able to identify very minute details in the image such as small rivers etc. One limitation however, to this approach is the possibility of false positives, that is the model may identify water in regions of relatively low intensity

		speckle noise, filtering techniques that preserve the boundaries of the river are applied to the SAR images. Ardhi Wicaksono Santoso performed a comparative study of filters based on properties such as Speckle Index (SI), Average Difference (AD), Equivalent Number of Looks (ENL), and have determined the Lee filter to have the best metrics.	
9. Urban water body detection from the combination of high-resolution optical and SAR images	Chuiqing Zeng, Jinfei Wang, Xiaodong Huang, Stephen Bird, James J. Luce	• This paper proposes an automated water body detection method to delineate detailed water bodies from high resolution satellite images. It consists of three steps: a) coarse water mask detection from optical imagery using unsupervised classification; b) water mask refinement using back scatter value from synthetic aperture radar (SAR) images; and c) advanced	• From the coarse water mask derived from optical imagery, SAR imagery plays a supporting role to remove mistaken land pixels from the water masks. The average backscatter (or dB) value from the SAR image, resulting from series of preprocessing steps, is the criterion for the refinement. An appropriate threshold is adaptively selected, as described in Section II, sub-section D (in our case dB<-10). • This thresholding of the coarse water mask produces a refined water mask. The refined water mask is further cleaned by morphological filtering. The minimum path length can be automatically determined by the

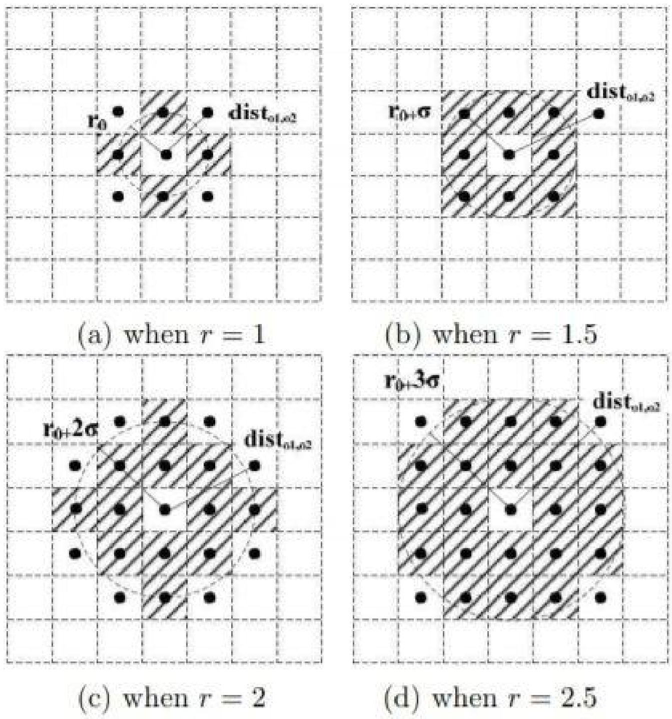
		morphological filtering to produce a final water mask. • This method integrates high-resolution optical imagery and SAR imagery to objectively derive a detailed water mask working on imagery with sub-meter resolution, based on a series of advanced image processing techniques. This method stands out from other methods by its sub-meter accuracy, its rules developed directly from the water's unique attribute without over-specific rules, and the automation with most parameters adaptively determined during the processing.	morphological profile in gray-scale imagery. In a binary image like the refined water mask, a profile of the entire mask is built and minimum path length for filtering is chosen from that profile.

3. Overview of the Proposed System

3.1. Introduction and Related Concepts

3.1.1. Feature Expansion Algorithm

Each image can be regarded as numerous grids consisting of pixels. In an image, each pixel is not self-existent. And adjacent pixel points may have some effects on target pixels. Therefore Feature Expansion Algorithm is used. First of all, each grid is mapped into a pixel point. Next, a point is chosen as a target point. Meanwhile, a circle is drawn whose center and radius are respectively target point and r. Then the distance between object point named o and adjacent point named oi,j is computed. Afterwards, for each target point, a related dataset which was made up of adjacent points where dist(o, oi,j) ≤ r, is obtained. Finally, for given features, the mean of the related dataset is calculated as a new feature. Meanwhile, we can adjust the length of r to find the best expansion distance.



Four examples of the Feature Expansion Algorithm

3.1.2. Stacked Sparse Auto Encoder

Sparse Autoencoder

An autoencoder neural network is an unsupervised learning algorithm which utilizes back-propagation algorithm, letting the target values equal to the inputs, such as y (i) = x (i). A **Sparse Autoencoder** is a type of **autoencoder** that employs **sparsity** to achieve an information bottleneck. Specifically the loss function is constructed so that activations are penalized within a layer.

Stacked Sparse Autoencoder.

Stacked Sparse Autoencoder (SSAE) is an encoder-decoder architecture where the “encoder” network represents pixel intensities modeled via lower dimensional attributes, while the “decoder” network reconstructs the original pixel intensities using the low dimensional features.

3.1.3 Modified Normalized Difference Water Index (MNDWI)

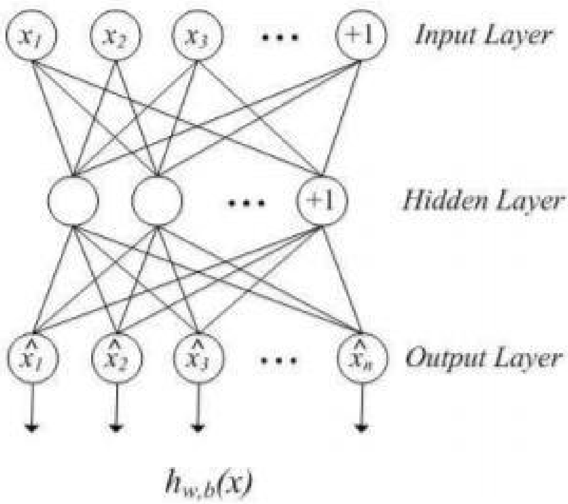
The Modified Normalized Difference Water Index (MNDWI) uses green and SWIR bands for the enhancement of open water features. It also diminishes built-up area features that are often correlated with open water in other indices.

3.1.4 Short-wave infrared (SWIR)

Short-wave infrared (SWIR) light is typically defined as light in the 0.9 – 1.7μm wavelength range.The visible light spectrum is not limited to all the colours that the human eyes and brain can distinguish and as we move away from visible light towards longer wavelengths of light, we enter the near infrared region which is followed by the SWIR region.

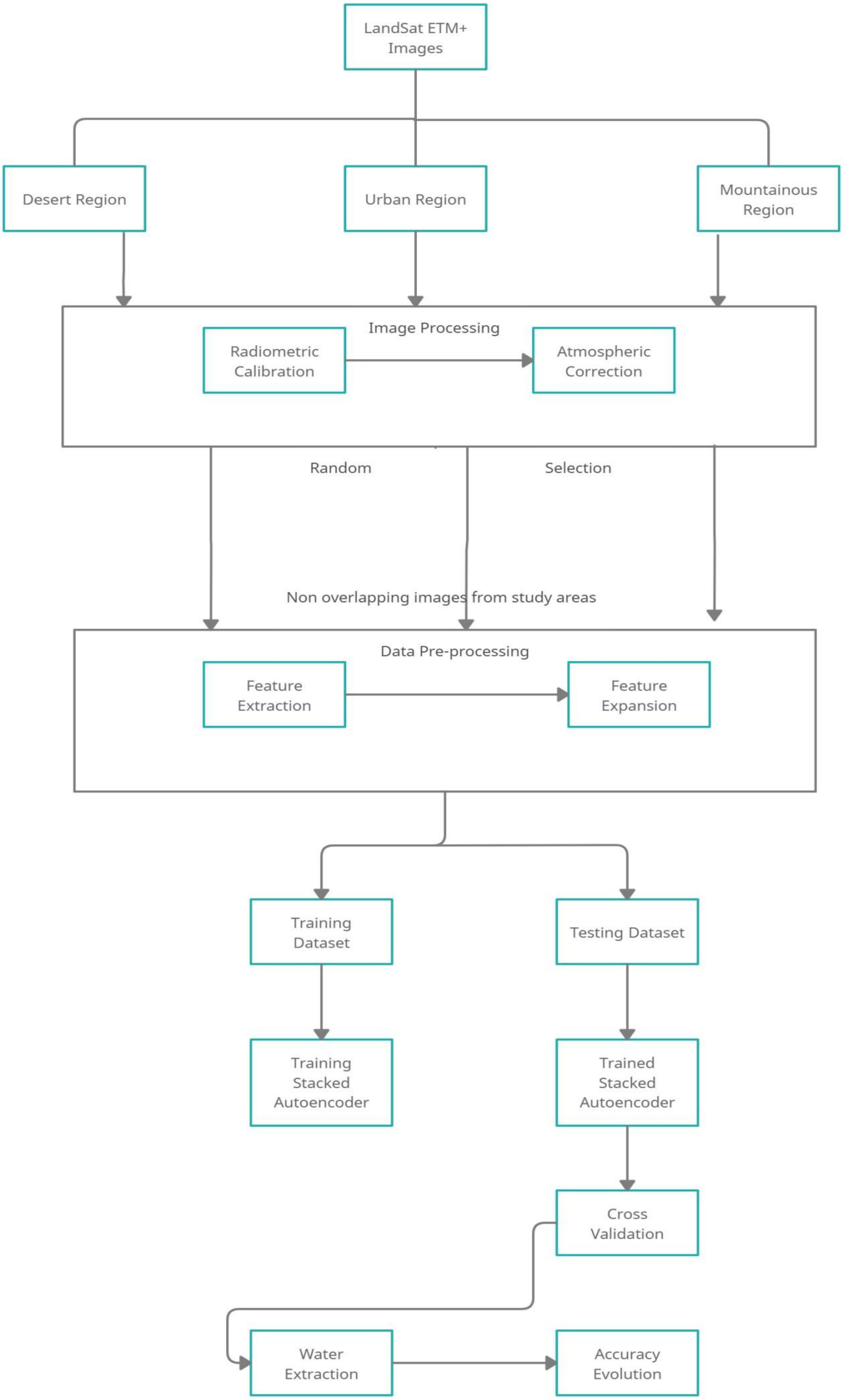
3.2. Framework, Architecture or Module for the Proposed System

The number of layers regarding stacked sparse autoencoder (SSAE) has additional to do with accuracy in results. An autoencoder neural network is an unsupervised learning algorithm that utilizes back-propagation algorithm, letting the target values equal to the inputs.
The autoencoder tries to learn a function hw,b (x) ≈ x. Like in the figure it attempts to learn an approximation to the identity function, namely, making output ˆx be similar to x.
And by inserting constraints on the network, implicational structure of the information are discovered.



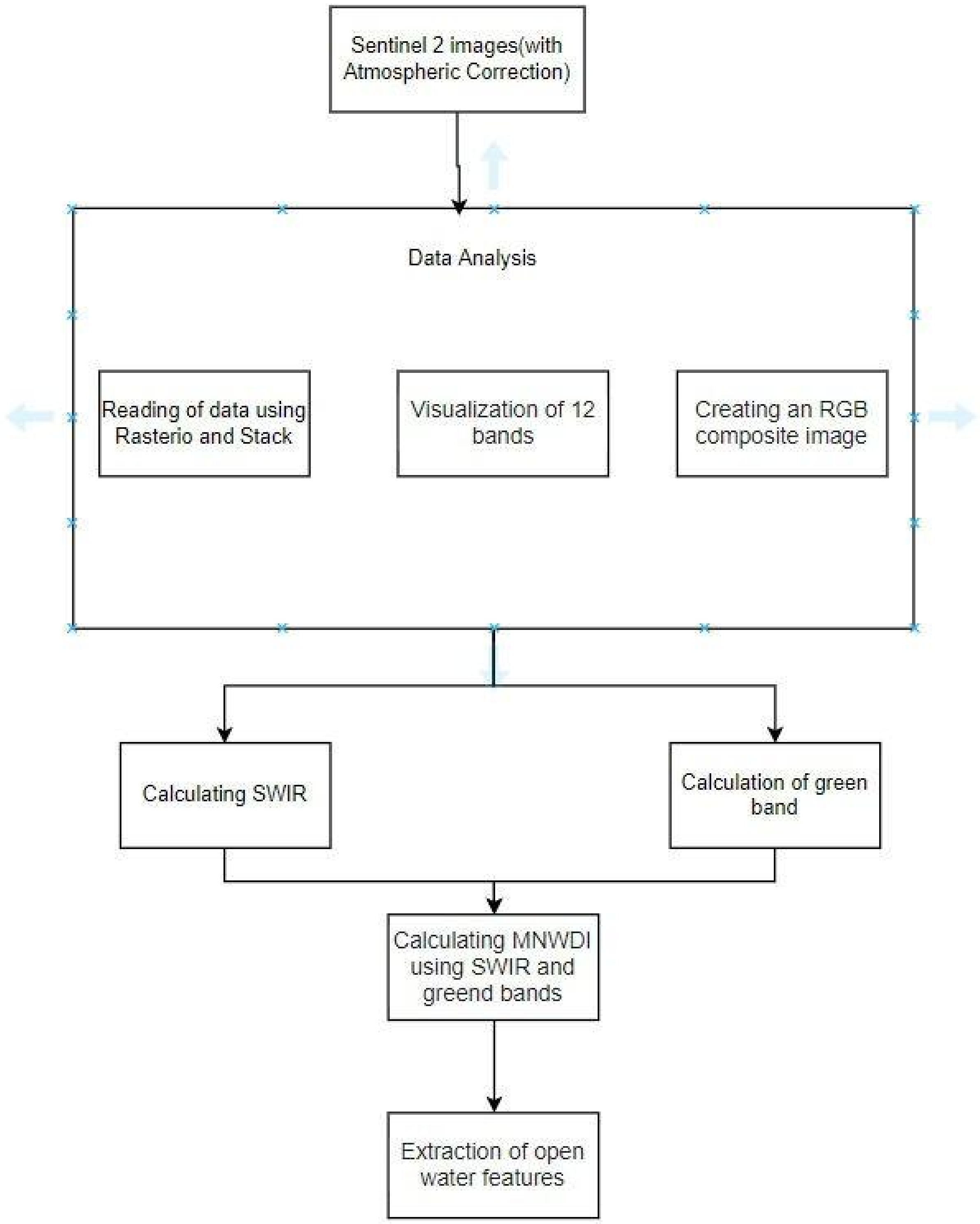
Structure of an autoencoder

3.3. Proposed System Model



Model proposed in paper

Model Implemented:

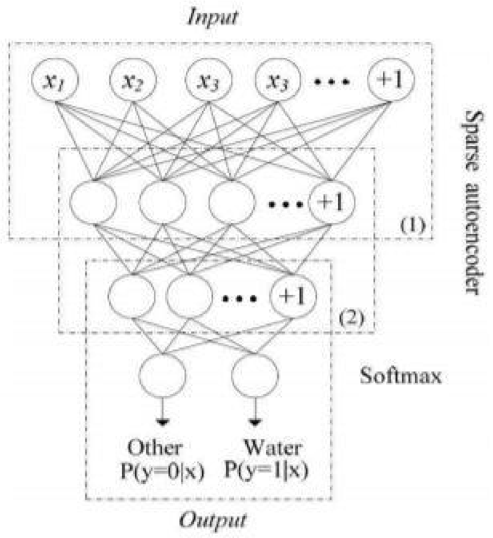


Model implementation diagram

4. Proposed System Analysis and Design

4.1. Introduction

To employ greedy layer-wise training method, the output of the previous layer should serve as the input of the next successive layer. This technique can only be applied by a highly efficient deep learning method, such as Stacked Sparse Autoencoder. Further it consists of hidden layers(set=2 for optimal results) and a further softmax classier layer which uses softmax regression technique to separate water from other objects in the image. This model further can obtain secondary features through the trained second sparse autoencoder. The system has considered an additional sparsity constraint on the hidden units(if the number is large).



The structure of a stacked autoencoder for water body extraction

Model Implemented:

SWIR light is reflective light; it bounces off of objects much like visible light. SWIR images are not in colour, making objects easily recognisable and yields one of the tactical advantages of the SWIR, namely, object or individual identification.

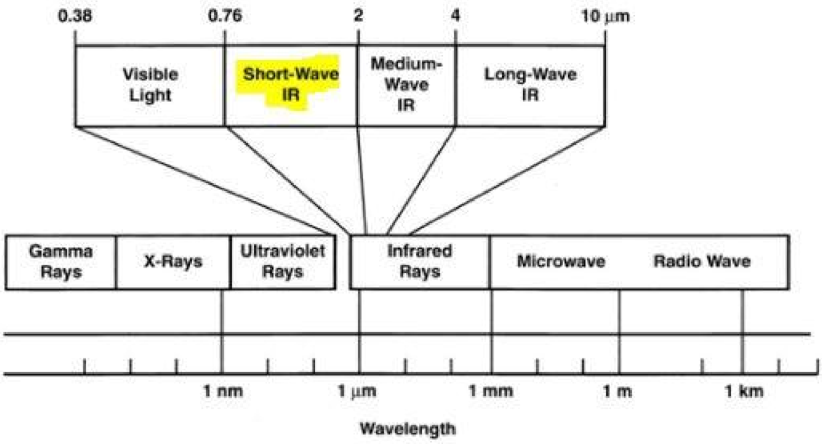


Fig: Electromagnetic Spectrum

MNDWI = (Green - SWIR) / (Green + SWIR)

SWIR = pixel values from the short-wave infrared band
GREEN = pixel values from the green band

4.2. Requirement Analysis

4.2.1. Functional Requirements

Product Perspective
Technical details and implementation decisions should be delegated fully to the respective machine learning scientist team working for the organization.The stakeholders shall be able to understand their relevant product requirements other than software requirements provided below only with additional deep learning knowledge.

Product features
The product is supposed to have an outstanding capability of unsupervised feature learning. It provides irreproachable accuracy even with limited number of training datasets.

Model Implemented:
The software is supposed to produce faster results as it is meant for mini demonstration .It might produce results with less accuracy.

User Characteristics
The user must have an in depth knowledge of machine learning models and deep learning algorithms.

Model Implemented:
The user should know how to use glob function for recursively appending the tiff images of different bands to the system.

Assumptions and Dependencies

- Accuracy of the model depends on the number of optimal number of layers in SSAE. Number of layers about SSAE has more to do with accuracy.
- The base length of the radius (1 unit) in the FAE has been assumed equal to the distance between the centres of two diagonally adjacent cells. For Feature Expansion Algorithm, the size of radius has effects on extractable accuracy.
- Extraction accuracy depends on data volume and maintains a steady increasing trend along with the growth of data volume.
- The number of features used to create the feature matrix is directly proportional to accuracy of the result set as, the farther the distance of adjacent pixels is, the less the target pixel is affected. Therefore, we expand the former 50 features to 100 by making use of Feature Expansion Algorithm.

Model Implemented:

- "Clip" argument allows the user to specify how much of the tails of the data that the user wants to clip off. The larger the number, the more the data will be stretched or brightened.

4.2.2 Domain Requirements

In distinctive terrain, there are numerous shadows or background noise to be removed. For example, in comparison to arid region, humid region possesses ample plant life that provides a challenge about eliminating data of vegetation from water. In mountainous land, due to the overlap region among water body and shadow spectral ranges, the extracted water might also additionally continually be blended with shadows of mountain. In urban regions, the varieties of surface objectives are complex. The primary mission of extracting water is to cast off built-up land and shadows of buildings.

- Hence, the main domain requirement entails an object- oriented analysis for extracting greater comprehensive capabilities of water in mountain area to construct the decision rule set. Through that, the extraction accuracy will increase to 95% and is even better in cloud-loose case.
- Based on Normalized Difference Built-up Index (NDBI), a technique was proposed to automate extracting built-up regions for mapping. So NDBI may be used for eliminating built-up land from water bodies.
- A repository is required to include spectral features, topological rules, shape features, size statistics and so forth to extract water types.
- A model based on Multiscale extraction, multispectral snapshots and SMA method.

Model Implemented :

- The main domain requirement entails the requirements of Satellite data of about 954 * 298 pixels(in .tiff format)
- Bands with the spectral resolution varying from 10 — 60 meters are required as input.
- A stable Python IDE with all latest packages installed

4.2.3 User Requirements

- When provided with high dimension remote sensing data(sar image) the user can expect the software to provide better results when applied on test datasets when the number of training sets is increased.

- The user can expect the software to give efficient results(extracting water indices out of the background) with minimum accuracy around 90%

Model Implemented :
The user can expect the software to help in visualizing the bands of the hyperspectral image dataset understand the distribution of pixels/values of the bands.

Input data has multiple numbers of bands that contain the data ranging from visible to infrared. So it is hard to visualize the data for humans. Hence, the user can expect the software to stretch the pixel brightness values in the image to extend the values to the full 0-255 range of potential values to increase the visual contrast of the image. A RGB Composite Image should get displayed

4.3 Non Functional Requirements

4.3.1 Product Requirements

Efficiency
Time: O(r), where r is the radius[O(n)].
Space: $O(n^2)$ for Feature Expansion Algorithm, we have to create a new matrix where each grid was mapped into a pixel point.

Model Implemented:
Time complexity: O(n^2), because bands are stored as 2d matrices and further stacked in a numpy array

Space: O(n), because the numpy array has n matrices

Reliability
From excessive to low, the accuracy of 3 models may be organized as: SSAE, NN and SVM. The proposed version is highly reliable because it has marked unique benefits that can study higher degree features from the lower ones because of FEA.
The proposed model can study full-scale features of the entire water types even from a limited dataset. SSAE adopts greedy layer-wise training method hence, can specify substantial traits of water preferably.

Usability
Domain experts in the field of machine learning as well as deep learning algorithm as it uses advanced techniques such as softmax regression, unsupervised learning, auto encoder.

4.3.2 Implementation Requirements
We can use tensorflow.js, flask(using any cloud services like GCP) to deploy the deep learning model. To carry out image processing we can use MATLAB or python libraries such as OpenCV/ dlib/pillow.

Model Implemented: We have used two special packages other than standard python libraries(like matplotlib, numpy etc) which are quite specific to Satellite Imagery Analysis:

Earthpy package: EarthPy is a python package that makes it easier to plot and work with spatial raster and vector data using open source tools. Earthpy depends upon geopandas which has a focus on vector data and rasterio with facilitates input and output of raster data files. It also requires matplotlib for plotting operations.

Rasterio package: Rasterio is a highly useful module for raster processing which you can use for reading and writing several different raster formats in Python. Rasterio is based on GDAL and Python automatically registers all known GDAL drivers for reading supported formats when importing the module. Most common file formats include for example TIFF and GeoTIFF, ASCII Grid and Erdas Imagine .img -files.

4.3.3 Engineering Standard Requirements
- The system must have good capacity of hierarchical feature learning from unlabelled data, system must implement object orientated analysis to build the decision rule set.
- System must implement pattern recognition methods as these are widely used in landsat imagery.
- The system must implement methods where the probability to obtain optimum results is higher.
- The system must implement any k layer model as it will help in classifying waterbody more precisely
  (k-1 parsing happens) irrespective of terrain.
- The system must be accommodating any change in the number of features and should not inhibit the production of output feature matrix.

4.4 System Requirements
4.4.1 Hardware Requirements

- 1600Mhz DDR3L SDRAM

- PCI Express bus 2.0
- Serial ATA 6Gb/s
- DDR3L-1333 MHz / 1600 MHz SODIMM × 2

4.4.2 Software Requirements

MATLAB software, for matlab there is a class: Autoencoder class, keras for implementing autoencoder, OOPS analysis for extracting more comprehensive features of water in mountain area to build the decision ruleset.

Model Implemented:

Python IDE with libraries such as glob, earthpy,rasterio, matplotlib,numpy, plotly

4.5 Operational Requirements

Economic
Water body extraction by remote sensing is an important method of water resources. It can tell us a lot about increasing and decreasing levels of water which can be used for mitigation and preparation ahead.

Environmental
Having an idea about various water resources available to us in turn helps in better management and conservation of the given resources.

Social
There are various mainland areas which cannot be reached due to social reasons. This technology helps us map and regulate water resources from afar.

Political
We have often seen political land and water disputes. Mapping can help us resolve such conflicts with ease.

Ethical
Remote sensing techniques offer inherent advantages to the practice of monitoring activities through the efficiency of areal perspective, temporal definition, change detection, and accurate mensuration capabilities.

Health and Safety
There is about 3% of freshwater available for utlization. Imaging is necessary for discovering such resources.

Sustainability
To make the best use of water resources present with us at the moment, we need to be calculative and intuitive while using them. Having a deep knowledge about the said resources helps us in being mindful, sustainable and in conserving them for coming generations.

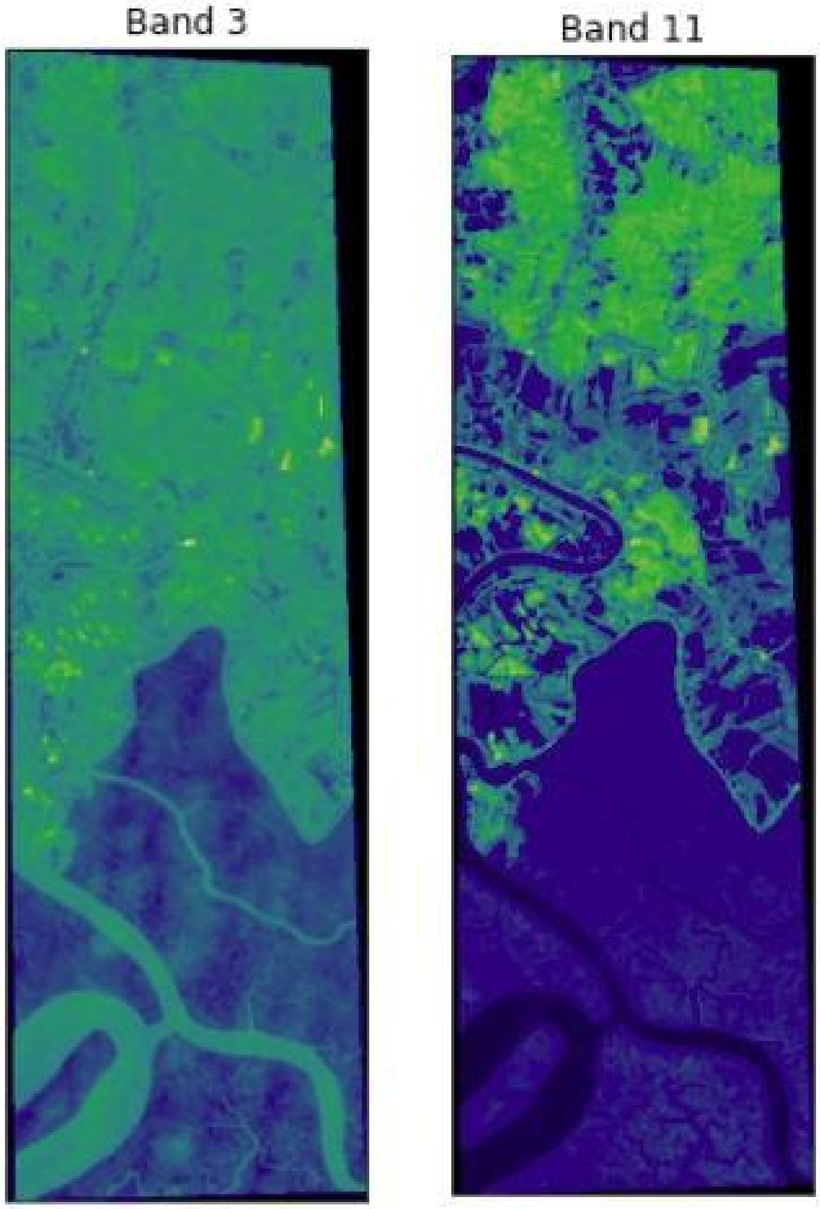
Legality
Because of its efficacy and intrusiveness, the technology has always been of interest to the legal community, and, while Constitutional concerns about remote sensing technology have always existed, it has usually not caused any great problem due to technological limitations.

5. Results and Discussions

The removal of diverse shadows (including shadows of mountains, buildings, and clouds, among other things) and noise within water is still a long-standing difficulty in water body extraction. We suggested a model for water body extraction based on the stacked sparse autoencoder to find this out. Meanwhile, we proposed a Feature Expansion Algorithm (FEA) to uncover more water body properties. In comparison to the Support Vector Machine (SVM) and standard neural networks, the experiment results demonstrated that the suggested model has remarkable feature learning capability and achieves better outcomes (NN). Because of the suggested model's unsupervised feature learning, it may be used with a small number of training samples and achieve higher accuracy. Reducing the cost of preparing training data makes a lot of sense. By using the proposed model to obtain reliable information about a water body, we can monitor the state of water resources in a timely and efficient manner. It is of critical importance right now for environmental protection and long-term growth.

Model Implemented:

1. **Band 3 is Green**
2. **Band 11 is SWIR**
3. **Output is for extracting water indices**
4. **Histogram for all 12 bands**
5. **LHS: RGB Composite Image; RHS: After Contrast Stretching**



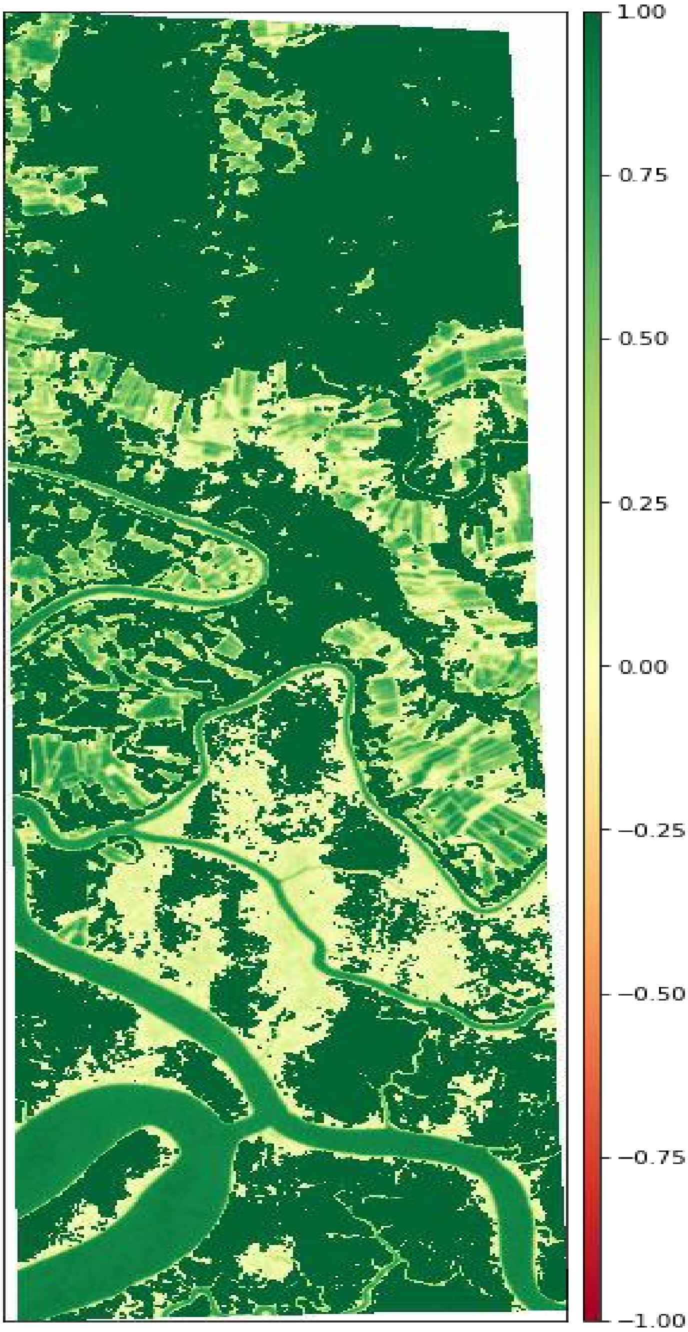


Fig: Water Extraction Output

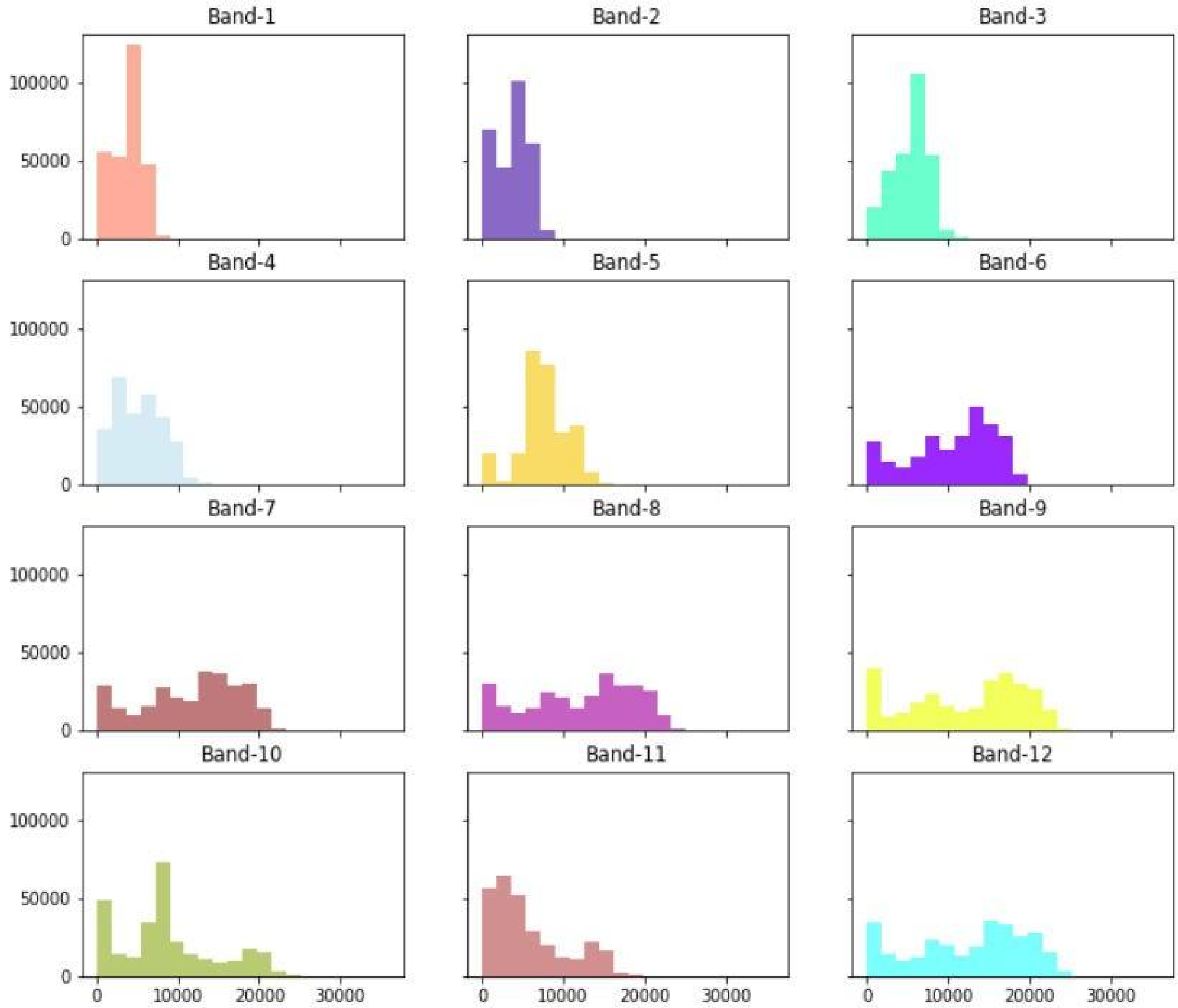


Fig:histogram

Fig:RGB composite image

Fig:After Contrast stretch

6. References

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