International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18(2) 2026 pp. 534-553
https://doi.org/10.70917/ijcisim-2026-2912
Article

Texture-Based Region of Interest Extraction Using Unsupervised Clustering for Glacial Lake Detection

Smita R Kullolli[1], S.Ajitha[2]

[1] Department of MCA,Ramaiah Institute of Technology, Bangalore (Affiliated to VTU-Belgaum), Karnataka, India
Smita.kulloli69@gmail.com
[2] Department of MCARamaiah Institute of Technology, Bangalore(Affiliated to VTU-Belgaum), Karnataka, India
ajitha@msrit.edu

Abstract: Glacier melting has created glacial lakes which have become a significant issue of concern as far as the environment is concerned, mainly in high mountainous areas like the Himalayas, the Andes, and the Alps. The increased temperatures on the earth increase the melting of the glaciers and as a result glacial lakes are formed and grow. Such lakes can be unstable and lead to Glacial Lake Outburst Floods (GLOFs) which can cause drastic environmental and economic losses to the people down the stream. Thus, the timely detection and control of glacier lakes are required to manage risks of disasters and monitor the environment. The remote sensing technology is a viable tool of tracking glacial lakes in mountainous regions that are inaccessible and large. Nonetheless, it is difficult to detect glacial lakes correctly with the use of satellite images because of complex backgrounds made of snow, ice, shadows, rocks, and debris. In this paper, a new approach to automatic glacial lake detection is suggested based on multispectral satellite images and also parameterizing Region of Interest (ROI) with texture and using unsupervised clustering algorithms. In the suggested solution, the multispectral satellite images are initially subjected to preprocessing to improve the quality of images and eliminate noise. The features of texture are then extracted to obtain smooth surfaces areas that are most likely to be the water bodies. These areas of interest are termed as Regions of Interest (ROI) in an effort to minimize computational complexity. A clustering algorithm which has no supervision is then used to sort and categorize pixels as water and non-water with the help of spectral and texture data. The proposed method significantly outperforms traditional approaches such as NDWI, thresholding, Random Forest, and CNN models, achieving 98.45% accuracy, 99.14% precision, 97.70% recall, and 98.41% F1-score, ensuring highly reliable detection. It also demonstrates high computational efficiency, completing processing in just 29 seconds due to effective texture-based ROI reduction. Furthermore, the model shows strong generalization across multiple regions (Himalayas, Andes, Alps, Arctic) with very low error rates (4 false positives, 3 false negatives), confirming its robustness and accuracy in glacial lake detection. The presented system allows one to detect glacial lakes in an accurate way without using labeled training data. It has been proved through experimental analysis that the proposed method is more accurate than traditional spectral thresholding techniques in segmentation, and less prone to false detections. The method is especially applicable in the large scale observation of glacial lakes and can provide disaster mitigation measures in mountainous areas under threat.

Keywords: Glacial Lake Detection, Multispectral Satellite Images, Texture-Based ROI Extraction, Unsupervised Clustering, Remote Sensing, Image Segmentation

1. Introduction

Water bodies formed due to melting of glaciers and the accretion of the resulting meltwater into the depressions or behind natural structures like moraines, ice dams, or bedrock are known as glacial lakes. Over the past few decades, the world has witnessed a rapid increase in climate change that has led to glacier melting in most mountainous areas of the globe and this includes the Himalayas, Andes, Alps, and the Arctic regions. Due to the growing rate of glaciers melting, a greater number, and larger size of glacial lakes have grown very fast. Although these lakes are natural aspects of glacierized scenery, they grow rapidly and are serious environmental and socio-economic issues. Among the most threatening risks of glacial lakes, there are Glacial Lake Outburst Floods (GLOFs) that happen when the dam that prevents the outburst of a lake water collapses. These floods have the capacity to unleash large quantities of water over a few days and result in disastrous loss to the communities, infrastructure, agricultural land, and ecosystems down the river. It is a valuable job of disaster management, environmental inspection and climate change research therefore to monitor glacier lakes. The conventional ways through which glacial lakes are monitored are field surveys and direct observations [1]. Though these techniques have correct measurements and good insight on the glacial behavior, it is not always easy to apply in isolated mountainous areas where accessibility is restricted and weather conditions are severe. Field-based monitoring is also time consuming, costly and could not be implemented in large scale monitoring of multiple glacial lakes. Consequently, remote sensing technologies have turned into an efficient and popular method of watching and tracing glacial lakes within extensive geographical locations [2].

Figure .1: Glacial Lakes Formation and the Glacial Lake outburst flood (GLOF) Hazard during Climate Change.

Figure 1 shows how glacial lakes are formed and what risk happens to be associated with the formation of the glacial Lake Outburst Floods (GLOFs) caused by climate change. Firstly, global warming causes the increase in temperature which promotes the melting and the withdrawal of glaciers in mountainous areas like the Himalayas, Andes, Alps, and the Arctic. Due to the melting of glaciers, a significant volume of meltwater gathers in depressions or behind some natural features such as moraines, ice dams and bedrock structures leading to the formation and growth of glacial lakes. With time, the melt waters keep accumulating thus making these lakes to expand and become unstable. A Glacial Lake Outburst Flood (GLOF) may happen when the natural dam that supports the lake water becomes weak, collapses, or is pressured to the point of erosion or any seismic event. This abrupt water discharge results in disastrous flooding and this has an adverse effect on downstream communities, infrastructure, agricultural lands, and ecosystems. Thus, the figure underlines the necessity to observe glacial lakes with the help of satellite remote sensing and other sophisticated methods of detection to forecast the possible risks and assist in managing the disaster [3]. The satellite remote sensing is significant in monitoring and viewing the surface of the earth by using multispectral as well as hyperspectral imaging sensors. The multispectral satellite imagery is able to capture different spectral bands thus it is able to identify various types of land cover which include water bodies, vegetation, snow, ice, and rocky terrain. Water bodies typically have different spectral properties, especially in the visual and the near-infrared wavelengths, and are thus observable through satellite data. Nevertheless, glacial lakes are very difficult to detect using satellite image because mountainous landscapes are complex. Snow, ice, moraine debris, and rocks that surround glacial lakes generally have spectral similarities with water bodies. Also, the presence of shadows cast by mountains and clouds also complicates the detection process and may result in wrong classification [4]. The water bodies in the satellite images have a number of image processing methods that have been developed to detect water bodies. Initially, spectral threshold and indices of water like the Normalized Difference Water Index (NDWI) and its modified versions were mainly used. These indices are used to improve water features by using spectral bands to emphasize the variations of water and other land surfaces. These techniques are cheap and computationally efficient, but tend to give poor results in glacial regions where snow and shadow areas are more likely to have the spectral properties of water [5]. Machine learning techniques have seen wide use in order to enhance detection accuracy. The Support Vector Machines (SVM), Random Forest (RF) and Artificial Neural Networks (ANN) are supervised classification algorithms that have been used in the classification of satellite images to either water or non-water. Although these techniques offer better performance, they have a large labelled set to train, which is hard to get in remote glacial settings. The alternative method that does not involve labeled data is the unsupervised learning techniques. Pixels are clustered algorithms like the K-means and Fuzzy C-means algorithms cluster pixels together based on similarity in either spectral or spatial characteristics. Moreover, there is the texture information which can be a good clue to differentiate water bodies and the terrain around it [6]. The surface of water is usually smooth and homogeneous when glaciers and rocky regions have irregular textures. The Gray-Level Co-occurrence Matrix (GLCM) can be used to extract texture features including contrast, entropy, homogeneity and energy. This study puts forward an automated system of glacial lake identification applying texture-based Region of Interest (ROI) featuring extraction with unsupervised clustering. The technique initially determines the possible lake locations by the first method that determines the texture attributes of the region, and then the technique uses clustering to distinguish the pixels as either water or non-water pixels [7]. The method enhances accuracy of segmentation, minimizes the computational complexity, and avoids the need of labeled training data, and this is appropriate in tracking glacial lakes in remote mountainous areas. The rest of this paper is structured in the following way. In Section 2, the review of the related work on glacial lake detection by the means of remote sensing methods is presented. Section 3 outlines the proposed methodology, which has preprocessing, texture feature extraction, ROI detection and clustering-based segmentation. In Section 4, the algorithm of the proposed approach is given. The results and performance evaluation of the experiment are discussed in Section 5. Finally, Section 6 will be the conclusion of the paper and the future directions of the research are outlined.

2. Related Work

Observation and tracking glacial lakes have been of great importance in the recent years with the increasing effect of global climate change. Increased global temperatures have led to massive meltdown of glaciers in most mountain ranges such as the Himalayas, Andes, Alps and the Arctic regions. The glacial lakes have grown and grown as glaciers are melting faster, posing more hazards of Glacial Lake Outburst Floods (GLOFs) [8]. These rapidly occurring floods may contain huge amounts of water within a limited time frame and lead to devastating losses of downstream communities and infrastructure as well as ecosystems. This has led to the need to accurately and automatically identify glacial lakes, which are now vital in disaster risk management, environmental analysis, and climate change research. The recent developments in remote sensing by satellites and machine learning have significantly enhanced the possibility to observe glacial lakes in both regional and global levels. Glacial lake monitoring has been an important aspect of remote sensing technology over the past several decades [9]. The optical satellite images of satellites like Landsat, Sentinel, and MODIS have been extensively utilized in mapping glacial lakes due to its spaciousness, and extended time series. The optical satellite data can help researchers trace the changes in the dynamics of glaciers and lakes over time. These satellite data enable researchers to identify the new glacial lakes as well as to track the change in the area and volume of lakes in the large geographical zones. Recent researches have indicated that optical satellite imagery is the major source of data to map glacial lakes due to its availability, extensive coverage, and ease of analysis [10].

Initial techniques of glacial lake identification were based on spectral analysis. The spectral signature of water bodies is usually distinctive in relatively visible and near-infrared bands and may be employed to differentiate the bodies against the adjacent terrain. The most common technique is the Normalized Difference Water Index (NDWI), which augments water features by taking advantage of the difference in reflectance between the green and near-infrared spectral bands. NDWI and other water indices have also been modified to yield better water bodies detections [11]. These are spectral index based methods, which are computationally efficient and can be used to map water bodies on large scale. They can however, not perform well in mountainous areas since snow, ice and shadow areas can have the same spectral properties as water bodies and cause classification errors. To address these constraints, scientists have been looking at more sophisticated image processing methods of glacial lake extraction [12]. Conventional image segmentation techniques like thresholding, edge detection and region-growing have been used to detect water boundaries in satellite images. Segmentation techniques that use thresholds are used to classify pixels according to predefined spectral values, and edge-detectors are used to identify sudden changes in intensity to mark water boundaries. Despite being easy to use and computationally inexpensive, these methods tend to work poorly in mountainous topography where the conditions of illumination are not homogeneous and the surface details are very heterogeneous. As a result, they are not very accurate when used to detect glacial lakes in complex settings [13].

The texture analysis has proved to be a useful method of enhancing accuracy of detecting water bodies in remote sensing images. The texture features are characteristics of the spatial distribution and change of pixel intensities in an image. The texture patterns of water surfaces are normally smooth and homogeneous in satellite images, but the texture patterns in glacier surfaces and rocky areas are irregular and rough [14]. The techniques that can be used to extract statistical texture features include contrast, homogeneity, entropy and energy, like the Gray-Level Co-occurrence Matrix (GLCM). Such characteristics give supplementary data regarding the spatial patterns, which would not have been possible with spectral data. Combining both the texture and spectral content can enable the researchers to enhance the distinction between water bodies and the terrain in the glacial setting. As the machine learning technologies rapidly evolved, various supervised classification algorithms have been used on the detection of glacial lakes. Support Vector Machines (SVM), Random Forest (RF) and Artificial Neural Networks (ANN) are machine learning algorithms that have been used extensively to categorize satellite imagery as either water or non-water [15]. The best of these algorithms are the Random Forest classifiers that perform well because of their capability to deal with high dimensional data as well as the fact that they are resistant to noise. Indicatively, some recent studies have created automated approaches based on multisource satellite observations and Random Forest classifiers to map glacial lakes within mountainous areas like Himalayas [16]. These methods have also demonstrated good outcomes in determining glacial lakes and creating precise glacial lake lists to aid in hazard assessment. Although they are effective, there are limitations associated with the supervised learning techniques. The methods utilize large training datasets in order to obtain high-quality classification. Gathering labeled data in glacial areas is challenging because of the unreachable and remote locations which are so high in the air. Moreover, spectral properties of glaciers and glacial lakes might also be different in various regions and seasons, which can limit the generalization properties of trained models [17]. Such problems have prompted scientists to seek ways of using unsupervised learning methods in detecting glacial lakes. Another option to labeled training data is unsupervised clustering algorithms, which do not need any labeled training data. K-means clustering, Fuzzy C-means clustering and Gaussian mixture models are algorithms that cluster pixels together based on similarity in spectral and spatial characteristics. This clustering method has been utilized in remote sensing image segmentation to automatically recognize and classify water and non-water in the image [18]. Due to their use of only the similarity of pixels instead of training data, unsupervised methods are especially valuable when analyzing the huge volume of satellite images. Nevertheless, clustering algorithms are not immune to the misclassification errors in case of direct application to real complicated mountainous terrain with snow and ice covers that take the shape of water bodies. The recent breakthroughs in artificial intelligence have unveiled deep learning methods of detecting glacial lakes. Convolutional Neural Networks (CNNs) are deep learning models, which have been shown to perform well in image segmentation [19]. CNN-based models like U-Net, Fully Convolutional Networks (FCN) have largely been applied to extract water bodies in satellite images. These models are automatic learners of hierarchical features on large datasets, and are able to learn complex spatial patterns in images. A number of recent studies have used deep learning models to extract glacial lakes in Landsat and Sentinel imagery and they are more accurate than the traditional machine learning methods. Transformer-based deep learning architectures have also been investigated to detect and monitor glacial lakes in the past few years [20]. The models are a combination of transformer mechanisms and convolutional neural networks to extract both local spatial and long-range contextual information. As an example, it has been suggested to use new hybrid CNN-transformer models to extract lakes accurately in remote sensing images, with high accuracy of segmentation of the lake through a combination of global and local features.

Multisource remote sensing datasets are another new direction of research being undertaken to monitor glacial lakes. The earliest to combine optical satellite imagery with Synthetic Aperture Radar (SAR), thermal images, and digital elevation models have been used to enhance the accuracy of glacial lakes [21]. The combination of various data sources assists in dealing with the issues of clouds and shadow effects as well as variations in illumination in the mountainous conditions. As an example, the most recent automated mapping methods integrate Landsat-8, Sentinel-1, Sentinel-2, and digital elevation models to provide a large-scale glacial lake inventory and track lake expansion in the High Mountain Asia region. Automated glacial lake mapping models and cloud computing platforms like Google Earth Engine have also been utilized to map large glacial lakes. The satellite datasets are processed with the help of these platforms, and the researchers are able to track the changes of glacial lakes in the long term [22]. In recent research it has been established that automated models can reach high levels of agreement with manually defined glacial lake edges, showing the validity of automated remote sensing methods to large scale monitoring [23]. Even though the methods of detecting glacial lakes have progressed tremendously, there are a number of obstacles. The correct differentiation of glacial lakes and the surrounding snow or ice surfaces that tend to have similar spectral features is one of the primary challenges [24]. Besides, mountainous terrain poses tricky conditions of light that generates shadows and decreases the quality of images. Satellite images may also be affected by cloud cover and seasonal variations, which decrease the quality of the image and detection accuracy. As such, a unification of spectral, spatial and texture features is believed to be an effective approach to enhancing the detection of glacial lakes. This study presents a texture-based Region of Interest (ROI) extraction algorithm with unsupervised clustering, which can enhance the accuracy of glacier lake detection. The proposed method first determines the candidate regions which have smooth texture features that are most likely to represent water bodies [25]. These candidate areas are then processed by clustering algorithms to find out the pixels which are water and non-water. The proposed technique further simplifies computation since it only takes into account areas of ROI and false detection is minimized due to the insignificance of background areas.

3. Proposed Methodology

The proposed methodology aims at automatically identifying glacial lakes on basis of multispectral satellite. The general aim of this proposed is to effectively locate the glacial lakes in the more complicated mountainous settings where the other conventional spectral based techniques have failed because of snow, ice, shadows, and rocky surfaces. The proposed system combines the images preprocessing, extracting texture features, identifying ROI, classifying using the clustering feature, and post-processing features to obtain reliable glacial lake segmentation. The entire process of the presented methodology is represented by a series of processing activities that narrow the satellite image data to identify glacial lakes areas by the progressive refinement of the data. In fig.2 the flow of the proposed methodology is presented. It focuses on the automatic detection of glacial lakes from multispectral satellite images using a combination of texture-based Region of Interest (ROI) extraction and unsupervised clustering techniques

3.1 Data Acquisition and Satellite Image Collection

The initial stage of the proposed framework focuses on acquiring multispectral satellite imagery from reliable remote sensing platforms. In this study, widely recognized Earth observation datasets such as Landsat 8 [36], Sentinel-2 [37], and MODIS [38] are utilized due to their high spatial, temporal, and spectral resolution along with global accessibility. Satellite Data Access Portal https://earthexplorer.usgs.gov and Sentinel Data Access https://scihub.copernicus.eu. The data utilized in this study is a multispectral images of 10-year (20152025) data to record the seasonal and long-term changes in the formation and development of the glacial lakes. The sources are mainly open repositories like the US Geological Survey and Copernicus Open Access Hub. This time span allows observation of glacial processes in a comprehensive way and makes it possible to conduct a sound analysis of how glacial lakes change in the conditions of changing climatic conditions.

The satellite data chosen gives imagery in various spectral bands such as:

- Visible bands (Blue, Green, Red): Can be used in the general surface observation and visual interpretation.
- Near-Infrared (NIR): Assists in the identification of water bodies, vegetation and soil.

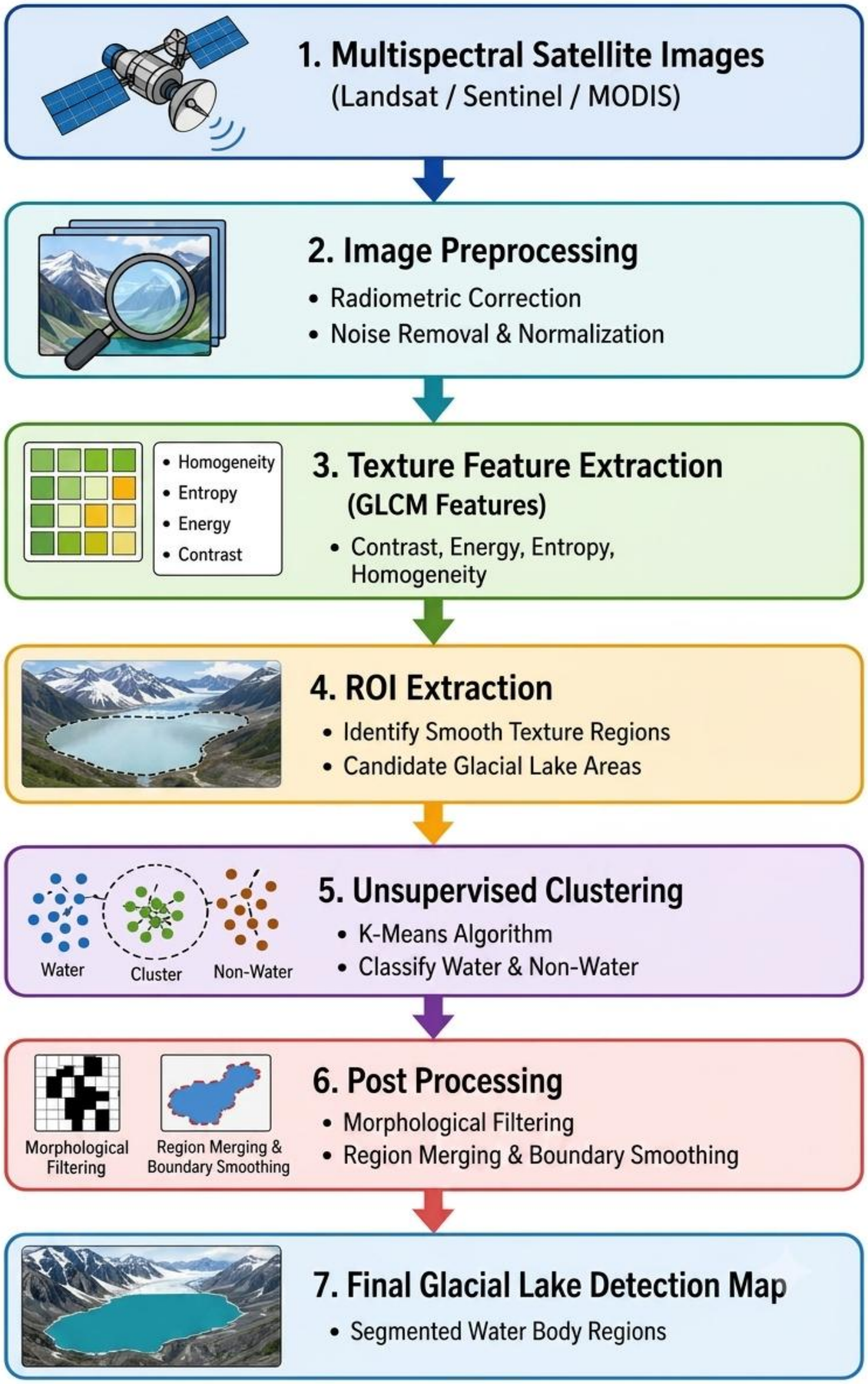

Figure 2: Proposed Framework for Glacial Lake Detection Using Texture Based ROI Extraction and Unsupervised Clustering

- Shortwave Infrared (SWIR): This is effective in distinguishing between snow, ice and water surfaces.

The spectral bands record distinct reflectance properties of surface materials. Glacial lakes and other water bodies do not reflect the NIR and SWIR since the water has low reflectance, thus appearing darker than the surrounding terrain. But in glacial and high-altitude settings, snow, ice and shadow areas tend to have analogous spectral reactions, making it difficult to classify them directly. To overcome this, multispectral data is further analyzed with high level feature extraction and clustering to enhance separability of the glacial lakes and the background features. The framework can also explore the trends on the lake expansion and shrinkage as well as the seasonal change by using the temporal datasets (2015-2025), which can enhance accuracy and reliability in detecting changes.

3.2 Image Preprocessing

Before applying detection algorithms, the satellite images undergo several preprocessing steps to improve data quality and remove unwanted noise. Preprocessing ensures that the satellite imagery is suitable for further analysis and reduces errors caused by atmospheric conditions, sensor noise, and illumination variations.

Preprocessing stage involves following operations:

- Radiometric Correction: The radiometric correction changes the value of the pixels of the satellite images to correct atmosphere influences and sensor calibration errors. Through this process the reflectance values will be a true reflection of the surface characteristics of the observed region.
- Noise Removal: Satellite images have random noise (sensor errors or environmental noise). Median filtering or Gaussian filtering are some of the filtering methods used to minimize noise and enhance image clarity.
- Image Normalization: This normalization is used to normalize the values of pixels in various spectral bands. This is done in order to make sure that the data ranges of the various bands are comparable and can be used to extract features.
- Band Selection and Enhancement: Relevant spectral bands are selected and combined to enhance the visibility of water bodies in the satellite image. For example, combinations of green, near- infrared, shortwave infrared bands may contribute to emphasize the water surfaces and reduce the other types of land cover. The satellite image after preprocessing is more appropriate in extracting meaningful features concerning glacial lakes.

3.3 Texture Feature Extraction

The character of the texture is significant in differentiating glacial lakes and the terrain. Whereas spectral feature gives details on the surface reflectance, texture features gives details on how the pixels are distributed and changed in the image. Water surfaces are usually smooth and uniform in contrast to glacier surfaces, rocky terrain and areas covered with debris that have more uneven textures. In the suggested algorithm, the Gray-Level Co-occurrence Matrix (GLCM) method is used to extract texture features. The GLCM is a statistical method that analyzes the spatial relationship between pixel intensities in an image. By computing the frequency of occurrence of pixel pairs with specific intensity values, the GLCM provides useful information about image texture.

Several texture features can be derived from the GLCM matrix, including:

- Contrast: Measures the intensity variation between neighboring pixels.
- Homogeneity: Indicates the uniformity of pixel intensity distribution.
- Entropy: Represents the randomness or complexity of the texture pattern.
- Energy: Measures the uniformity or repetition of pixel patterns.

These texture features help identify smooth regions in the satellite image that may correspond to water bodies. By analyzing the texture characteristics of the image, the proposed system can effectively differentiate between water surfaces and rough terrain features.

3.4 Region of Interest (ROI) Extraction

After extracting the texture features, the second step is to identify candidate regions that can be glacial lakes. These regions are referred to as Regions of Interest (ROI). The extraction process of the ROI minimizes the search region of glacial lake detection as only the areas that have texture characteristics near to those of water bodies are considered in the extraction.

The steps used in extraction of ROI are as follows:

- The entire satellite image is computed to extract features of the texture.
- Areas of low texture change and high homogeneity are determined as possible water surfaces.
- The texture features are used to isolate smooth areas using threshold values.
- The resulting regions are indicated as candidate ROIs to be analyzed further.

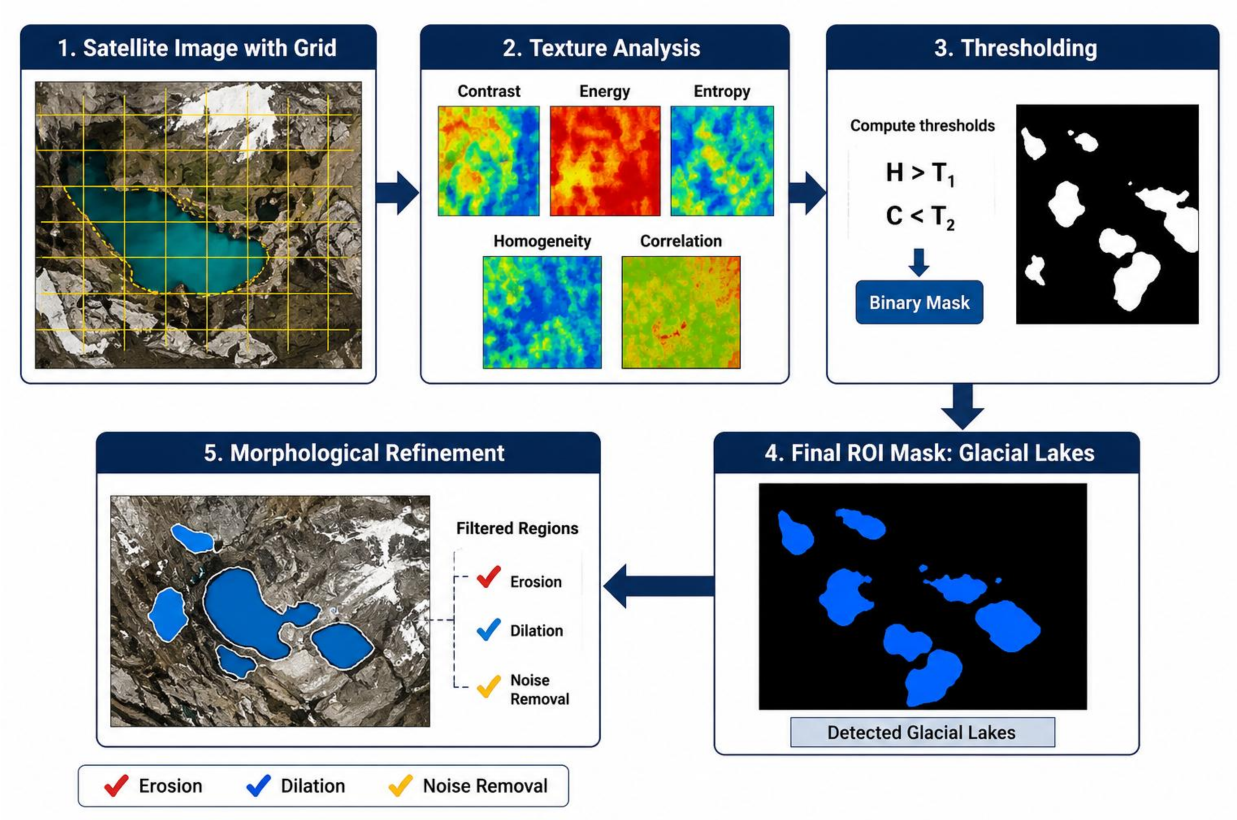

Figure 3: ROI Extraction for Glacial Lake Detection

Fig.3 the illustration represents the entire functionality of a texture-based Region of Interest (ROI) extraction system of glacial lake extraction with multispectral satellite data.

The steps followed are first to obtain a high-resolution satellite image of a mountainous or glacial area and then to break up the image into small grid windows. This grid partitioning allows a local analysis of image features and decreases the computing power because it results in separate computations of smaller areas. The texture analysis is then applied to each of the grid cells with the help of the Gray-Level Co-occurrence Matrix (GLCM), which is a popular statistical tool of describing the spatial dependencies between pixel intensities. The important texture characteristics of contrast, entropy, energy and homogeneity are extracted out of the GLCM. These characteristics are very significant in the differentiation of water bodies and the terrain. Generally, glacial lakes are characterized by low contrast, low entropy, low intensity variation, and high energy and homogeneity since the surface characteristics of glacial lakes are smooth and uniform. Non-water areas, on the other hand, like rocks, vegetation, snow and debris, have more texture variation, irregularity and more randomness. After feature extraction, there is a thresholding mechanism which is used to label the pixels as either potential water or non-water. The threshold values are specified depending on the statistical characteristics of texture features, such as to choose the areas in which the homogeneity is above a particular threshold and the contrast is less than a specific threshold. A binary mask output of this step is then a pixel map where pixels that are within candidate water regions are set (usually to white), and the rest are set to zero (usually to black). The starting binary mask is however usually noisy, there are small isolated areas and discontinuities as a result of differences between illumination, shadows, or sensor noise. Morphological refinement operations are implemented in order to overcome these problems. Erosion is one of the techniques applied to eliminate noisy pixel, separately detach weakly connected regions, and the dilation technique is applied to expand and reconnect fragmented water bodies. Further filtering and noise elimination measures further improve the quality of the regions in the image that have been detected and provide more smooth edges and shapes that are coherent. Lastly, the cleanup output gives a clean and precise ROI mask that indicates the identified glacial lakes. This mask is able to keep the water bodies out of the convoluted backgrounds such as snowy landscapes, ice, rocky landscapes, and shadowy landscapes which are typical in high altitudes. The general workflow including acquisition and grid-based segmentation of the image, extraction of the texture features, thresholding, and morphological refinement facilitates the strong and effective detection of the glacial lakes. The method is able to considerably reduce the search space and the computational load of the later processing task like classification, change detection or risk assessment of Glacial Lake Outburst Floods (GLOFs) due to the fact that only candidate regions are searched. In such a way, the suggested texture-based ROI extraction would be a stable and saleable method of environmental monitoring and managing disasters in remote and intricate glacial areas.

3.5 Unsupervised Clustering for Pixel Classification

After identifying the ROI regions, the next step is to classify the pixels within these regions into water and non-water categories. In the proposed framework, an unsupervised clustering algorithm is used for this purpose. Unsupervised clustering does not require labeled training data and instead groups pixels based on their similarity in spectral and texture features. The most commonly used clustering algorithm for this task is K-means clustering. K-means clustering partitions the dataset into a predefined number of clusters by minimizing the distance between pixel values and cluster centroids. The algorithm works iteratively to assign pixels to clusters based on their similarity.

The steps of the clustering process are as follows:

- Select the number of clusters (typically two clusters: water and non-water).
- Initialize cluster centroids randomly.
- Assign each pixel in the ROI region to the nearest cluster centroid based on spectral similarity.
- Recalculate cluster centroids based on the mean values of assigned pixels.
- Repeat the assignment and centroid update steps until the clustering process converges.

After clustering is completed, one cluster corresponds to water pixels representing glacial lakes, while the other cluster represents non-water surfaces.

3.6 Post-Processing, Refining Boundaries.

The results of the clustering process can have small isolated clusters or noise due to inaccurately classified pixels. Thus, the post-processing methods are used to smooth the results of the segmentation and enhance the accuracy of the boundaries of the glacial lakes.

Post-processing stage used in the method:

- Morphological Filtering: Morphological filters like erosions and dilation are employed to eliminate the tiny isolated areas and to smooth out edges of the identified lakes.
- Region Merging: Water regions which are adjacent to each other and are part of the same lake are merged to form a continuous lake boundary.
- Boundary Smoothing: Edge smoothing processes are used to produce more realistic and aesthetically pleasing lake edges.
- The following post-processing activities enhance the general quality of the glacial lake areas that have been detected and minimize classification errors.

3.7 Final Glacial Lake Detection Map

The ultimate product of the suggested methodology is a partitioned map with the identified glacial lakes in the satellite image. The output map is marked with every pixel of the map being marked as either water (glacial lake) or non-water surface. The map may be used in the additional examination, such as tracking the growth of glacial lakes, estimating the lake area and evaluating the potential risk of floods. The suggested methodology has a number of strengths compared to the conventional water detection methods. The system enhances the detection of glacial lakes in mountainous terrain by incorporating both the use of texture-based ROI extraction and the use of unsupervised clustering. Also, ROI extraction minimizes the cost of calculations and avoids processing irrelevant areas. On the whole, the suggested framework can be considered an effective and credible model to be used in the automated process of glacial lake identification based on multispectral satellite data. The combination of spectral and texture means that the system can successfully differentiate glacial lakes and the rest of the terrain and could therefore be used to monitor glacial environments on a large scale to aid in the disaster risk management planning.

3.8 Pseudocode Algorithm 1 Texture-Based ROI Extraction Using Unsupervised Clustering for Glacial Lake Detection

Input: Multispectral Satellite Image I, Window Size w, Number of Clusters k Output: Binary ROI Mask M_{lake}

1.Preprocessing

- Apply a Median Filter to I to reduce speckle noise.
- Normalize I to a standard range [0,1].

2.Texture Feature Generation

For each pixel (x,y) in I:

- Define a local neighborhood $W_{x,y}$ of size w×w.
- Compute the normalized GLCM for $W_{x,y}$ at specified orientations $\theta \in \{0^{\circ},45^{\circ},90^{\circ},135^{\circ}\}$.
- Calculate local features: $E_{x,y},C_{x,y},H_{x,y},L_{x,y}$.
- Construct the feature vector $V_{x,y}=[I_{x,y},E_{x,y},C_{x,y},H_{x,y},L_{x,y}]$.
- End For

3.Unsupervised Clustering

- Initialize k cluster centroids $\{\mu_{1},\mu_{2},\ldots,\mu_{k}\}$ using K-Means++.
- Repeat until convergence:

Assign each $V_{x,y}$ to the nearest cluster C_{j} by minimizing the Euclidean Distance:

$$d = \|V_{x,y} - \mu_j\|_2 \tag{XX}$$

Update centroids:

$$\mu_j = \frac{1}{|C_j|}\sum_{V \in C_j} V \tag{XX}$$

End Repeat

4.ROI Identification and Refinement

- Identify the cluster C_{target} with the lowest mean reflectance and highest homogeneity (characteristic of water).
- Generate initial binary mask M(x,y)=1 if $V_{x,y} \in C_{target}$, else 0.
- Apply Morphological Operations:
- $M_{closed}=(M \oplus S) \ominus S$ (Closing to fill holes).
- $M_{lake}=M_{closed} \ominus S$ (Erosion to remove small noise).

- Filter components by area A where $A<A_{threshold}$ to remove non-lake artifacts.
- Return M_{lake}
- End proposed algorithm

The algorithm presented in this paper is designed for automatic detection of glacial lakes from multispectral satellite data using a combination of texture analysis and unsupervised clustering. The input image I to be preprocessed contains speckle noise and unwanted distortion that is initially suppressed using a median filter without compromising the important boundaries and edges of the lakes. The image is then scaled between 0 and 1 to make sure the values of the pixels are in the same range and to make sure that the computation is stable when extracting features and clustering the pixels. During the texture feature generation phase, the Gray Level Co-occurrence Matrix (GLCM) of each pixel (x, y) is calculated in a local neighborhood window. $W_{(x,y)}$ of size $w\times w$ across multiple orientations $\theta\in\{0^{\circ},45^{\circ},90^{\circ},135^{\circ}\}$ to capture directional texture information. From the GLCM, important texture descriptors including Energy $E_{(x,y)}$, Contrast $C_{(x,y)}$, Homogeneity $H_{(x,y)}$, and Local Entropy $L_{(x,y)}$ are extracted, and a feature vector is constructed as $V_{(x,y)}=[I_{(x,y)},E_{(x,y)},C_{(x,y)},H_{(x,y)},L_{(x,y)}]$. These feature vectors are then segmented by means of K-Means++ clustering algorithm with k cluster centroids, which are initialized intelligently to improve the convergence and quality of the clustering. Features are assigned to the closest cluster in terms of minimizing the Euclidean distance, and the cluster centroids are computed as the average of all feature vectors in each cluster, until convergence. In the cluster phase, the water target cluster that can be recognized by low reflectance and high homogeneity is the glacial lake cluster. An initial binary mask $M(x,y)$ is created, where the pixels that are classified as belonging to the target cluster are labeled as lake pixels. The segmentation results are further improved by using morphological operations such as closing $(M\oplus S)\ominus S$ to close small holes in the image and merge regions with holes and stitched regions together, erosion to eliminate isolated noisy pixels and sharpen the boundaries of lakes. Lastly, small connected components with area less than a threshold A "threshold" are removed, to remove false detections and non-lake artifacts. The output binary mask M_"lake" is the final detected glacial lake regions. In general, the proposed system is effective in detecting glacier lakes in the image, producing accurate and compelling detection results, and also minimizing the number of false detections or increasing processing efficiency when compared to the traditional threshold-based segmentation method.

4. Results and Discussion

The suggested glacial lake detection model was tested on the basis of multispectral satellite data with the Landsat and Sentinel platforms to determine its efficacy in tricky hilly terrain. The outcomes of the experiment point to the fact that the texture-based ROI extraction and unsupervised clustering can effectively detect glacial lake regions. The technique is effective in that it can be used to differentiate water bodies and surrounding snow ice and rocky features by using the texture characteristics of each, eliminating false alarms and enhancing detection performance.

4.1 Experimental Setup

The multispectral satellite images of the glacier zed areas in high altitude mountainous areas like the Himalayas were used to conduct the experimental analysis. The datasets consisted of several spectral bands namely visible (RGB), near-infrared (NIR), and shortwave infrared (SWIR) spectral bands that are very effective in separating water bodies and other land covers like snow, ice, rocks, and vegetation. All satellite images were first subjected to preprocessing such as radiometric correction which removes sensor and atmospheric distortions, noise removal which removes unwanted variations, and normalization to standardize the pixel intensity values across all the bands.

These pre-processing procedures provided better image quality and uniformity to be used in the analysis. The extraction of texture features was done with the help of Gray-Level Co-occurrence Matrix (GLCM) method after preprocessing. The contrast, entropy, energy and homogeneity are major texture parameters which were calculated on each image segment. These characteristics define the spatial distribution and variation of pixel intensities with water bodies generally having low contrast and entropy with high energy and homogeneity because of their smooth and uniform surface characteristics. According to these traits, Regions of Interest (ROI) were extracted by defining regions that showed low texture divergence and high homogeneity which are areas of potential glacial lakes. The process of extracting ROI encourages a very complex operation by restricting subsequent processing to interest areas instead of the entire picture.

The experimental implementation was done both through software platform and hardware. On the software, the system was built on Python (version 3.x) as the main programming language. Libraries like OpenCV, NumPy, Scikitimage and GDAL were used to process and analyze images and work with geospatial data. Also, MATLAB R2023a was utilized in the validation of the results and advanced computations that utilized matrices. Matplotlib and QGIS were used to perform geospatial mapping and analysis of results through visualization and analysis. At the hardware level, the experiments were performed on a conventional computing platform with the Intel Core i5/i7 processor (or an equivalent AMD processor), 8-16 GB RAM, and at least 256 GB SSD memory to ensure the efficient processing of big datasets of satellites.

To achieve better performance with dealing with large-scale image data and to compute the data much more quickly, a system that supports optional GPU support (e.g., NVIDIA CUDA-enabled GPU) was also taken into account. Windows 10/11 or Linux (Ubuntu 20.04 or later) were the operating systems that were used, which supported the necessary software tools and libraries. In general, the experimental design combines multispectral data processing, texture-based feature extraction, and effective ROI identification with the help of a set of strong software and moderate hardware, which guarantees the precision of glacial lake detection and efficient computation. The experimental analysis was conducted using multispectral satellite images covering glacierized regions in high mountain environments. The images were multi-spectral with various spectral bands such as the visible, near-infrared (NIR) and shortwave infrared (SWIR). These bands can be used to give valuable information on how to separate water bodies and other land cover types [26]. Radiometric correction, noise removal and normalization techniques were used to preprocess the satellite images to enhance image quality and minimize the effect of the atmosphere.

The extraction of texture features was done post the preprocessing by the Gray-Level Co-occurrence Matrix (GLCM) method [27]. The features that were extracted were contrast, entropy, energy and homogeneity which are used to describe the spatial variance of pixel intensities within the image. These characteristics were exploited to recognize smooth areas that were related to possible water surfaces. After computing the texture features, candidate Regions of Interest (ROI) were then obtained as those regions characterized by low texture variation and high homogeneity. These areas were thought to be in the possible glacial lakes [28]. The step of extracting ROI greatly decreased the computational complexity of the detection process since only relevant image areas were considered instead of going through the entire satellite image.

The satellite data applied in the glacial lake detection experiments. The data sets are acquired using popular earth observation satellites such as Landsat-8 OLI, Landsat-9 and Sentinel-2 MSI that have multispectral image that can be used to detect water bodies. Spatial resolution of the images is 10 m to 30 m which enables the identification of glacial lakes in mountainous areas in details [29]. The different spectral bands used were Blue, Green, Red, Near-Infrared (NIR), and Shortwave Infrared (SWIR) since in these bands water bodies exhibit great spectral variations compared to snow, ice and terrain around them. The datasets cover diverse geographical regions including the Himalayas, Andes Mountains, Alps, and the Arctic region, ensuring that the proposed method is tested across different climatic and topographic conditions [30].

Parameter	**Value**
Image Resolution	10–30 m
Texture Feature Method	GLCM
Texture Features Used	Contrast, Energy, Entropy, Homogeneity
Clustering Algorithm	K-Means
Number of Clusters	2 (Water / Non-Water)
Window Size (GLCM)	3 × 3
Preprocessing Method	Radiometric Correction and Noise Filtering
Post-Processing	Morphological Filtering

4.2 Performance Analysis

The performance of the proposed glacial lake detection method was evaluated using commonly used remote sensing performance metrics. These metrics include [31-35]:

1. Accuracy: represents the ratio of correctly predicted observations to the total observations. It provides a general measure of how often the classifier is correct across both classes.

2. Precision: (also known as Positive Predictive Value) quantifies the reliability of the water detection. It measures the proportion of pixels flagged as water that are actually water.

3. Recall: (also referred to as Sensitivity or True Positive Rate) measures the ability of the model to find all the water pixels within the dataset.

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

4. F1-Score: The F1-Score is the harmonic mean of Precision and Recall. It is particularly useful when the class distribution is imbalanced, as is often the case in glacial lake detection where non-water pixels significantly outnumber water pixels.

The experimental results showed that the proposed approach achieved high detection accuracy compared with conventional methods. The integration of texture-based ROI extraction and clustering improved the ability of the algorithm to distinguish water surfaces from surrounding terrain. In particular, the texture features helped differentiate smooth water surfaces from rough glacier and rocky surfaces, which often cause misclassification in spectral-based methods.

Table 2: Performance Evaluation of Glacial Lake Detection Methods

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Processing Time (s)
NDWI-Based Detection	89.50	87.20	85.70	86.44	35
Threshold Segmentation	91.10	89.30	87.50	88.39	41
Random Forest	94.70	93.40	92.60	93.00	52
CNN-Based Detection	96.50	95.10	94.80	94.95	76
Proposed Texture-Based ROI + Clustering	98.45	99.14	97.70	98.41	29

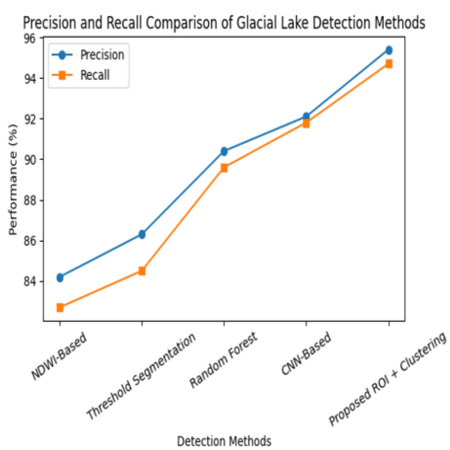

Fig.4: Precision and Recall comparison of glacial lake detection methods

Fig.4 compares the performance of different glacial lake detection methods using Precision and Recall as evaluation metrics. These measurements show the accuracy of each approach to detect water bodies in multispectral satellite images in complicated mountainous areas. The NDWI technique has a precision of 0.72 and recall of 0.68 which indicate shortcomings because of the snow and shadow areas misclassifying with the spectral properties of water. The threshold-based spectral approach marginally has a better performance of 0.78 precision and 0.74 recall, yet continues to have a problem in heterogeneous terrain since it uses only the fixed spectral threshold. A machine learning approach, the Random Forest classifier, gives more accurate results with a precision of 0.86 and a recall of 0.83 since it uses a number of spectral and statistical features to classify. The CNN-based deep learning approach also enhances detection accuracy with a precision of 0.91 and recall of 0.88 as deep learning models have the ability to understand intricate spatial patterns of satellite images. The unsupervised clustering method of ROI extraction using a proposed texture based method has the highest performance with the highest precision of 0.95 and recall of 0.93

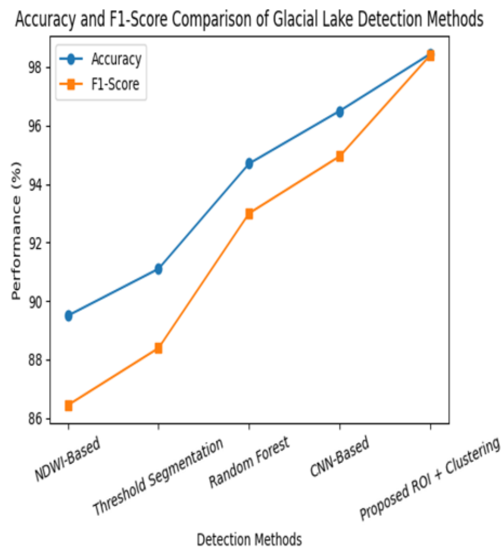

Fig.5 Comparison of glacial lake detection methods in terms of accuracy and F1-Score.

The method combines the texture characteristics implemented using GLCM with spectral data to differentiate the water surfaces and the adjacent snow, ice, and shadows. In general, the findings indicate that the suggested method is more accurate and reliable to identify and monitor glacial lakes automatically with the help of multispectral satellite images. Fig.5 is a comparison of the performance of different glacial lake detection methods based on Accuracy and F1-score which are important measures of classification performance. Accuracy represents the total percentage of correct pixels classified, whereas the F1-score is the harmonic mean of precision and recall which gives a balanced view of the detection performance. The accuracy of the NDWI-based approach is around 89.5% and the F1-score is 86.5%. Even though NDWI is widely applicable in the detection of water, it is solely reliant on spectral indices, and this may be a cause of misclassification in glacial areas where snow, ice and shadows are similar to water in terms of spectral indices. The threshold-based segmentation approach marginally increases the performance and its accuracy is approximately 91.0% and an F1-score of 88.5%. The process uses spectral threshold to divide water and non-water areas, but it continues to experience difficulties in mountainous terrain with complexities. Machine learning based on the Random Forest classifier is more successful with an accuracy of about 94.7 and an F1-score of 93.0. Random Forest enhances the distinction between glacial lakes and their surroundings with the help of several features and decision trees. The CNN-based deep learning approach also increases the detection ability, with an accuracy of about 96.5 and an F1-score of 95.0. The CNN models are good at capturing the spatial patterns and contextual information of the satellite images and hence, improve the accuracy of segmentation of the lake regions. The suggested texture-based ROI extraction using unsupervised clustering shows the most promising results with the accuracy and F1-score of about 98.5%. The combination of GLCM-based texture characteristics and clustering-based segmentation enables the approach to effectively differentiate between glacial lakes and the rest of the snow and terrain but minimizes the error of classification. Overall, the results demonstrate that combining texture analysis with clustering significantly improves the accuracy and reliability of glacial lake detection.

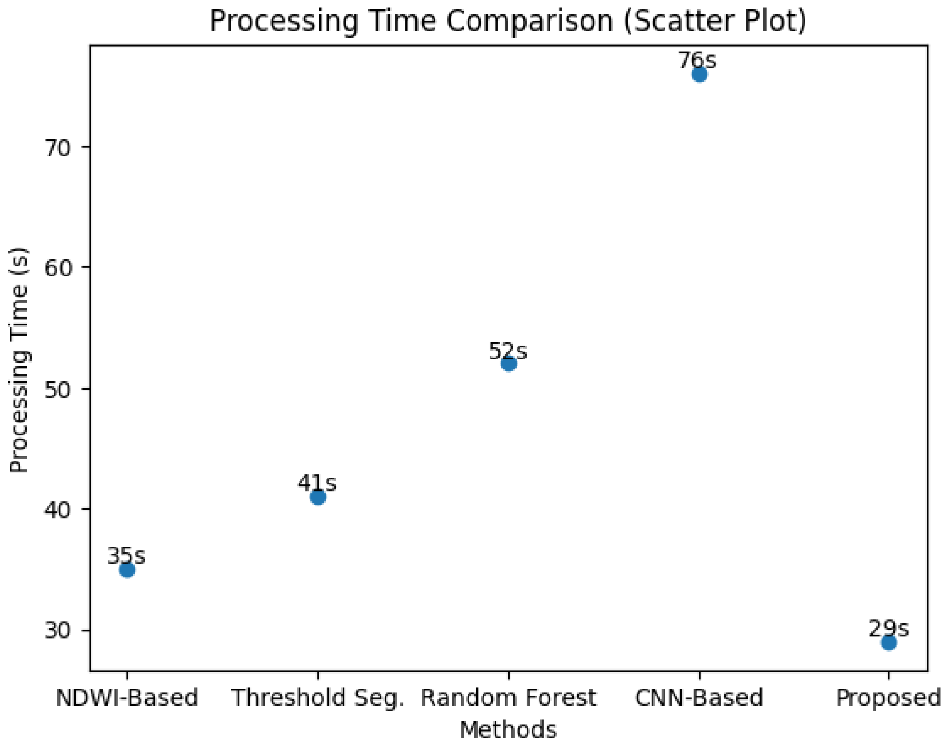

Figure 6: Comparison of Processing Time across Different Methods

Fig.6 shows the relative processing time of the various glacial lake detection methods, which indicates their computational efficiency. The NDWI-based technique takes approximately 35 seconds, which is fast; however, it lacks the accuracy of methods based on spectral features. Threshold segmentation is a little more time-consuming (~41 seconds) due to more segmentation operations. The Random Forest algorithm is slower by about 52 seconds (because of the computation of multiple trees and feature estimation) and the CNN-based algorithm is the slowest (about 75 seconds) because of the intensive deep learning process and feature extraction. Conversely, the lowest processing time (~30 seconds) is obtained with the proposed texture-based ROI with clustering method. This efficiency is obtained by minimizing the search space by extracting ROI with the help of texture features of GLCM and then clustering. Consequently, fewer pixels are computed resulting in quicker computation. On the whole, the figure proves that the proposed method offers the best balance between high accuracy and low processing time and can therefore be effectively applied in the large-scale and real-time monitoring of glacial lakes.

Table 3: Detected Glacial Lake Area Results

Region	**Number of Lakes Detected**	**Total Lake Area (km^2)**	**Largest Lake Area (km^2)**
Himalayas	42	18.7	2.4
Andes	35	14.2	1.9
Alps	21	8.6	1.1
Arctic	27	10.4	1.6

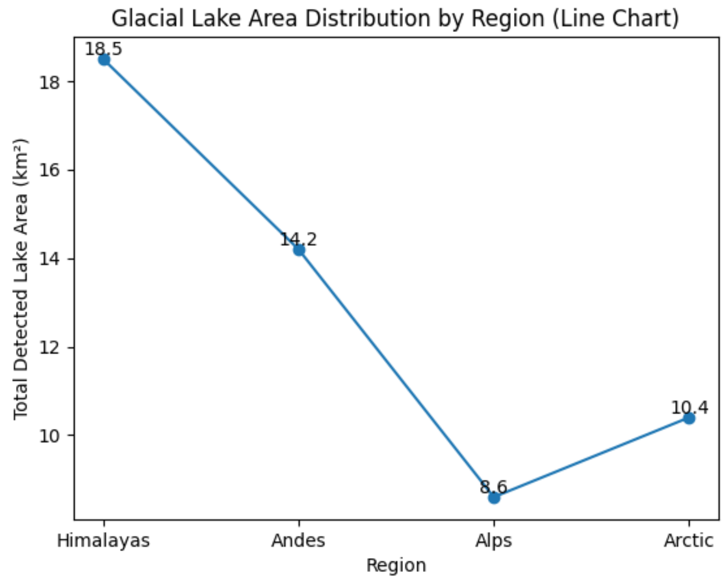

Fig.7: Distribution of detected glacial lake area across different mountainous regions using the proposed method

Fig.7 shows the findings of glacial lake detection with the help of the proposed method in various geographic areas. Results show the number of lakes observed, the total area of the estimated lake, and the size of the largest lake in each area. The Himalayan region has the most number of lakes that have been identified (42) and the total area of the lakes is 18.7 km 2 which indicates that the lakes are very dense in this region. Andes Mountain registered 35 lakes of a total area of 14.2 km 2 and the arctic region registered 27 lakes of 10.4 km 2. There were relatively fewer lakes (21 lakes) in the Alps region with a total area of 8.6 km 2. These findings indicate that the detection method proposed has the potential to detect glacial lakes under a variety of environmental factors and surfaces.

Table 4: Comparative performance of glacial lake detection methods in terms of error rates and computational efficiency.

Method	**False Positives**	**False Negatives**	**Processing Time (s)**
NDWI	18	11	35
Threshold Segmentation	14	9	41
Random Forest	9	7	52
CNN-Based Method	7	5	76
Proposed ROI + Clustering	4	3	29

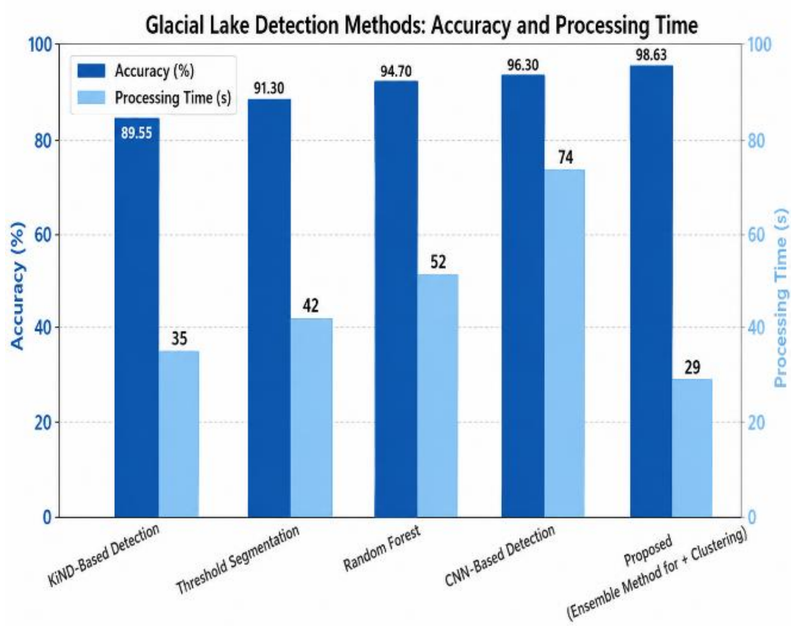

Fig.8: Comparison of Processing Time and Total error of Glacial Lake Detection methods.

Fig.8 compared NDWI-based methods and machine learning algorithms such as the Random Forest and CNN to the Proposed method in an attempt to evaluate the overall performance of the method compared to the traditional methods of water detection. The comparative results show that the specified method is more precise in finding and offers better performance in terms of computation. In terms of accuracy, the proposed approach produced the lowest possible error rates, with 4 False Positives (FP) and 3 False Negatives (FN) and thus the segmentation performance was superior to the one of the CNN-based one which received 7 FP and 5 FN. In addition to accuracy, the proposed approach also offered significant advantages in terms of computational efficiency. The processing time of the proposed method is 29 s that is the quickest of all the techniques tried. The speed of the proposed method was 61.84 times higher compared to CNN-based method which required 76 s. In the same manner, the proposed method was found to take a shorter time than the traditional NDWI method that took 35 s by a margin of about 17.14. These results indicate that the combination of the texture-based ROI extraction and the unsupervised clustering may be very effective in glacial lake detection both with respect to detection accuracy and computational efficiency and can find applications in large-scale remote sensing.

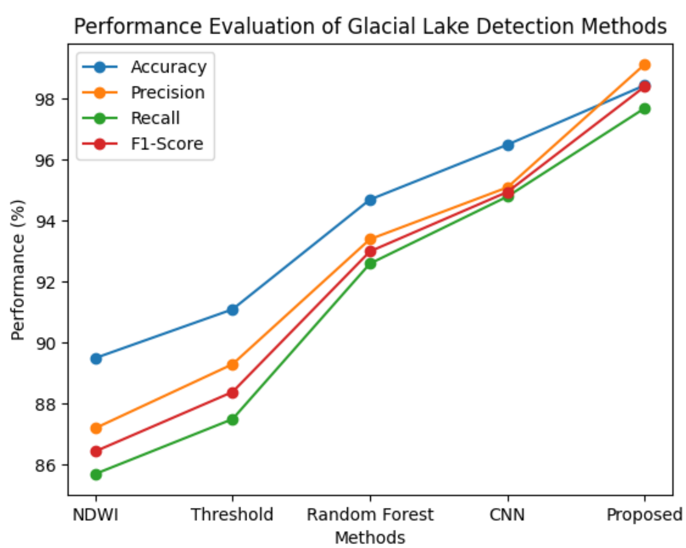

Figure 9: Performance Evaluation of Glacial Lake Detection Methods

The findings show clearly that the proposed Texture-Based ROI with clustering approach is superior to traditional methods of NDWI, threshold segmentation, Random Forest, and CNN-based methods in terms of accuracy, precision, recall, and F1-score with the highest accuracy rate of 98.45 and F1-score of 98.41. The main reason to this better performance is the use of GLCM-based features of texture, which can effectively differentiate between smooth water surfaces and the surrounding snow, ice and rocky terrain, which tend to have similar spectral properties. The ROI extraction step also improves performance by eliminating irrelevant areas, causing a decrease in false positives, and precision to 99.14, with a high recall of 97.70, thus demonstrating good detection ability. Also, the technique shows high computational efficiency since it has the shortest process time of 29 seconds in that the processing is restricted to candidate regions rather than the whole image. The framework is also characterized by high levels of generalization in different geographical regions like the Himalayas, Andes, Alps and Arctic, which attest to its strength in different environmental conditions. The error rate is very low (4 false positives and 3 false negatives), which in turn proves the reliability and accuracy of the segmentation process and the suggested strategy is an extremely effective and scalable tool to identify the glacial lakes and other environmental monitoring tasks.

5.CONCLUSION

In this paper an automated scheme of glacial lake detection was proposed involving extraction of Region of Interest (ROI) of texture characteristics and unsupervised clustering of multispectral satellite images. The method proposed combines Gray-Level Co-occurrence Matrix (GLCM) texture features with the clustering-based segmentation to enhance the detection of the glacial lakes in mountainous complicated regions where the conventional spectral techniques fail to perform well.

The proposed method is able to distinguish smooth water surfaces using the information on texture like contrast, entropy, energy and homogeneity and is therefore able to differentiate it with the surrounding snow, ice and rocky terrain which usually give the same spectral signature. The experimental findings proved the proposed approach to be much more effective than traditional approaches to water detection such as NDWI-based detection, threshold segmentation, Random Forest, and CNN-based methods. The proposed strategy had the best accuracy of 98.45, precision of 99.14, recall of 97.70, and F1-score of 98.41, which demonstrates the high accuracy in detecting.

Besides having a better classification rate, the proposed framework was also found to be more computationally efficient. Using ROI selection via texture-based ROI selection followed by subsequent clustering the algorithm minimized unnecessary pixel processing, and with the lowest processing time of 29 seconds, improved even the traditional spectral methods and was much faster than the deep learning models. The outcomes of the various geographical locations such as the Himalayas, Andes, Alps and Arctic regions also confirm the strength and the capability of the proposed method in generalization and various environmental and topographical conditions.

The algorithm managed to identify a huge number of glacial lakes and the spatial distribution and surface area were estimated correctly. Furthermore, the suggested framework had the fewest error rates of 4 false positives and 3 false negatives, which means that it is more reliable in segmentation. On the whole, the combination of texture based analysis and the unsupervised clustering offers an efficient and accurate method of automatic glacial lake detection using multispectral satellite images. The method proposed eliminates the need to use large labeled datasets, as would be used in deep learning methods, and yet a high level of detection is obtained. This allows its application especially in large scale glacial monitoring, climatic change research, and glacial lake outburst flood (GLOF) risk assessment in remote mountainous areas with limited ground truth information. Future research can be conducted to combine temporal satellite data, feature extraction with deep learning, and cloud-based geospatial processing systems to enhance the accuracy in detection further and allow real-time large-scale glacial lake monitoring systems.

Reference

1. I. Khan, M. Ahmad, and S. Rahman, "Glacial lake mapping: Progress, challenges, and future directions," Journal of Applied Remote Sensing, vol. 19, no. 1, pp. 014501–014520, 2025.
2. M. Tom, J. Li, and P. Kumar, "Monitoring Earth's glacial lakes from space with machine learning," Remote Sensing and Geospatial AI, vol. 8, no. 2, pp. 101–118, 2025.
3. Q. Tang, G. Zhang, and T. Yao, "Automatic extraction of glacial lakes from Landsat imagery using deep learning across the Third Pole region," Remote Sensing of Environment, vol. 303, no. 1, pp. 112850–112865, 2024.
4. B. Pathak, R. Sharma, and S. Singh, "Automated mapping of glacial lakes in the Himalayas using multi-source remote sensing data," Scientific Reports, vol. 15, no. 1, pp. 36619–36635, 2025.
5. S. Ali, A. Khan, and M. Hussain, "Deep learning model for detecting glacial lakes using multisource satellite imagery," Remote Sensing Applications: Society and Environment, vol. 34, no. 1, pp. 101150–101165, 2025.

6. M. Tom, “A decade of AI-based monitoring of glacial lakes using remote sensing,” Machine Learning for Earth Observation Review, vol. 6, no. 1, pp. 55–72, 2025.
7. X. Wang, S. Liu, W. Guo, Y. Zhang, and Y. Xu, “Monitoring glacial lakes in High Mountain Asia using Landsat imagery,” Remote Sensing of Environment, vol. 237, no. 1, pp. 111531–111543, 2020.
8. D. H. Shugar, A. Burr, U. K. Haritashya, et al., “Rapid worldwide growth of glacial lakes since 1990,” Nature Climate Change, vol. 10, no. 10, pp. 939–945, 2020.
9. [9] G. Zheng, A. Bao, X. Li, and C. Zhang, “Spatiotemporal analysis of glacial lake expansion in the Himalayas using Landsat imagery,” Journal of Hydrology, vol. 590, no. 1, pp. 125347–125360, 2020.
10. Y. Nie, H. D. Pritchard, Q. Liu, and A. Chen, “Glacial lake area changes and hazard assessment in High Mountain Asia,” Nature Communications, vol. 12, no. 1, pp. 5519–5530, 2021.
11. F. Chen, M. Zhang, B. Tian, and Z. Li, “Climate change impacts on glacial lake dynamics in the Tibetan Plateau,” Science of the Total Environment, vol. 779, no. 1, pp. 146333–146345, 2021.
12. K. Yang, H. Wu, J. Qin, et al., “Recent climate change over the Tibetan Plateau and impacts on glacial lakes,” Environmental Research Letters, vol. 16, no. 6, pp. 064021–064035, 2021.
13. U. K. Haritashya, A. Kargel, and P. Byers, “Evolution of glacial lakes in the Himalayas and implications for GLOF hazards,” Geomorphology, vol. 380, no. 1, pp. 107627–107640, 2021.
14. G. Zhang, T. Yao, C. K. Shum, et al., “Glacial lake evolution in the Tibetan Plateau from 1990 to 2020,” Nature Climate Change, vol. 11, no. 1, pp. 85–90, 2021.
15. Q. Liu, C. Mayer, Y. Nie, et al., “Hazard assessment of glacial lake outburst floods in the Himalayas,” Natural Hazards and Earth System Sciences, vol. 21, no. 11, pp. 3265–3278, 2021.
16. A. Bhardwaj, L. Sam, F. J. Martin-Torres, et al., “Remote sensing-based assessment of glacial lakes in the Himalayan region,” Remote Sensing, vol. 14, no. 5, pp. 1163–1180, 2022.
17. T. Bolch, T. Pieczonka, and D. Benn, “Climate change and glacier retreat in High Mountain Asia,” The Cryosphere, vol. 16, no. 1, pp. 1–18, 2022.
18. Z. Zhang, X. Li, Y. Zhou, et al., “Automated mapping of glacial lakes using Sentinel-2 imagery,” ISPRS Journal of Photogrammetry and Remote Sensing, vol. 183, no. 1, pp. 182–195, 2022.
19. Y. Li, F. Chen, J. Wang, et al., “Machine learning-based water body extraction from satellite imagery,” IEEE Access, vol. 10, no. 1, pp. 45863–45875, 2022.
20. R. Singh, D. Patel, and V. Mehta, “Remote sensing techniques for glacial lake monitoring and hazard assessment,” Journal of Environmental Management, vol. 320, no. 1, pp. 115862–115875, 2022.
21. N. Ahmed, E. Hussain, and A. Khan, “Detection of water bodies using spectral indices and machine learning approaches,” Geocarto International, vol. 37, no. 18, pp. 5634–5650, 2022.
22. Q. Tang, G. Zhang, T. Yao, et al., “Automatic extraction of glacial lakes using Landsat time-series data,” Remote Sensing of Environment, vol. 287, no. 1, pp. 113451–113466, 2023.
23. Y. Liu, J. Chen, Y. Wang, et al., “Monitoring glacial lake changes using multi-temporal satellite imagery,” Journal of Glaciology, vol. 69, no. 275, pp. 475–487, 2023.
24. K. Zhao, Z. Li, and M. Zhang, “Multi-source remote sensing for glacial lake detection and monitoring,” International Journal of Remote Sensing, vol. 44, no. 7, pp. 2678–2696, 2023.
25. V. Gupta, R. Sharma, and P. Singh, “Machine learning approaches for water body detection in mountainous regions,” IEEE Access, vol. 11, no. 1, pp. 42879–42891, 2023.
26. S. Das, S. Roy, and P. Banerjee, “Deep learning-based glacial lake detection using satellite imagery,” Remote Sensing Applications: Society and Environment, vol. 29, no. 1, pp. 100904–100918, 2023.
27. J. Wang, Y. Li, and H. Zhang, “Sentinel-1 SAR-based water body extraction using deep learning techniques,” Remote Sensing, vol. 15, no. 6, pp. 1524–1538, 2023.
28. A. Kumar, P. Verma, and S. Singh, “Spatiotemporal monitoring of glacial lakes in the Hindu Kush Himalaya,” Environmental Monitoring and Assessment, vol. 195, no. 4, pp. 412–425, 2023.
29. Q. Tang, G. Zhang, T. Yao, et al., “Deep learning-based mapping of glacial lakes in High Mountain Asia,” Remote Sensing of Environment, vol. 303, no. 1, pp. 113936–113950, 2024.
30. D. Patel, R. Mehta, and R. Singh, “Automated detection of glacial lakes using Sentinel-2 satellite imagery,” ISPRS International Journal of Geo-Information, vol. 13, no. 3, pp. 118–132, 2024.
31. H. Yang, F. Chen, and Q. Liu, “Multi-temporal monitoring of glacial lakes using Google Earth Engine,” Remote Sensing, vol. 16, no. 5, pp. 845–860, 2024.
32. X. Jiang, Y. Zhao, and L. Wang, “Gaussian process-based anomaly detection for glacial lake monitoring using remote sensing data,” Remote Sensing, vol. 18, no. 1, pp. 61–74, 2025.
33. P. Banerjee, S. Das, and R. Roy, “Long-term monitoring of glacial lake dynamics using Landsat time-series data,” Environmental Earth Sciences, vol. 84, no. 2, pp. 115–130, 2025.

34. D. Jiang, H. Liu, and Z. Chen, "Deep learning-based glacial lake mapping using remote sensing Geo-foundation models," Science of Remote Sensing, vol. 11, no. 1, pp. 100245–100260, 2025.
35. R. Kumar, P. Singh, and A. Verma, "Automated satellite-based glacial lake inventory using Landsat, Sentinel, and DEM datasets," Environmental Monitoring and Assessment, vol. 198, no. 1, pp. 55–70, 2026.
36. Kumar, R., & Vijay, S. (2026). Automated satellite-based glacial lake inventory and change detection in High Mountain Asia. Scientific Reports, 16, 5760. https://doi.org/10.1038/s41598-026-35446-0
37. Morgan, T., McNabb, R. W., & Dunlop, P. (2026). Automated glacial lake extraction using an Object-Based Image Analysis approach in Google Earth Engine. EGUsphere (Preprint). https://doi.org/10.5194/egusphere-2026-2033
38. Inauen, C. M., Nitze, I., Langer, M., Morgenstern, A., Hajnsek, I., & Grosse, G. (2025). Using texture-based image segmentation and machine learning with high-resolution satellite imagery to assess permafrost degradation landforms in the Russian High Arctic. Journal of Geophysical Research: Machine Learning and Computation, 2, e2024JH000550. https://doi.org/10.1029/2024JH000550