water

Review

Application of Artificial Intelligence in Glacier Studies: A State-of-the-Art Review

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Abstract: Assessing glaciers using recent and historical data and predicting the future impacts on them due to climate change are crucial for understanding global glacier mass balance, regional water resources, and downstream hydrology. Computational methods are crucial for analyzing current conditions and forecasting glacier changes using remote sensing and other data sources. Due to the complexity and large data volumes, there is a strong demand for accelerated computing. AI-based approaches are increasingly being adopted for their efficiency and accuracy in these tasks. Thus, in the current state-of-the-art review work, available research results on the application of AI methods for glacier studies are addressed. Using selected search terms, AI-based publications are collected from research databases. They are further classified in terms of their geographical locations and glacier-related research purposes. It was found that the majority of AI-based glacier studies focused on inventorying and mapping glaciers worldwide. AI techniques like U-Net, Random forest, CNN, and DeepLab are mostly utilized in glacier mapping, demonstrating their adaptability and scalability. Other AI-based glacier studies such as glacier evolution, snow/ice differentiation, and ice dynamic modeling are reviewed and classified, Overall, AI methods are predominantly based on supervised learning and deep learning approaches, and these methods have been used almost evenly in glacier publications over the years since the beginning of this research area. Thus, the integration of AI in glacier research is advancing, promising to enhance our comprehension of glaciers amid climate change and aiding environmental conservation and resource management.

Keywords: remote sensing; artificial intelligence; machine learning; glacier mapping; snow/ice differentiation; ice dynamics modeling

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1. Introduction

Glaciers worldwide are at serious risk due to climate change. For instance, the mass loss of mountain glaciers between 2006 and 2016 resulted in a global sea-level contribution of 335 ± 144 Gt per year [1]. Even though the rate of glacier loss is dependent on the region, it is expected to have significant environmental and social impacts [2,3]. In fact, nearly 10% of the world's population residing in mountainous regions depends on glaciers as a crucial water source, where they are utilized for agriculture, industry, hydropower generation, and domestic use [4,5]. Moreover, meltwater from glaciers contributes to the sustenance of rivers, lakes, and wetlands, supporting diverse aquatic life forms. Additionally, glaciers play a crucial role in regulating local microclimates [6], influencing vegetation patterns and providing a habitat for various species, thereby shaping the composition and dynamics of terrestrial ecosystems [7]. Therefore, evaluating and estimating changes in glaciers plays a crucial role in projecting future scenarios, particularly in regions where both the environment and society depend on them.

For a few decades, organizations and scientists have been developing inventories for glaciers throughout the world. For instance, the World Glacier Inventory (WGI) contains data for over 130,000 glaciers, providing information on parameters such as geographic location, area, length, orientation, elevation, and classification, primarily derived from aerial photographs and maps. However, the WGI inventory can provide a glacier distribution in the second half of the 20th century [8]. Similarly, the Randolph Glacier Inventory (RGI) serves as another valuable database for glaciers; however, its temporal coverage is limited as most of the glaciers were mapped around the 2000s [9]. Therefore, these inventories can only serve as baseline datasets, as they are unable to capture the latest changes in glacier dynamics. However, in the last decade, there has been a proactive effort to generate additional localized data using remote sensing methods, aimed at enhancing the temporal accuracy in monitoring glacier changes [10].

Methods relying on optical, synthetic aperture radar (SAR), and multisource datasets are well known in glacier mapping. Optical imagery (OI) is considered as the primary technique utilized for glacier extraction, leveraging the significant contrast between the minimal spectral reflectance of ice and snow in the shortwave infrared and their high reflectance within the visible spectrum [11,12]. However, its efficacy is constrained by weather variability and the difficulty in distinguishing glaciers, especially those covered with debris from surrounding rocks of mountains, due to their comparable spectral characteristics [13]. To address these challenges, SAR data are utilized in glacier extraction, leveraging two main principles. One principle focuses on the lower coherence observed in glaciers, both clean and debris-covered, compared to the higher coherence of surrounding bedrock, with commonly used data sources including Sentinel-1 and ALOS PALSAR [14,15]. However, the processing of SAR coherence is complex and limited by the presence of non-steady deformation processes. Additionally, SAR imaging can be hindered by factors such as layover and shadow effects in steep terrain, which may obscure certain glacier features and impede accurate mapping [16]. Furthermore, combining different data sources (i.e., multisource approach) from SAR, OI, and digital elevation models (DEMs) provides valuable insights into glacier dynamics and changes [17]. However, the multi-source method involves various drawbacks related to data integration complexity, temporal and spatial mismatch, cost and accessibility, data consistency and quality, as well as interpretation and validation challenges. Addressing these disadvantages requires careful consideration of data processing techniques, quality assessment measures, and validation procedures to ensure robust and accurate glacier mapping results [18].

Transitioning from traditional methods to artificial intelligence (AI) techniques marks a significant advancement in glacier mapping and monitoring. Indeed, studies have shown that AI methodologies demonstrate notable efficacy in classifying remote sensing (RS) data through feature extraction and selection, particularly in hyperspectral images [19,20]. These AI techniques have yielded promising outcomes across various RS applications, including tree delineation [21], land cover classification [22], building detection [23,24], fault diagnosis [25], and fault-tolerant control [26]. Moreover, within the realm of glacier studies, AI methods have also found applications in mapping large glaciers from RS data.

Recently, various advanced methods have been actively employed for evaluating changes in glacier-covered regions and ice formations during specific periods. Among these methods, segmentation techniques that rely on visual interpretation and RS are the most frequently used [27–29]. Moreover, these evaluations have begun to be studied using decision-tree, supervised, and unsupervised methods [30]. In the same way, band ratios and manual on-screen digitalization are utilized to classify debris-covered glaciers [31]. Furthermore, a number of researchers have suggested semi-automatic methods for classification purposes, and more recently, unmanned aerial vehicles (UAVs) have been employed to map glaciers with increased precision [32].

These AI algorithms offer powerful tools for glacier mapping applications, enabling researchers to analyze large-scale glacier datasets more efficiently and accurately than traditional manual methods. By leveraging the capabilities of AI, scientists can gain deeper insights into glacier dynamics, contribute to climate change research, and support informed decision making in environmental management [33]. Therefore, reviewing the latest works in this new area is necessary to understand the research trends in terms of AI methods applied for glacier studies.

In this study, we conduct a state-of-the-art review of the most recent research papers that have applied artificial intelligence (AI) methods in glacier studies. According to our observations, the application of AI methods for glacier studies has been active since 2019. The main reasons may be the increased access and availability of open-source AI tools such as Pytorch [34], Tensorflow [35], and Keras [36] for the general audience and continuous improvements in image-based AI techniques, which have significantly accelerated in the last few years [37]. This makes the recent works particularly relevant and of interest given the latest advancements.

Thus, the objective of the current state-of-the-art review is to understand the trend of AI-based method applications in glacier studies, as well as the types and classification of AI methods, and to evaluate the size and variety of glacier datasets used for training and validation in addition to the accuracy and efficiency of the selected AI methods in studying glaciers. Moreover, the reviewed works are classified based on the type of glacier studies, providing the reader with clear guidance on the AI methods applied for the relevant studies. For each type of glacier study that uses AI, the research works are reviewed and discussed in chronological order, offering valuable insights into how this research field is evolving over time. Additionally, comparative analyses are carried out for each type of AI-based glacier study. Hence, in the next section, the readers may learn about the approach to finding the research works among AI-based glacier studies, understanding the reviewed works in a general manner, and gaining knowledge from classification charts and illustrations. Furthermore, in the subsequent sections, the classified works are discussed in more detail, followed by a discussion section. Finally, conclusive remarks, including future works, are presented in the conclusion section.

2. Review Approach and Overview of the Collected Works

To find research works that apply AI methods and techniques to glacier studies, we used search terms and expressions such as "Glacier Deep Learning", "Glacier Machine Learning", "Artificial Intelligence in glacier studies", "Glacier studies with Neural Networks", and "Neural Network-based glacier studies" in various databases (Figure 1). Specifically, we conducted searches in databases such as Elsevier, Wiley, Springer, Taylor & Francis, IEEE, Copernicus Group, and MDPI. According to the Scimago Journal Rank (www.scimagojr.com), these publishers, under the category of Earth-Surface Processes, host the leading journals that publish environmental science, geology, and glaciology research works. Additionally, we used these terms and expressions in the Google search engine to find similar works in other databases to ensure comprehensive coverage. As shown in the flowchart, the research articles found are firstly classified in chronological order.

Furthermore, according to the inventory data of RGI [38], there are 19 glacier regions in the world, as shown in Figure 2. Once all the works are collected in chronological order, the second step in classification involves dividing them based on these regions. Such classification can be considered reasonable since the accuracy of AI models usually depends on the geological location of the training datasets, and they are often less accurate when tested on another dataset from a different location [39]. Thus, among the glacier regions studied using AI methods, the most prominent are those in South West and South East Asia, designated as Region 14 and 15, respectively, followed by Central Europe and other regions. This is clearly can be noticed in the second column of the Sankey Diagram illustrated in Figure 3. Furthermore, considering the main classification of the reviewed works, we focus on the purpose of AI applications in glacier studies (Figure 3), which are mainly divided into (i) inventory and mapping, (ii) glacier evolution, (iii) snow/ice differentiation, and (iv) ice dynamics modeling. Therefore, the main part of the current work, Section 3, is divided into subsections based on these classifications of glacier studies.

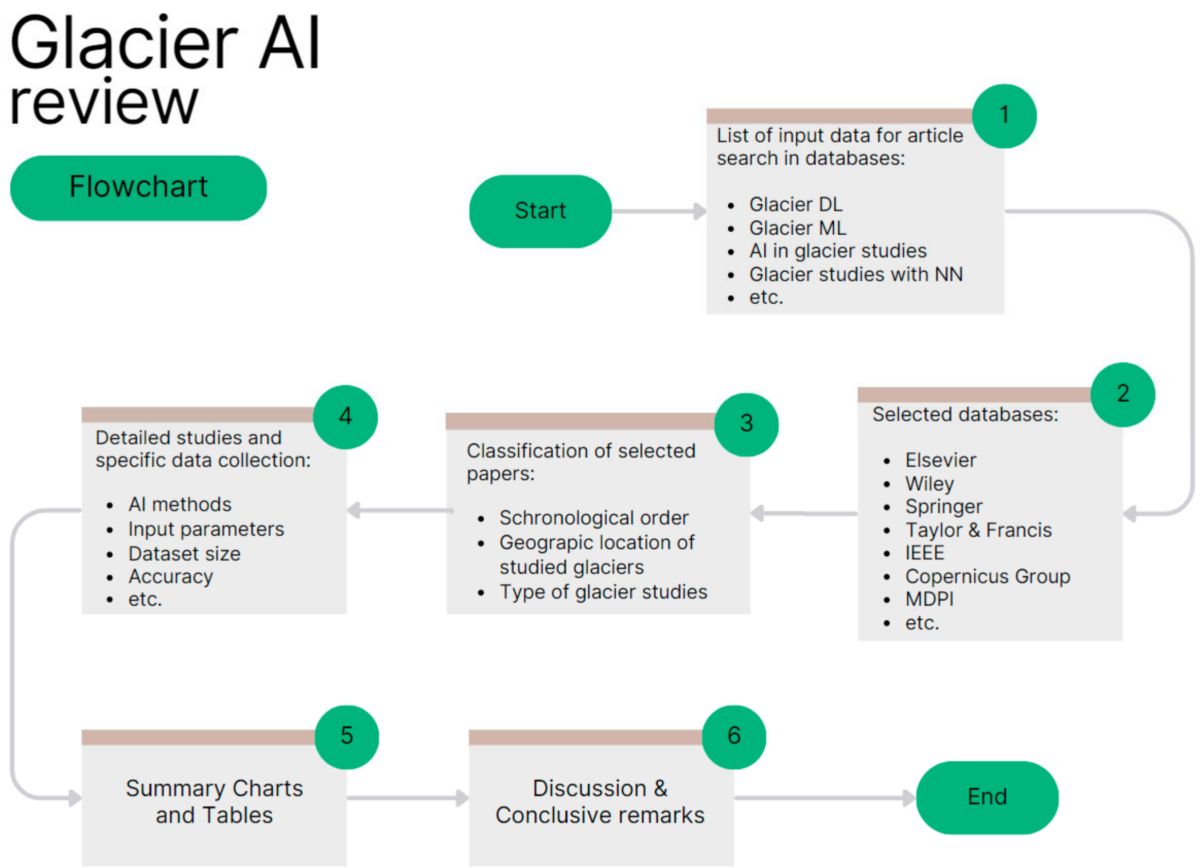

Figure 1. Flowchart for illustration of the methods used in the current review work.

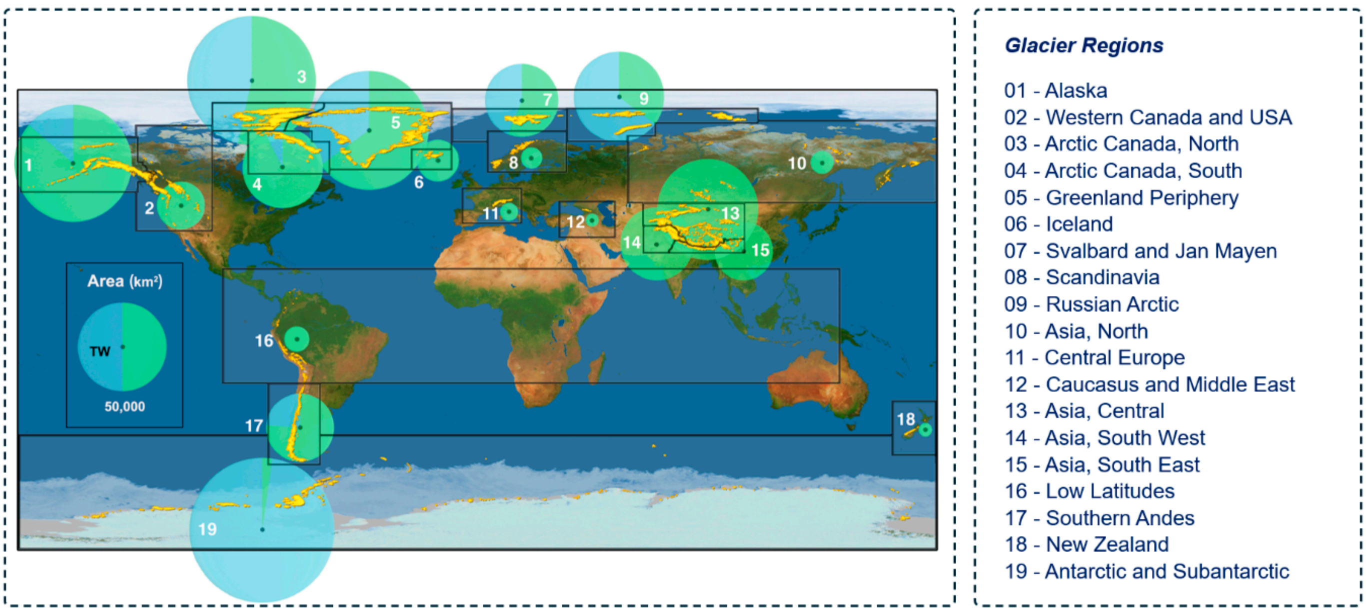

Figure 2. Glacier regions in the world (modified from [38]).

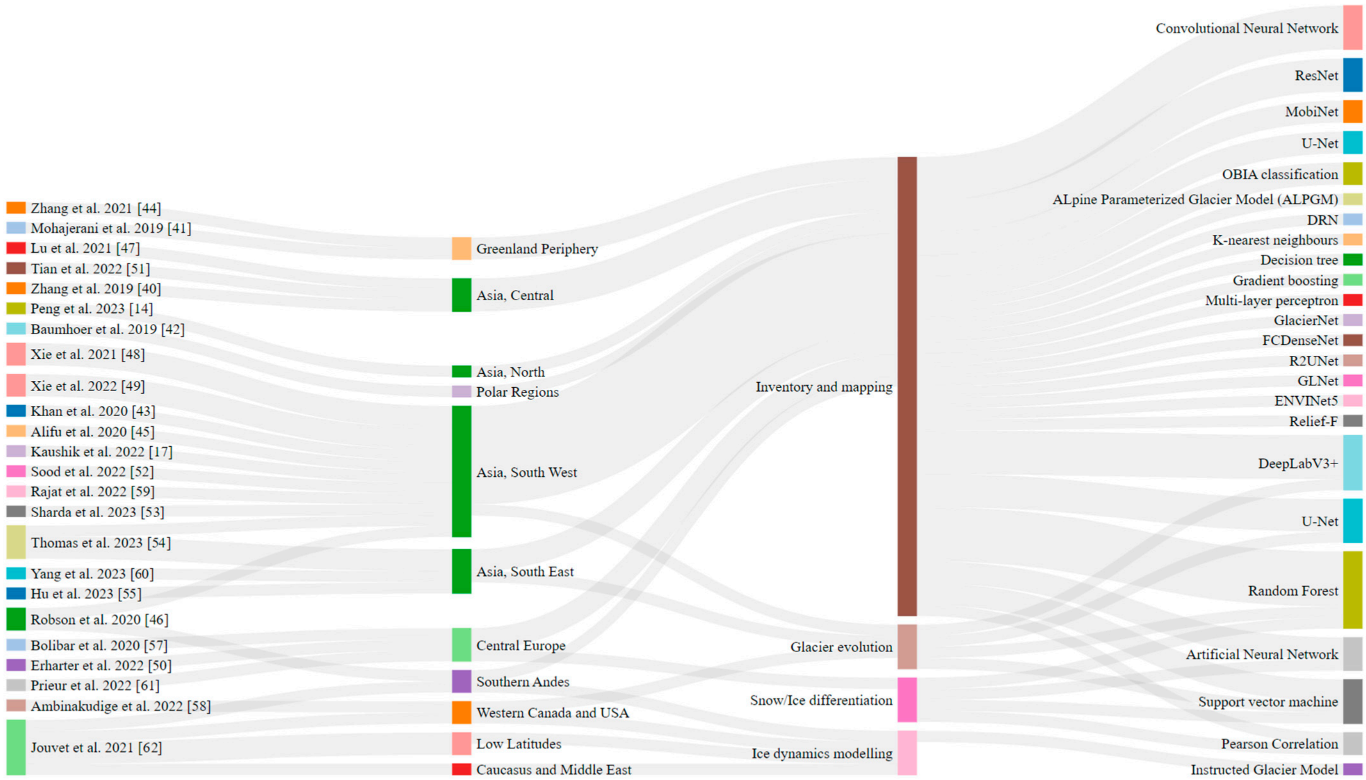

Figure 3. Classification of the collected research works based on glacier regions, type of glacier study, and AI models using a Sankey Diagram.

Inventory development and mapping of glaciers represent one of the most extensively studied areas within the field of AI-based glacier studies, and this is clearly shown in the Sankey diagram (Figure 3). Among the collected and reviewed works, XX papers dealt with the application of AI methods for inventory and mapping of glaciers. Thus, researchers and scientists have increasingly utilized AI methods such as machine learning (ML) techniques and deep learning (DL) techniques to automate the process of mapping glaciers, creating detailed inventories, and monitoring changes in glacier extent over time.

On the other hand, monitoring glacier evolution becomes crucial for understanding environmental changes, especially as glaciers worldwide are affected by the consequences of climate change. Therefore, in the latest works, applications of AI in this area can be found since AI offers powerful tools for continuously tracking glacier dynamics, enabling researchers to gain insights into changes in glacier extent, volume, and behavior over time.

There are certain unique applications of AI in snow/ice differentiation and ice dynamics modeling that allow us to distinguish glaciers from snow layers and simulate ice volume changes, mass balance, and their coupling to assess the development of icefields and ice sheets. Therefore, they are considered as separate areas of glacier studies in the current review work.

As shown in the flowchart (Figure 1), while reviewing each research work, the main findings—such as the location and type of the glacier, its classification/type based on GLIMS (Global Land Ice Measurements from Space) if applicable, the selected AI model, the input parameters, the datasets and dataset sizes, the accuracy of the model, and the software used to develop and run the AI model—are summarized in Table 1. Such a tabulated summary is highly suitable for a quick comparison of AI-based works, and it contains all the main findings in the form of organized data for readers to evaluate the past works and plan their future research.

Table 1. Summary of the review.

Author	Location	Glacier Location Name	Studied Glacier Types	Classification by GLIMS Manual	AI Model	Parameters	Dataset Size	Accuracy	Software
Glacier inventory and mapping									
2019 Zhang et al. [40]	Parlung Zangbo Basin, China	Tibetian Plateau glacier	• Non/partially debris-covered glaciers • Fully debris-covered glaciers	N/A	Random forest (RF)	• Landsat-8 images • Normalized difference vegetation index (NDVI) • Normalized Difference Water Index (NDWI) • Normalized Difference Snow Index (NDSI) • GF-1 PMS imagery • Digital Elevation Model (DEM) • 11 topographic parameters	2755	RF-98.6% (ovearall)	EnMAP-Box + DLL
2019 Mohajerani et al. [41]	Greenland	Jakobshavn, Sverdrup, Kangerlussuaq, Helheim	• Tidewater glaciers	N/A	U-Net	• Landsat images	Training data: images from Jakobshavn, Sverdrup and Kangerlussuaq. Test data: images from Helheim glacier	Mean deviation of 96.3 m from the true calving fonts	Python
2019 Baumhoer et al. [42]	Antarctica	• Sulzberg ice shelfSkackle-ton ice shelf • Wilkes Land • Victoria Land • Getz ice shelf • Ekstromisen • Wordie ice shelf • Oats land • Marie Byrd land	• Ice shelves, dynamic glaciers	N/A	Modified U-Net	• Sentintel-1, • TanDEM-X digital elevation model	38 pre-processed Sentinel-1 scenes 90m resolution TanDEM-X	Average f1-score = 90%	N/A

Table 1. *Cont.*

Author	Location	Glacier Location Name	Studied Glacier Types	Classification by GLIMS Manual	AI Model	Parameters	Dataset Size	Accuracy	Software
2020 Khan et al. [43]	Hunza Basin, Pakistan	Batura glacier	• Glaciers • Debris-covered glaciers • Non-glaciated areas	N/A	• Support vector machine (SVM) • Artificial neural network (ANN) • RF	• NDVI • NDSI • NDWI • New band ratio (NBR) • Mean • Variance • Homogeneity • Contrast • Dissimilarity • Entropy • Energy • Correlation • Angular second momentum • Slope • Aspect • Evaluation Land surface temperature	2,688,723 pixels Training: 70% Testing: 30%	Kappa: SVM = 0.89 ANN = 0.92 RF = 0.95 f-measure: SVM = 91.86% ANN = 92.05% RF = 95.06%	N/A
2021 Zhang et al. [44]	Greenland	Jakobshavn Isbræ, Kangerlussuaq, Helheim glaciers	Tidewater outlet glaciers	Tidewater outlet glacier	• U-Net • DeepLabv3+ with ResNet • DRN • MobiNet	Optical: • Landsat-8 • Sentinel-2 Synthetic aperture radar images: • Envisat • ALOS-1 • TerraSAR-X • Sentinel-1 • ALOS-2	Training: 110 Landsat-8, 13 ALOS-1, 76 TSX, 140 Sentinel-1 Testing: 74 Landsat-8, 52 Sentinel-2, 48 Envisat, 17 TSX, 90 Sentinel-1, 14 ALOS-2	Test-error studies: DRN-DeepLabv3+ is the lowest Refer to Table 3 from [44] for full test results	Python Open-source in GitHub: https://github.com/enzezhang/FrontDL3 (accessed on 7 July 2024)

Table 1. *Cont.*

Author	Location	Glacier Location Name	Studied Glacier Types	Classification by GLIMS Manual	AI Model	Parameters	Dataset Size	Accuracy	Software
2020 H. Alifu et al. [45]	Karakoram—Pakistan Shaksgam Valley, China	North-western Karakoram region and Shaksgam Valley glaciers	Debris-covered glaciers	Valley, Mountain glaciers	Machine learning classifiers (MLC): - K-nearest neighbors (KNN) - Support vector machine (SVM) - Decision tree (DT), - Gradient boosting (GB) - Random forest (RF) - Multi-layer perceptron (MLP)	• Sentinel-2A • Landsat-8 • Sentinel-1A • ALOS DEM • Geomorphometric parameters • Thermal Infrared images • GAMDAM dataset	Area 1: 2000 to 20,000 points. Area 2: 20,000 points	RF-97%	Python
2020 Robson et al. [46]	Chilean Andes, Chile Central Himalaya	La Laguna catchment Poilu catchment	Rock glaciers	Mountain glaciers	CNN with OBIA	• Sentinel-2: Blue, Green, Red, Near-Infrared, and shortwave Infrared bands • SAR coherence data	Not clear	• User's accuracy: 65.9% • Producer accuracy: 71.4%	Google Tensorflow
2021 Lu et al. [47]	China	High Mountain Asia	Debris-covered glaciers	Mountain glacier	RF CNN	• Landsat 8 • NDVI • NDWI • NDSI • Elevation • Slope • Aspect • Shaded relief	Eastern Pamir: 7499 samples Nyainqêntanglha: 3099 samples	Eastern Pamir and Nyainqentanglha User's accuracy: • RF = 91.59%, 92.53% • CNN = 87.96%, 78.75% • RF-CNN = 97.90%, 90.60% Producer's accuracy: • RF = 97.17%, 98.86% • CNN = 98.69%, 97.53% • RF-CNN = 98.33%, 74.54%	Python

Table 1. *Cont.*

Author	Location	Glacier Location Name	Studied Glacier Types	Classification by GLIMS Manual	AI Model	Parameters	Dataset Size	Accuracy	Software
2021 Xie et al. [48]	Kashmir Region. Nepal region	Karakoram glaciers Nepal glaciers	DCG	Mountain, Valley glaciers	• GlacierNet • Mobile-Unet • Res-UNet • FCDenseNet • R2UNet • DeepLabV3+	• Landsat 8 • ALOS DEM • Slope–azimuth divergence index • Slope angle • Tangential curvature • profile curvature • Unsphericity curvature	N/A	IOU: • DeepLabV3+ = 0.8623 • GlacierNet = 0.8599 • Mobile-UNet = 0.8531 • ResUNet = 0.8399 • FCDenseNet = 0.8265 • R2UNet = 0.8204 • Accuracy: • DeepLabV3+ = 0.9684 • GlacierNet = 0.9677 • Mobile-UNet = 0.9660 • ResUNet = 0.9636 • FCDenseNet = 0.9597 • R2UNet = 0.9582	N/A
2022 Xie et al. [49]	Northern Pakistan	Central Karakoram	DCG	Mountain, Valley glaciers	CNN	• 11 bands of Landslide 8 • DEM • Unsphericity • Profile curvature • Tangential curvature • Slope angle • Slope azimuth divergence index		Accucary: • GlacierNet: 0.9677 • DeepLabV3+: 0.9684 • GlacierNet & DeepLabV3+: 0.9685 • GlacierNet2: 0.9735	
2022 Erharter [50]	Austria Apls	Vienna, Burgenland, Lower Austria, Upper Austria	RG	Mountain glaciers	ANN with U-net	• DEM • Orthophotos	5769 RGs: • 3722 training • 800 validation	• Ranged values using probability map	Python, Keras

Table 1. *Cont.*

Author	Location	Glacier Location Name	Studied Glacier Types	Classification by GLIMS Manual	AI Model	Parameters	Dataset Size	Accuracy	Software
2022 Kaushik et al. [17]	12 sites across Himalaya	Himalayan glaciers	Glacier lake	N/A	GLNet—Deep convolutional neural network	• Sentinel-2: B, G, R, NIR, and SWIR) • Landsat 8 • Elevation • Slope NDWI	660 images	Accuracy = 0.98 Precision = 0.95 REcall f-score = 0.95	
2022 Tian et al. [51]	Pamir Plateau		RG	Mountain glaciers	Channel attention U-net (U-net+cSE)	• Landsat 8 SRTM DEM data	7821 images	Accuracy: U-net = 0.9756 GlacierNet = 0.9689 U-net + cSE = 0.9774	
2022 Sood et al. [52]	Bara Shigri, Himachal Pradesh, India			Valley glacier	ENVINet5	• Landsat 8		Accuracy = 91.89% Kappa = 0.8778	
2022 Sharda et al. [53]	Karakoram Range, Pakistan		DCG	Mountain, Valley, Icefields	• Relief-F • Pearson correlation Hybrid RF-Corr	• Landsat 8 • SRTM 1-Arc Second GDEM • Pamir and Karakoram inventories • GLIMS database		up to 99.8%	• MATLAB eCognition developer software
2023 Peng et al. [14]	Qilian Mountains, China		Not specified		U-net with LGT encoder and LGCB decoder	• SAR (Sentinel-1), • Optical (Sentinel-2) • Image band indices • DEM • NDSI • NDWI • NDVI	2072 glaciers: • Training: 70% • Testing: 30%	Accuracy: U-Net: 0.725 DeepLab V3+: 0.924 Attention DeepLab V3+: 0.960 Swin Transformer: 0.962 Proposed model: 0.972	NA

Table 1. *Cont.*

Author	Location	Glacier Location Name	Studied Glacier Types	Classification by GLIMS Manual	AI Model	Parameters	Dataset Size	Accuracy	Software
2023 Thomas et al. [54]	Khumbu—Nepal, China Manaslu—Nepal Hunza—Pakistan		DCG	Valley, Mountain, Icefields, Cirque	CNN with OBIA classification	• Sentinel-2 • Landsat-8 • ALOS DEM • Corona KH-4B • Geomorphometric data	69,500 samples Supraglacial debris-20,000 Non-glacial material-20,000 Vegetation-10,000 Lakes-7500 Clean ice glacier-5000 Snow cover-5000 Shadows-2000	• CNN-OBIA—93.8%	Trimble's eCognition Developer 10.2 TensorFlow library
2023 Hu et al. [55]	Western Kunlun Mountains, China	Western Kunlun Mountains	Rock glaciers	N/A	DeepLabv3+ with Xception71 backbone	• Sentinel-2, • ALOS-1 PALSAR • InSAR data • Google Earth images	Training (90%): 2007 images; Validation (10%): 223 images;	N/A	N/A
Monitoring of glacier evolution									
2022, 2020 Bolibar et al. [56,57]	French Alps	Écrins, Vanoise, Mont-Blanc glaciers	Mountain Glaciers	Mountain Glacier	ALpine Parameterized Glacier Model (ALPGM) based on ANN	• DEM • Glacier boundary shape files • SMB values • Glacier topographical data	32 glaciers in French Alps	47% in space 58% in time	Python
2022 Ambinakudige and Intsiful [58]	Columbia Icefields, Canada			Icefields	SVM RF MLC	• Landsat 8 • NDSI • NDVI • NDSI • NDII	1985, 1991, 2013, and 2020 Landsat satellite images 70% training 30% validation	Accuracy: RF = 99.8% MLC = 99.7% SVM = 99.7% Kappa: RF = 0.995 MLC = 0.993 SVM = 0.994	N/A
2022 Rajat et al. [59]	Himachal Pradesh, India	Himalayan mountains		Mountain glaciers	U-Net	• Landsat • Indian Remote sensing • DEM	75% training 25% validation	F1 score: 95%	N/A

Table 1. *Cont.*

Author	Location	Glacier Location Name	Studied Glacier Types	Classification by GLIMS Manual	AI Model	Parameters	Dataset Size	Accuracy	Software
2023 Yang et al. [60]	Southeast Tibet	Zelongnong ravine	Glacier Debris Flow susceptibility	Valley, Cirque	• DeepLabv3+ [FCN (fully convolutional networks)] DCNN	• SRTM X DEM • SRTM C • TanDEM-x DEM • Landsat 7/8 GLIMS		• MIOU (Mean Intersection over Union)—92.15% • MPA (Mean Pixel Accuracy)—95.89%	
				Snow/ice differentiation					
2022 Prieur C. [61]	Zermatt, Switzerland	Mont Rose massif	Temperate glacier/snow lines	Temperate glaciers	• Feed forward NN • SVM linear kernel • SVM Gaussian kernel Random forest	• Copernicus DEM • Landsat 8 Alps' glacier inventory from 2015	- Ice/snow—270,000 pixels - Glacier—200,000 pixels - Mountain shadow—140,000 pixels	• Feed forward NN—98% • SVM linear kernel—98.7% • SVM Gaussian kernel—99% Random forest—99.8%	-
				Ice dynamics modeling					
2021 Jouvet et al. [62]	• Andes • Canada • Caucasus • Colombi • Ethiopia			Icefields, Valley glaciers	Instructed Glacier Model (IGM) using CNN	-		≈20 direct speedup using CNN	Python

As supervised AI methods, random forest, ANNs (artificial neural networks), and support vector machines (SVMs) are commonly used, while deep learning methods such as U-Net, DeepLab, and CNNs (convolutional neural networks) represent another type of AI technique frequently used in glacier studies, as can be noted from the chart in Figure 3. Both supervised learning and deep learning methods have been actively used for years and have been deployed at nearly the same rate, except in 2021, when deep learning methods were dominant (Figure 4). In the next section, which is the main part, the reader will be able to access a summary of each work along with detailed tabulated information (Table 1) on the types of glaciers studied, their geographical locations, their classification according to the GLIMS glacier manual, the AI methods applied, the input parameters, the datasets used, and the accuracy of the studies.

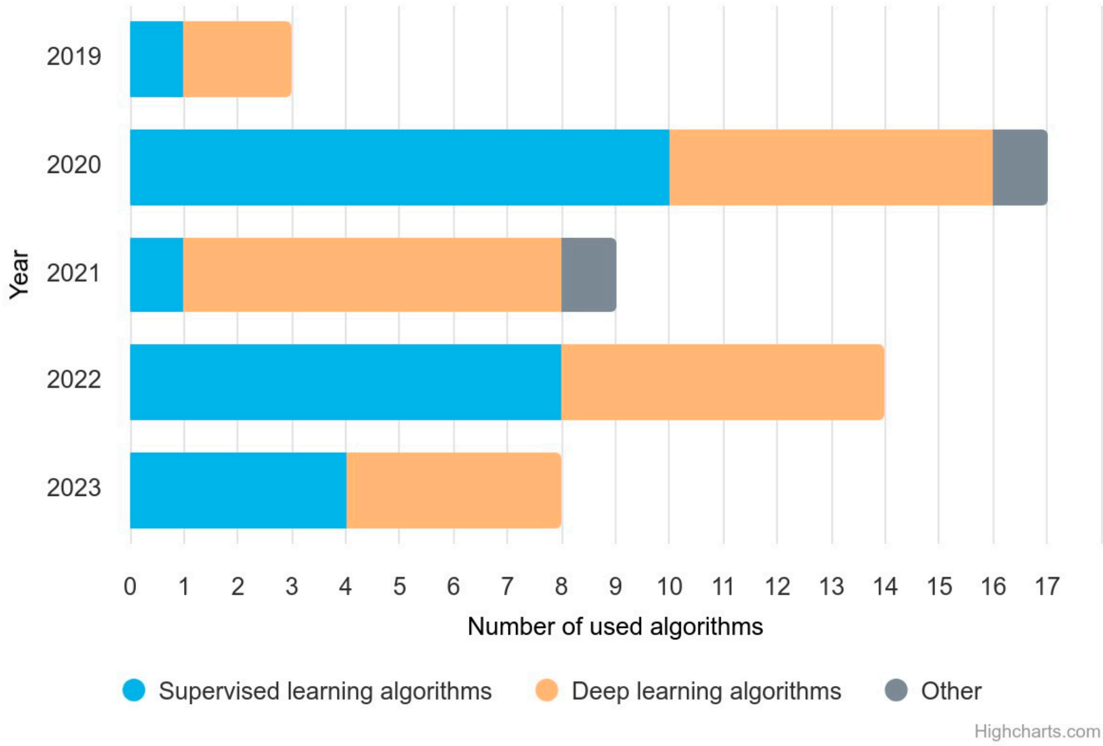

Figure 4. Yearly classification of AI algorithms applied for glacier studies.

3. AI-Based Glacier Studies

3.1. AI for Glacier Inventory and Mapping

Glacier inventory and mapping represent a promising area of application of AI, offering a transformative approach for optimizing the efficiency and accuracy of glacier monitoring efforts. Through extensive training on a variety of datasets, including satellite imagery, digital elevation models (DEMs), and historical records, AI models can quickly learn to recognize various glacier features, delineate glacier boundaries, and quantify glacier extent with unprecedented accuracy. This capability not only speeds up the creation of glacier inventories and maps, but also improves the reliability and consistency of glacier monitoring data, which are critical for understanding glacier dynamics, assessing climate impacts, and making environmental management decisions. A summary of the works on glacier inventory and mapping can be found in the first section of Table 1.

Earlier works in AI-based glacier inventory and mapping start from 2019, and one of them was written by Zhang et al. [40]. In their work, the authors studied glaciers in the Parlung Zangbo basin located within the Tibetan Plateau. The glacier data were collected from Landsat-8 images with 30 to 100 m spatial resolutions, and the image textures were analyzed using the Grey Level Co-occurrence Matrix (GLCM). Moreover, the authors calculated the Normalized Difference Water Index (NDWI), Normalized Difference Vegetation

Index (NDVI), and Normalized Difference Snow Index (NDSI) and used them as a dataset together with topographic parameters from ASTER Global Digital Elevation Model (GDEM V2), including other DEMs such as TanDEM-X and Shuttle Radar Topography Mission (SRTM) DEM to obtain elevation change data. Random forest (RF) with 100 decision trees was selected as the AI method as shown in Figure 5, and there were three steps, preprocessing, RF classification, overlaying of classification results, and accuracy assessment, to achieve the final mapping. The overall accuracy of the RF classification was 98.6%. The study showed 1476 glaciers spanning 2011.32 km^2 in the Parlung Zangbo basin, where 20.7% of the glacier region was debris-covered and it was between 4600 m and 4800 m above sea level (a.s.l.). Additionally, 77.5% of the glaciers (1558.79 km^2) were located between 4600 m and 5600 m a.s.l., with smaller glaciers (<1 km^2) mostly found at lower elevations.

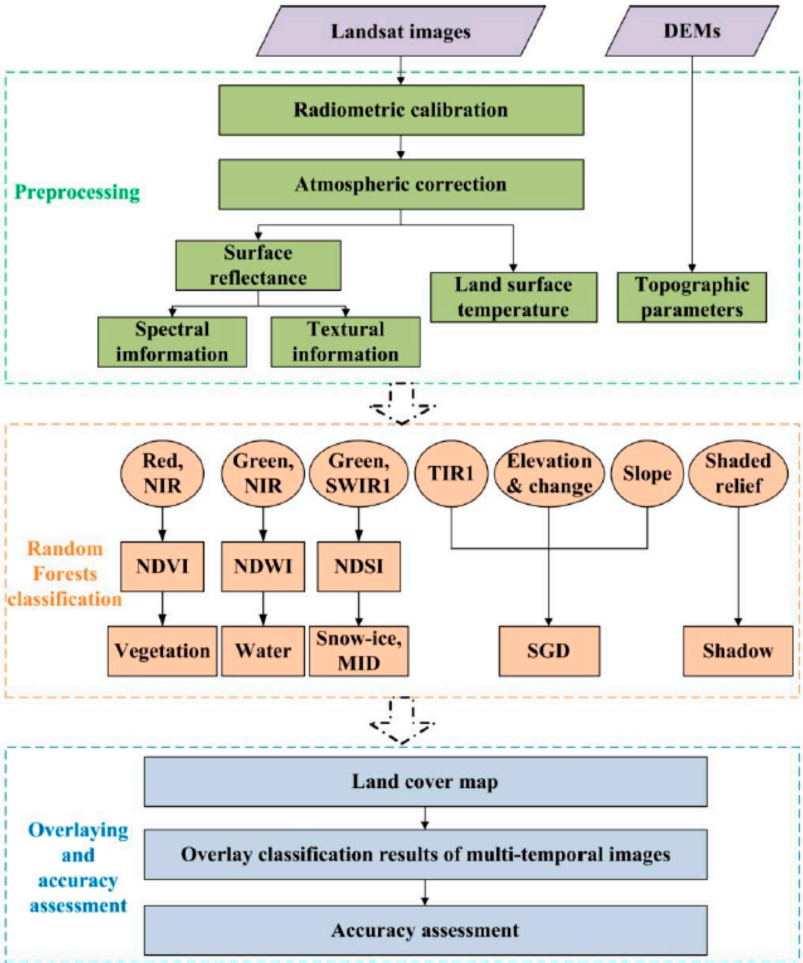

Figure 5. Flowchart for glacier mapping by Zhang et al. [40].

Mohajerani et al. [41] developed an ML toolkit that utilizes CNNs with a modified U-Net architecture for automatic detection of glacier calving front margins from satellite imagery (Figure 6). This approach was trained on a dataset of Landsat images of Greenland periphery glaciers. The study utilized Landsat 5, 7, and 8 imagery, focusing on the "green" and "panchromatic" bands, respectively. The optimized 29-layer deep neural network incorporated 3 × 3 ReLU convolutional layers, 0.2 Dropout layers for regularization, and 2 × 2 MaxPooling for downsampling and upsampling layers. A sample-weighted loss function and data augmentation techniques were also employed to enhance the performance. The model's effectiveness was evaluated not only on validation datasets, but also on a new glacier with higher spatial resolution to assess transferability across different fjord geometries. After training on the Jakobshavn, Sverdrup, and Kangerlussuaq glaciers, the network was tested on the Helheim glacier, achieving a mean deviation error of 96.3 m (1.97 pixels on average). This accuracy was comparable to manual delineation errors (92.5 m) and significantly outperformed traditional edge-detection methods like the Sobel filter.

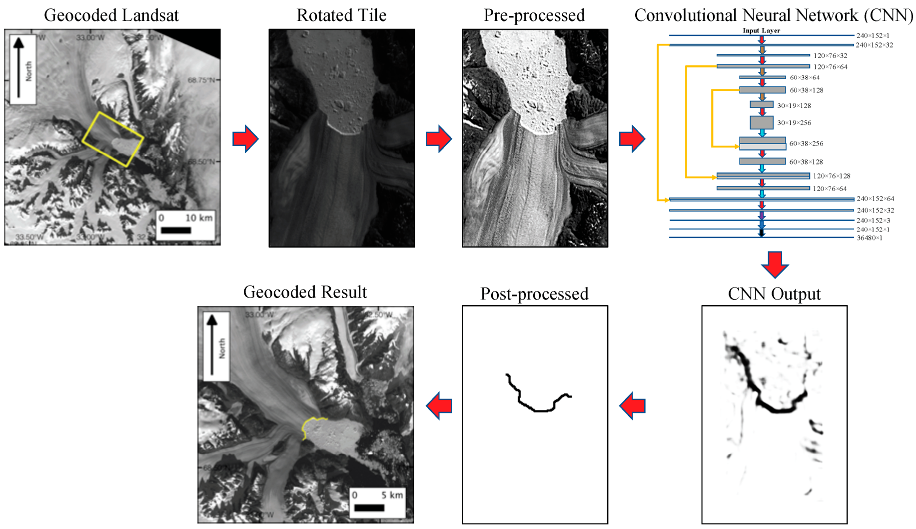

Figure 6. Outline of the methodology by Mohajerani et al. [41].

The study highlights the advantages of using DL for glacier mapping, particularly in enhancing the efficiency and accuracy of detecting calving fronts. The modified U-Net architecture employed in this research effectively segments the calving fronts from satellite images, providing a robust tool for continuous monitoring. The automated system allows for the rapid delineation of calving fronts, which is essential for understanding regional changes on the ice sheet periphery over several decades. This method not only reduces the manual effort required, but also provides a consistent and scalable solution for processing large volumes of satellite data, paving the way for more detailed seasonal and long-term analyses of glacier dynamics.

Similarly, a modified U-Net model developed by Baumhoer et al. [42] can process dual-polarization Sentinel-1 radar data along with elevation information from the TanDEM-X digital elevation model to accurately delineate the Antarctic coastline (Figure 7). This method outperforms traditional image processing techniques, especially in challenging areas with low contrast between ice and water or the presence of sea ice. The ability to automatically process large volumes of Sentinel-1 data enables the creation of dense time series to track glacier and ice shelf front movements at continental scales.

The automated approach allows for consistent and objective coastline extraction, overcoming the limitations of time-consuming manual delineation and subjective interpretations in complex areas. When tested on multiple sites around Antarctica, the model achieved average deviations of 78–108 m compared to manually drawn coastlines. Importantly, the method demonstrated spatial and temporal transferability, successfully generating a 15-month time series of front positions for the Getz Ice Shelf without additional training. This capability to produce frequent, large-scale measurements of glacier and ice shelf front dynamics is crucial for improving our understanding of ice sheet mass balance, calving processes, and potential sea level rise contributions from Antarctica.

The paper by Khan et al. [43] investigates the application of supervised ML techniques to automatically classify glacier layers using a blend of Sentinel-2 images along with texture, topographical, and spectral data. The study focuses on the Passu watershed in the Hunza Basin, Pakistan. Three well-known supervised ML methods, namely, support vector machine (SVM), artificial neural network (ANN), and RF, were explored for the classification.

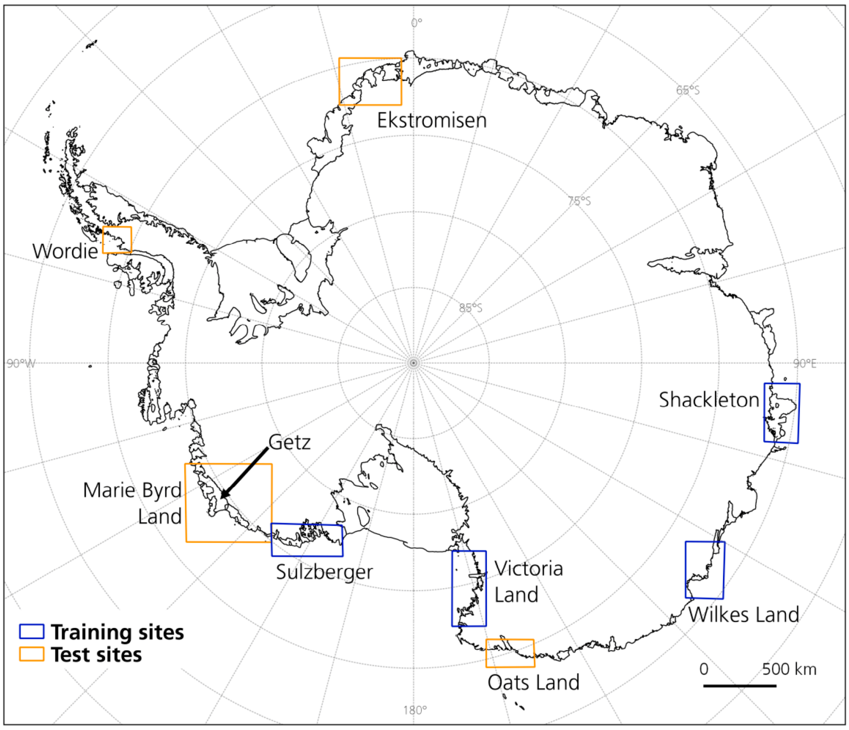

Figure 7. Training and testing sites [42].

Similar to Zhang et al. [40], the method proposed by Khan et al. [43] involves three main steps: feature extraction, machine learning classification, and accuracy assessment. The extracted features encompass spectral reflectance data, textural properties obtained from the GLCM, and topographical attributes acquired from the DEM. The classifiers are then trained and tested on the data, producing classification maps for debris-covered glaciers, usual glaciers, as well as non-glacier areas. The flowchart of the proposed method is provided below in Figure 8. By comparing the output data with the reference data, an accuracy evaluation is conducted.

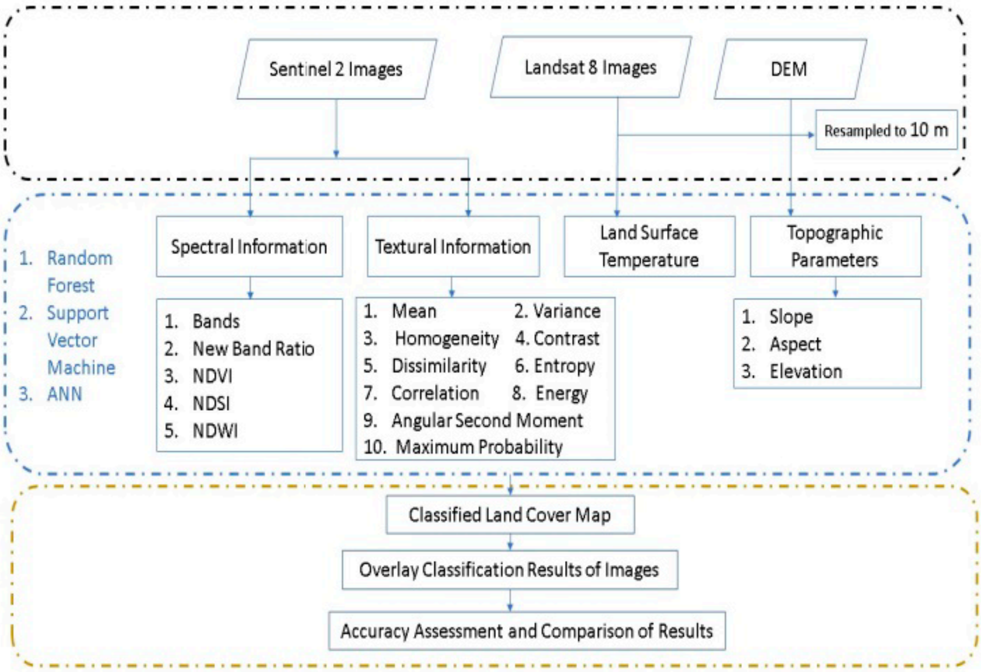

Figure 8. Flowchart of methodology by Khan et al. [43].

The results indicated high accuracy for all classifiers, with RF outperforming SVM and ANN consistently across all classes. The accuracy was measured by means of the Kappa coefficient, or Cohen's Kappa, a statistical technique that evaluates the consistency of agreement between two raters classifying items into mutually exclusive categories. Thus, the overall accuracy, Kappa coefficient, and other indicators demonstrated the effectiveness of the proposed method. For example, the overall accuracy reached as high as 92.77%, and the Kappa value was 0.92. A comparison with existing glacier inventory datasets revealed discrepancies, highlighting the need for more consistent and reliable classification approaches. The study suggests that ML approaches, particularly RF, coupled with remote sensing data, offer robust and accurate means of mapping glaciers and debris-covered glaciers, which is crucial for water resource management and hazard assessment.

In another research work, to map debris-covered glaciers, Haireti Alifu et al. [45] developed an ML-based classification technique. As the multi-sensor input data, they considered SAR coherence, thermal, topographic, and optical data obtained from remote sensing devices to evaluate the accuracy of ML methods such as SVM, decision tree, gradient boosting, and k-nearest neighbors. Furthermore, from Google Earth images, the authors created outlines of debris-covered ice by applying manual delineation (Figure 9). Northwestern region of Karakoram in Pakistan (Location 1) and Shaksgam Valley in Western China (Location 2) were selected as areas for testing the ML methods. In particular, datasets from the testing locations, such as RGI-based vector data and GAMDAM glacier inventory, were used for validation purposes.

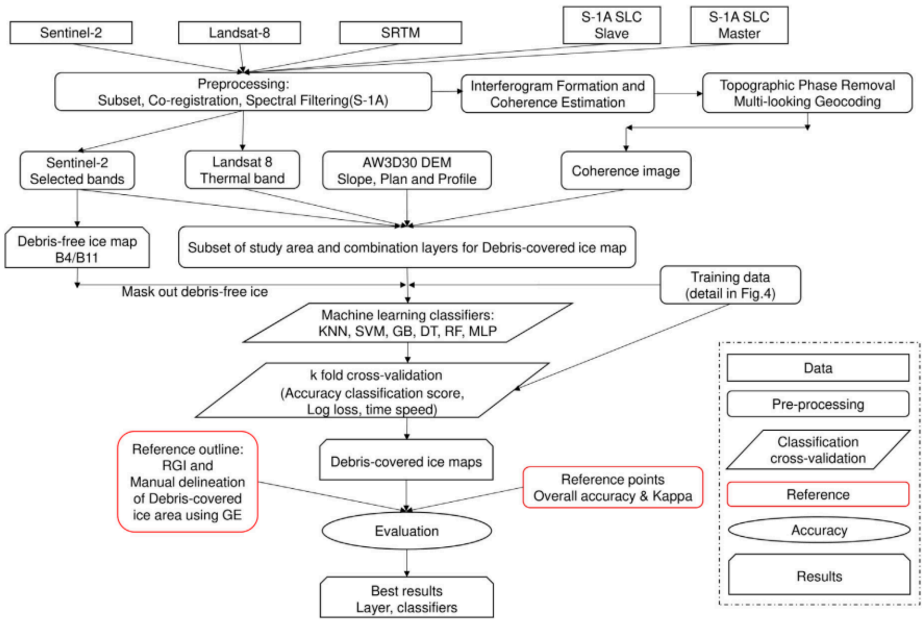

Figure 9. Proposed flowchart of the methodology [45].

The analysis included how training data size affected (up to 20,000) the accuracy of the selected ML-based classification methods, and they were compared between each other to select the most effective method. The outcomes obtained from this increased volume of training data indicated that RF attained greater accuracy, nearly 97%, compared to the GB and SVM methods. Furthermore, the data points increased from 2000 to 20,000, increasing the accuracy of the mapping by 1–2%. When isolated pixels were excluded from the dataset, the accuracy was further improved by up to 1.5%.

In another work [46], the authors combined a CNN with object-based image analysis (OBIA) to predict rock glaciers (RG) in an automated way. Thus, the CNN produced a prediction raster or heatmap, with pixel values ranging from 0 to 1, as shown in Figure 10. Further, OBIA was used to classify objects from the generated heatmaps. In fact, OBIA, a common remote sensing method, segments images into homogeneous objects for subsequent classification.

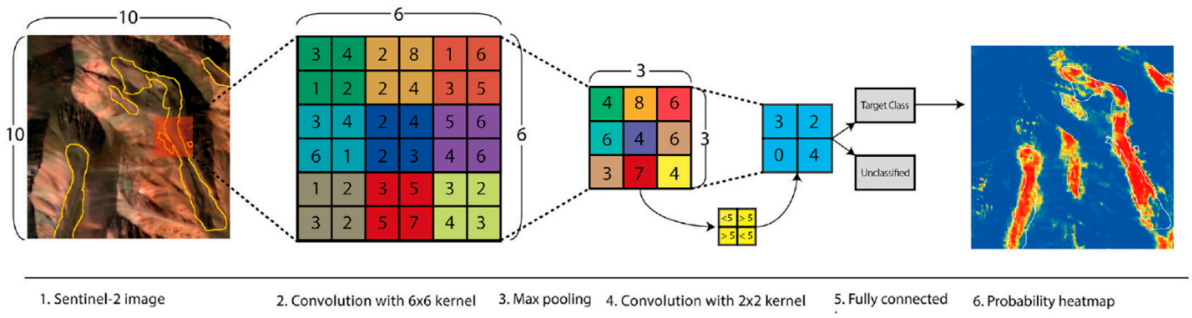

Figure 10. The illustration of CNN with a heatmap output for RG evaluation [46].

Two areas with glaciers, namely, the La Laguna (Chile) and Poiqu (Central Himalaya) catchments, were considered for AI-based RG mapping (Figure 11). The La Laguna catchment, located at the Elqui River's headwaters in Chile, encompasses glaciers and RG, contributing 4–13% of the annual streamflow in an elevation range of about 4000 to 6000 m across an area of approximately 140 km^2 and hosting 105 RGs. On the other hand, the Poiqu catchment, a transboundary watershed in the Himalayas draining into Nepal and the Ganges River, spans over 2000 km^2 with elevations from 1100 to over 8000 m, featuring a variety of glaciers. The study focuses on approximately 1500 km^2, including about 140 rock glaciers, with sizes ranging from <0.01 to >1 km^2. Approximately 30% of manually interpreted outlines from the Pléiades imagery (RG_Man) were used for training. The rock glaciers from the La Laguna and Poiqu catchments had sizes of 2.3 km^2 and 6.1 km^2, respectively, while an additional 0.7 km^2 was extracted from the Pléiades subset. All these outlines were integrated with adjacent polygons, merged, and small ones were removed. To evaluate the accuracy, the leftover polygons—50 from La Laguna, 117 from Poiqu, and 7 from the Poiqu Pléiades subset—were utilized. Around 300 random training points were created within the RG outlines, along with extra points representing debris-covered glaciers, pristine ice glaciers, and stable terrains. As a result, the CNN_OBIA classification technique detected a combined 108 rock glaciers, encompassing an area of 26.0 square kilometers, out of the total 120 (spanning 20.3 square kilometers in the validation dataset (RG_Man) across both study areas. This led to an overestimation of 28.0%, with the end-user's and producer's accuracy indicating a relatively high percentage of correctly identified rock glaciers, but with some instances of false positives.

The study by Lu et al. [47] focused on mapping debris-covered glaciers (DCG) around the Tibetan Plateau, in particular, High Mountain Asia (HMA). The selected AI models were RF and CNN. The study employed data from Landsat 8 OLI, thermal infrared sensors, GDEM (Reflection Radiometer Global Digital Elevation Model), and ASTER (Advanced Spaceborne Thermal Emission) for the mapping of debris-covered glaciers on the Tibetan Plateau, namely, in the Eastern Pamir and Nyainqentanglha areas. Various classification models, including RF and CNN, were compared and integrated to achieve the best classification performance. The relationship between debris coverage and ML model parameters was investigated, revealing that debris coverage directly influences model performance and aids in detecting both active and idle DCG.

The authors proposed an approach combining RF and CNN models, referred to as an RF-CNN composite classifier, to enhance the classification accuracy of debris-covered glaciers. By leveraging the respective advantages of the RF and CNN models, the RF-CNN composite classifier achieved promising results, providing valuable insights for glacier mapping and boundary extraction. The study demonstrates that the performance of ML techniques and the accuracy of glacier extraction are closely tied to the intensity of debris coverage, highlighting the importance of considering local characteristics in mapping efforts.

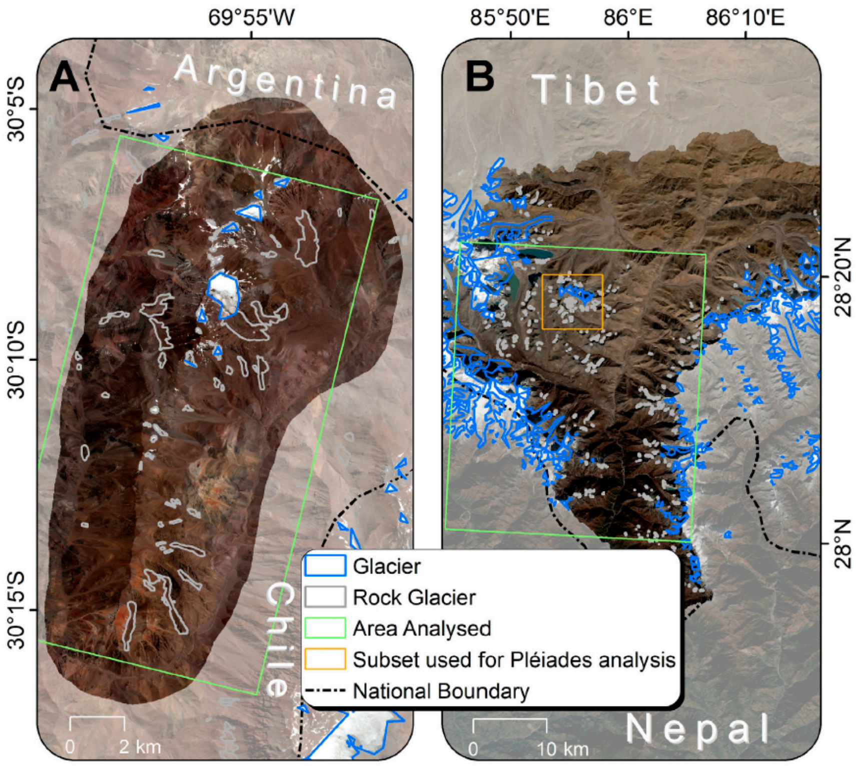

Figure 11. Study areas: La Laguna catchment, Chile, and Poiqu catchment, Central Himalaya, by Robson et al. [46].

Furthermore, the study evaluated the performance of the RF-CNN model against existing glacier inventory datasets, showcasing its effectiveness in accurately delineating debris-covered glaciers. The results indicated that the RF-CNN model outperformed individual classifiers, offering a more reliable approach for glacier mapping. The study underscored the significance of machine learning methods in improving the efficiency and accuracy of glacier mapping, laying the groundwork for future research in this field. Future work will focus on refining the RF-CNN model and exploring its applicability to SAR images for enhanced glacier classification.

Xie et al. [48] compared the performance of GlacierNet with other CNN-based methods such as Mobile-UNet, Res-UNet, FCDenseNet, R2UNet, and DeepLabV3+. Each model underwent training using 15% of the total study area, specifically focusing on the Karakoram glaciers (shown in Figure 12), followed by evaluation across twelve glaciers (represented as yellow dots in figure) beyond the training domain. These glaciers exhibited diverse surface and topographical characteristics.

Due to computational intensity, the input image for GlacierNet was sub-sampled by means of a sliding window approach with a stride of 32 and sizes of 256 × 256 or 512 × 512. As the input consisted of multi-channel images, the networks were configured with an input layer comprising 17 channels instead of the typical 3 channels for RGB images. The CNN output is a binary image representing the input data category, which was then combined into a larger binary image as shown in Figure 13. Additional refinement steps, including region size thresholding, water index-based removal of excess water pixels, and hole filling, were applied to enhance the accuracy.

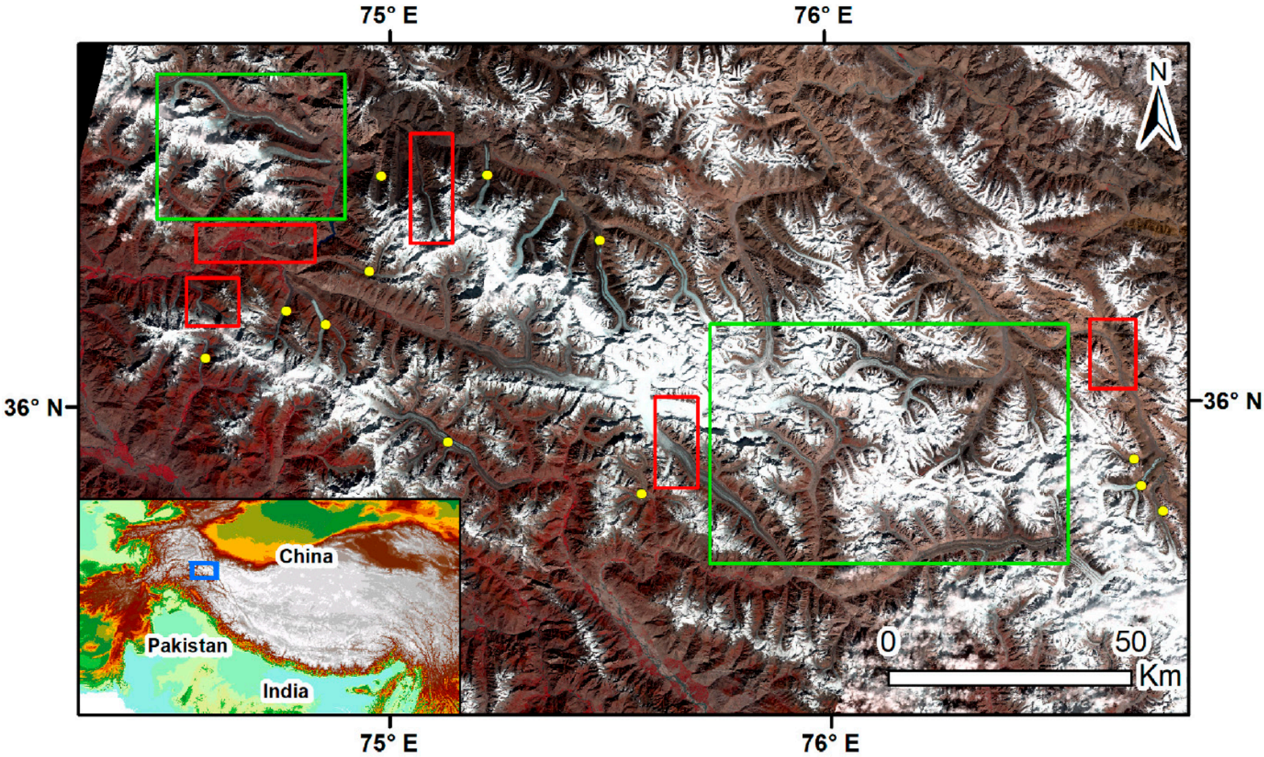

Figure 12. Selected area for the study by Xie et al. [48], Central Karakoram.

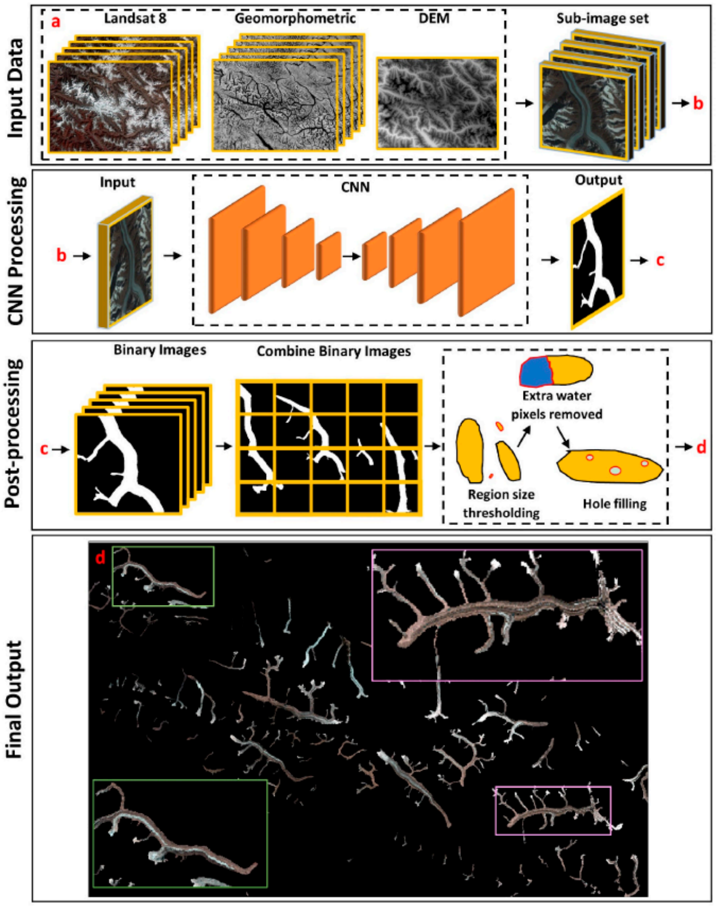

Figure 13. GlacierNet architecture [48].

The analysis revealed DeepLabV3+ as the frontrunner, demonstrating the highest intersection over union (IOU), F-measure, kappa, and accuracy values, with GlacierNet following closely behind. The authors noted variations in performance among the models concerning the estimation of melting zones and terminus, with DeepLabV3+ exhibiting superior performance in this regard. Notably, terminus estimation emerged as a significant challenge across the compared models, prompting suggestions for potential enhancements in network architecture to address this issue.

Furthermore, computational expenses were assessed, revealing FCDenseNet and R2UNet as the most resource-intensive, DeepLabV3+ as moderately demanding, and Mobile-UNet and GlacierNet occupying the lower end of the computational cost spectrum, akin to Res-UNet.

The authors highlighted the suitability of DeepLabV3+ for large-scale glacier mapping tasks, noting its superior performance compared to other models. The GlacierNet emerged as a viable option for regional-scale mapping. The careful selection of training data was emphasized as pivotal given its significant impact on overall model performance.

Later, Xie et al. [49] upgraded the previous model and presented a multi-model learning architecture, GlacierNet2, for glacier mapping. The architecture is based on data subsampling and DL using CNN models such as GlacierNet and DeepLabV3+, and it can estimate the terminus, ablation, and snow-covered accumulation zones of glaciers (SCAZ). Glaciers of central Karakoram in northern Pakistan were selected to test the predictive performance of GlacierNet2. Two scenes of Landslide 8 from September and October of 2016 were used. Notably, mapping glaciers is most achievable in the September–October timeframe due to the end of the ablation season. The architecture has a 17-channel input, which receives the following data: 11 bands of Landsat 8; a digital elevation model (DEM); and five layers of geomorphometric parameters such as unsphericity, profile, tangential curvatures, slope angle, and slope azimuth divergence index. Thus, GlacierNet2 showed the best accuracy in terms of mapping the ablation zone relative to DeepLabV3+ and GlacierNet.

Erharter et al. [50] applied ANN based on U-net architecture to map rock glaciers of Austria. The dataset they used consisted mainly of DEM and orthophotos obtained from Google Maps satellite images. The inventory consisted of 5769 rock glaciers covering an overall area of 303 km^2 from Austrian states such as Vorarlberg, Salzburg, Tyrol, Styria, Carinthia, and the alpine of Upper Austria. The inputs were images 512 $\times$ 512 in pixel size, with a rough precision of 2 m, meaning the overall size of an image was 1 $\times$ 1 km. The slope maps were computed using the QGIS software based on DEM data. On the other hand, in the second channel, the greyscale orthophotos were inputted, allowing the landscape's surface and vegetation characteristics to be evaluated. Therefore, the output data consisted of a 512 $\times$ 512 binary raster, indicating whether each pixel represented a rock glacier or not. As shown in Figure 14, the U-Net architecture consisted of five contracting and five expanding blocks. It employs 2D convolution layers, batch normalization, and max pooling to reduce the image dimensions. The center part utilizes two conv2d layers, a two-dimensional convolution operation in neural networks that extracts features from images using sliding filters to produce feature maps. This is essential for tasks like image classification, object detection, and image segmentation, and is highly suitable for glacier studies. The final output is generated through a last conv2d layer with sigmoid activation (i.e., $f(x) = 1/(1 + e^{-x})$, producing a binary output to predict RGs. ANN was trained using the Adam optimizer at a learning rate of 0.0001. To evaluate the accuracy of the model, the dice similarity coefficient (DSC) was used, where 0 and 1 referred to dissimilarity and perfect similarity, respectively, between the ground truth and ANN output.

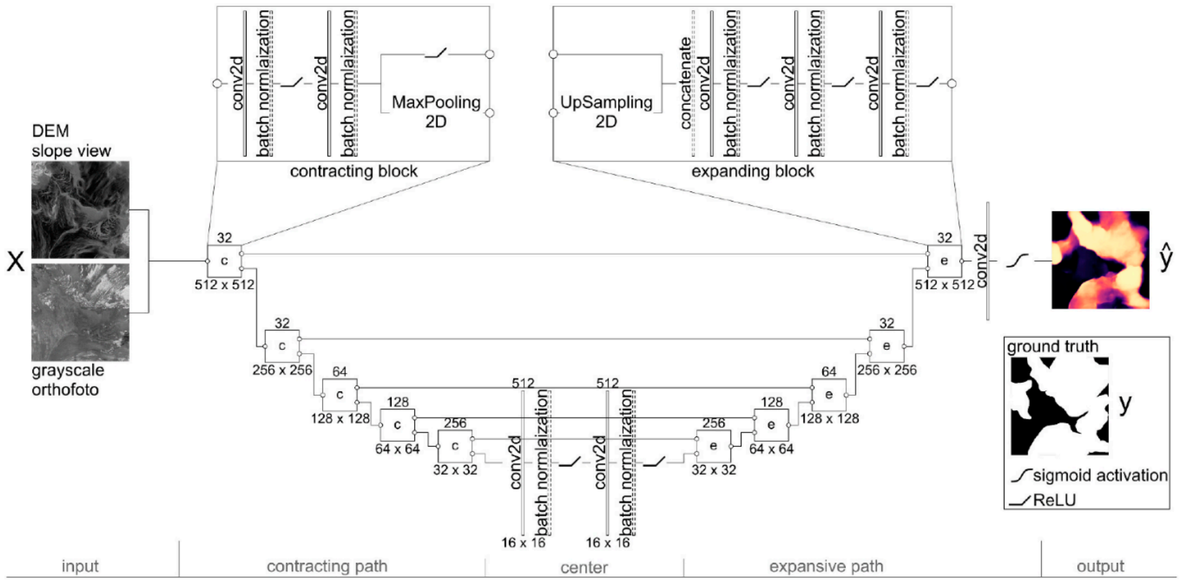

Figure 14. ANN architecture U-Net used to map rock glaciers in Austria by Erharter et al. [50].

Figure 15 illustrates RG examples and an ANN-based probability map. Thus, after testing thresholds ranging from 0 to 1 in steps of 0.05, the authors identified 0.4 as the optimal value to divide results into two categories: values $\leq$ 0.4 represented no rock glacier, and values > 0.4 indicated the existence of a rock glacier. It should be noted that a maximum DSC of 0.616 was obtained at a threshold of 0.4.

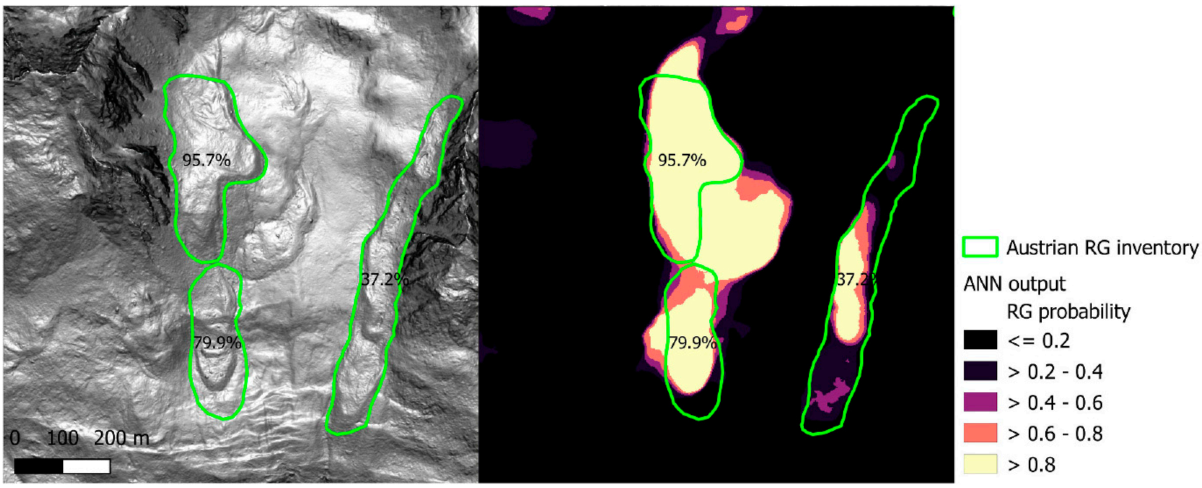

Figure 15. RG examples from North Tyrolean "Wurmeskar", Austria (left), and RG probability map based on ANN (right) developed by Erharter et al. [50].

Kaushik et al. [17] trained a deep CNN (DCNN), named GLNet, using a dataset of 660 images from multiple sources such as DEM, thermal, microwave, and other remote sensing techniques, as shown in Figure 16. The dataset was obtained from 12 locations within and around the Himalayan glaciers, and the overall selected region was divided into four testing sites.

The GLNet demonstrated a strong performance overall, achieving high accuracy, F1 scores, and correctness in mapping glacial lakes across multiple test sites. However, challenges such as erroneous predictions in certain areas, particularly related to shadows and wet ice pixels, were observed, leading to false positive and false negative results in some instances. One of the evaluation results is shown in Figure 17, specifically for site 3, in eastern Himalaya. Despite these challenges, the model showed an improvement in its performance over different test sites, highlighting its potential, but also the need for continued refinement to address specific limitations.

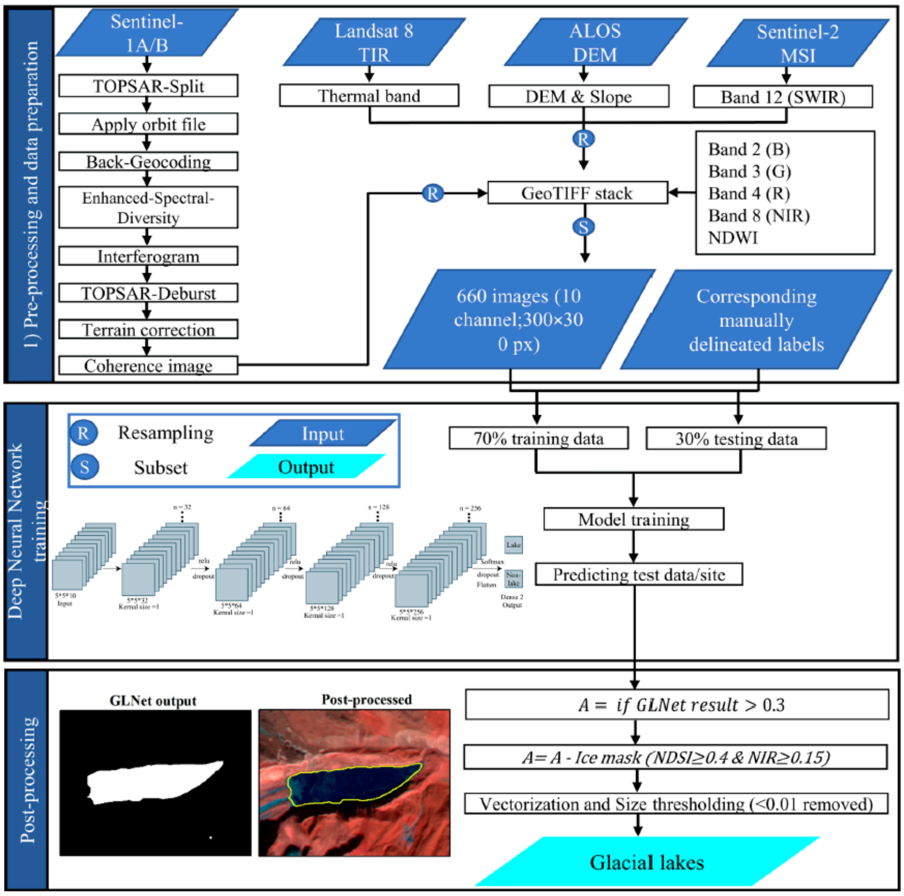

Figure 16. A general representation of the workflow for the GLNet technique [17].

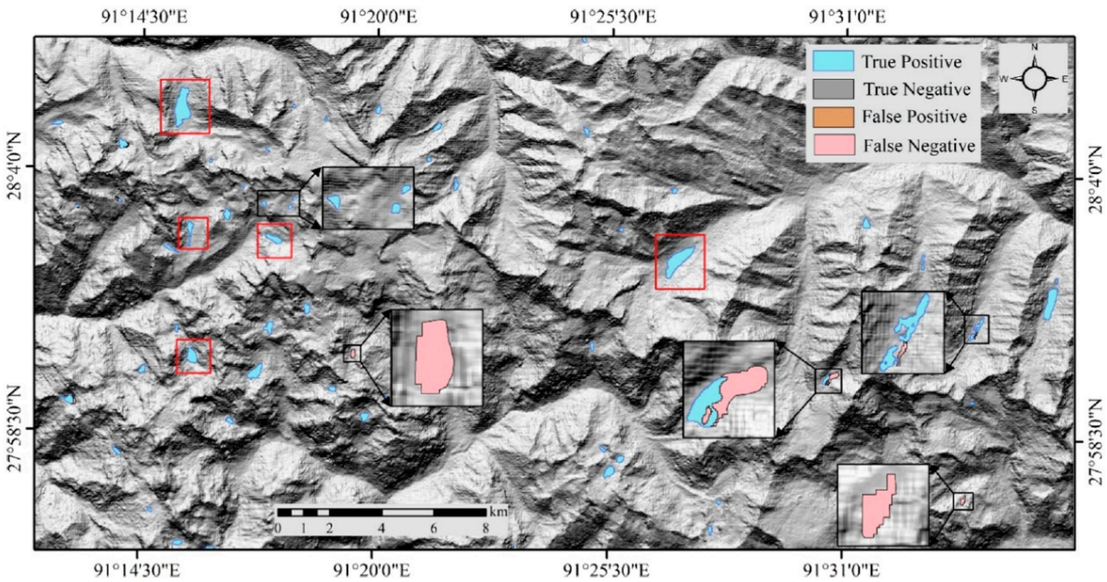

Figure 17. Glacial lakes in the Eastern Himalaya's test site 3 were mapped and compared with the reference data to identify errors in false positives and false negatives [17].

Tian et al. [51] proposed an enhanced U-Net model, incorporating a channel-attention mechanism, for glacier mapping and evaluated its performance using Landsat 8 OLI and

Shuttle Radar Topography Mission (SRTM) digital elevation model (DEM) data obtained for the Pamir Plateau.

The results demonstrate that the channel-attention U-Net model achieved superior accuracy in glacier identification compared to the standard U-Net and GlacierNet models. Furthermore, fine-tuning with a conditional random field (CRF) model effectively reduced background misidentification, enhancing the overall accuracy of glacier extraction. Evaluation metrics such as accuracy, recall, and F1-score validated the effectiveness of the proposed approach, with the channel-attention U-Net model outperforming other methods, albeit with a slight reduction in recall due to its focus on glacier features.

The Pamir Plateau, characterized by its high altitude and extensive glacier coverage, served as the study area, highlighting the relevance of the research in a region highly vulnerable to climate change. Utilizing Landsat 8 OLI imagery and SRTM DEM data, the study ensured data consistency and accuracy, which are critical for reliable glacier mapping. The incorporation of ground-truth data from the Global Land Ice Measurements from Space (GLIMS) database enhanced the reliability of the findings, despite temporal discrepancies necessitating manual modifications.

Despite the promising results, the study acknowledges certain limitations, such as challenges in distinguishing glaciers from similar geological features like water bodies and debris-covered glaciers. Additionally, issues like cloud cover and shadows pose challenges to optical remote sensing-based glacier mapping, requiring careful selection of input imagery. Future research directions include exploring additional data sources, such as synthetic aperture radar (SAR) images, and further refining the model to address specific challenges like the underestimation of debris-covered glaciers.

Sood et al. [52] proposed a deep learning classifier ENVINet5 based on U-Net architecture for glacier monitoring over the Bara Shigri glacier and compared that to the ANN model. ENVINet5 and ENVI Net-Multi are based on the U-Net model and are specifically designed for single-class and multi-class classification, respectively (Figure 18). ENVINet5 utilizes a mask-based encoder–decoder architecture, incorporating features such as convolutional layers, feature fusion, dimensionality reduction, co-convolution, and 1×1 convolutions. On the other hand, ENVINet-Multi is tailored for classifying multiple class categories, leveraging the spectral and spatial properties of input datasets along with field data knowledge. These architectures demonstrate the potential of deep learning in handling complex classification tasks in remote sensing. The overall accuracy of the ENVINet-5 was 91.89%, while ANN had 88.38%, and the kappa coefficient was 0.8778 versus 0.8241. The authors mentioned that errors using the ENVINet-5 are high due to the spatial resolution of the input data and parameter selection during the training process. Furthermore, the results may be affected by clouds or topographic effects. Therefore, these effects should be tested.

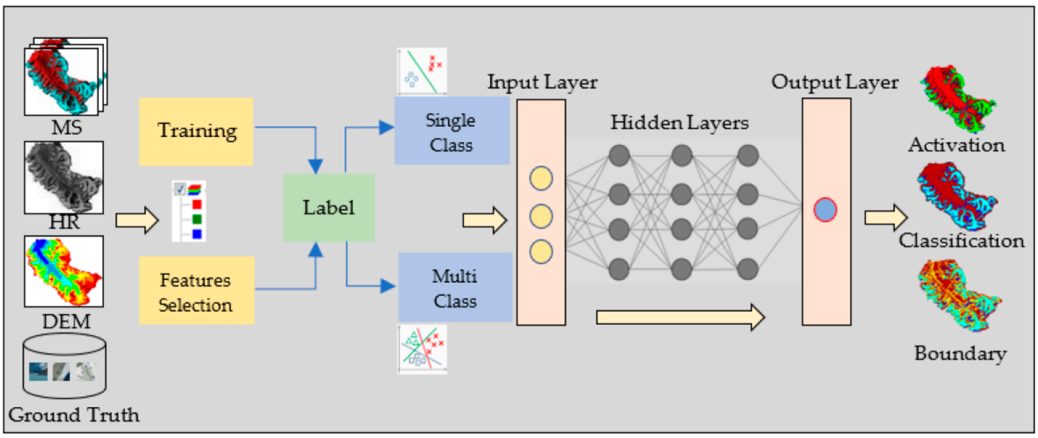

Figure 18. The flowchart of the model [52].

In another work, a hybrid feature selection (FS) approach was created to reduce classifier intricacy and enhance prediction accuracy by Sharda et al. [53]. This method automatically selects the optimal feature set and removes irrelevant or redundant features. Additionally, a supervised ML-based classifier was integrated to automatically select threshold parameters. This reduced the need for trial-and-error iterations in choosing suitable threshold values for assigning objects to various classes.

The FS method they created involved three stages: initial screening, identifying shared features, and fine-tuning. The integration of Relief-F and Pearson correlation filter-based methods improved the feature space. Additionally, the DT classifier enhanced the refined feature space using the Twoing split criteria. The suggested ML-based automatic classification approach, as depicted in Figure 19, underwent testing in the Central Karakoram Region and demonstrated significant resilience across all glacier types.

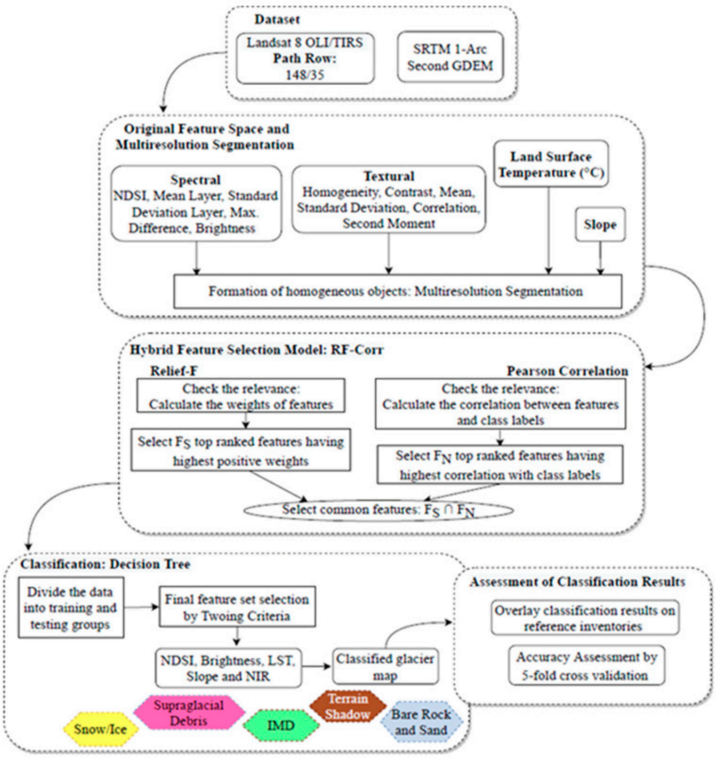

Figure 19. Flowchart of the hybrid feature selection mechanism for automatic object-based glacier mapping [53].

They developed method consisted of three stages: an initial screening stage, a selection of general properties stage, and a refining stage. Thus, the future space was optimized by means of Pearson correlation and Relief-F algorithms. Twoing split criteria were used in the decision tree classifier (DT) classifier to optimize the feature space. Thus, the developed ML-based automatic classification method was validated based on the glacier data from the Central Karakoram area and further demonstrated accurate results in other selected glaciers. The efficiency of the hybrid FS method was assessed by computing the prediction accuracy via 5-fold cross-validation. Compared to the Relief-F and Pearson correlation approaches, the hybrid model showed a minor enhancement in classification accuracy of 0.04% for the Siachen glacier and 0.17% for other glaciers.

Peng et al. [14] introduced a transformer-based DL method using a U-Net architecture with a Local–Global Transformer encoder and Local–Global CNN Blocks in the decoder, integrating global and local information. Out of 2740 glaciers covering 1514.01 km^2 in Qilian Mountains, China, those between 1 and 10 km^2 accounted for the largest glacierized areas (832.52 km^2); our study focuses on 2072 glaciers larger than 0.05 km^2, totaling 1498.06 km^2.

Thus, trained on Sentinel-1, Sentinel-2, HMA DEM, and SRTM DEM data, the DL model achieved 0.972 accuracy.

Thomas et al. [54] introduced a method for mapping debris-covered glaciers (DCG) that combined a CNN and object-based image analysis into a single categorizing workflow. This method was applied to open-source datasets, including thermal (Landsat-8), multispectral (Sentinel-2), interferometric coherence (Sentinel-1), and geomorphometric records (Figure 20). Central Himalayan areas in China and Nepal, including the Karakoram glaciers in Pakistan, were selected to apply and test the developed method.

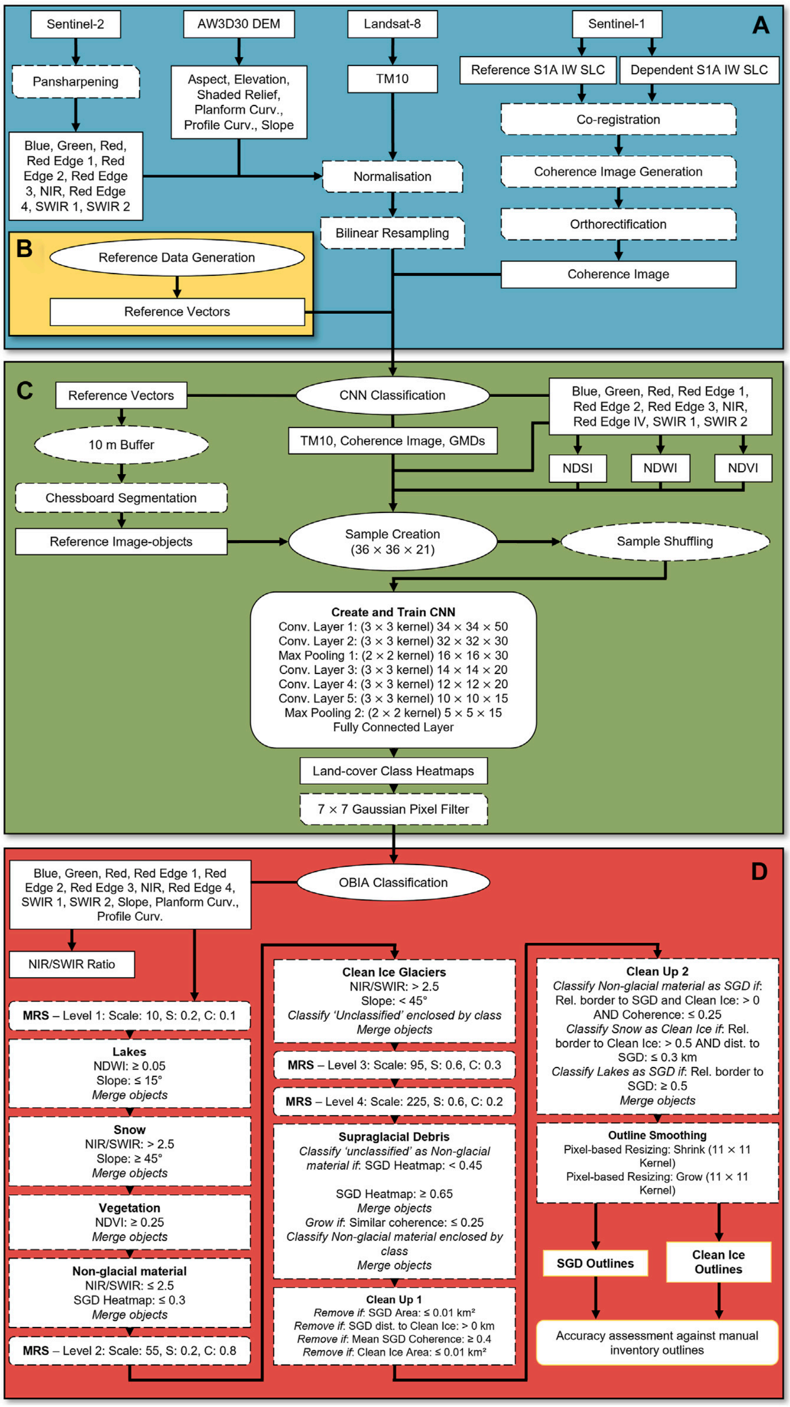

Figure 20. Flow chart of the developed approach. The steps include dataset pre-processing, reference vector dataset generation, convolutional neural network classification, and object-based image analysis refinement [54].

A precision–recall graph was produced for supraglacial debris outlines in the Khumbu region, initially delineated without object-based image analysis (OBIA), with a set probability heatmap threshold of ≥0.65. Furthermore, the recall and precision accuracies increased by 0.9% and 4.2%, as shown by the precision–recall curve. As a result, the F-score accuracy was improved up to 2.6%, meaning that by utilizing OBIA after CNN classification, one can access more accurate mapping of DCG extents compared to relying solely on CNN classification.

However, as the authors stated, the complex topography and precipitous slopes in certain sections of the selected areas led to errors of omission in mapping DCG termini. Specifically, the CNN-OBIA method underestimated the locations of glacier termini with gradients exceeding 24° in the Hunza region and steep tributaries covered with debris in the Manaslu area. These challenging terrains posed difficulties for the CNN, as there was limited variation within the samples of supraglacial debris, hindering accurate classification.

In another study [55] of the Western Kunlun Mountains, researchers combined Interferometric Synthetic Aperture Radar (InSAR) techniques with a DL model, DeepLabv3+, to create a comprehensive inventory of rock glaciers. The workflow for automatic mapping of rock glaciers is shown in Figure 21. The deep learning method improved the mapping efficiency by automating identification and delineation tasks, while also overcoming limitations of InSAR-based methods such as coherence loss and insensitivity to certain movement directions.

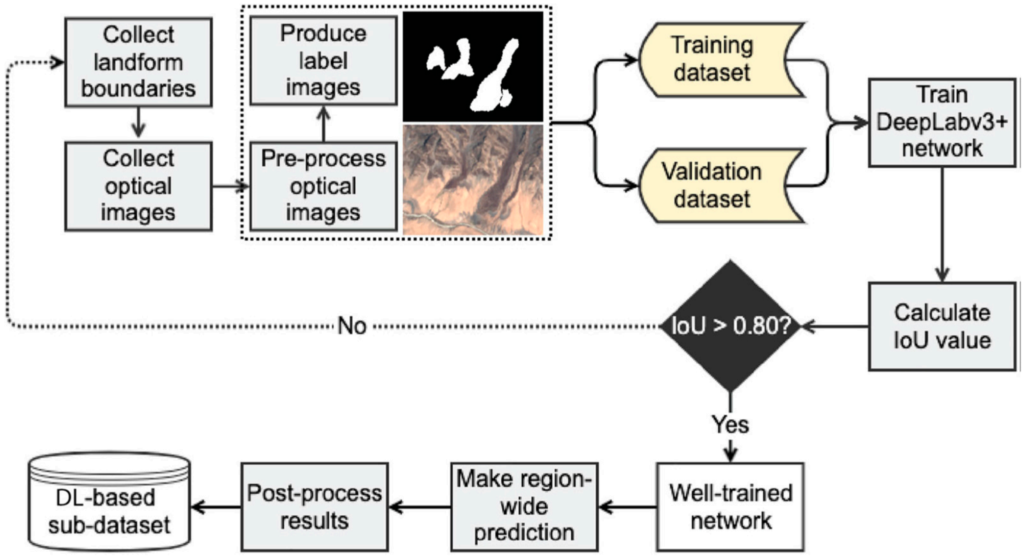

Figure 21. Workflow diagram [55].

The combined AI and remote sensing approach enabled the first regional-scale mapping of rock glaciers in this arid mountain range, resulting in an inventory of 413 rock glaciers. Of these, 290 were active rock glaciers mapped manually using InSAR, while 123 were newly identified and delineated by the DL model applied to Sentinel-2 optical imagery. This semi-automated workflow allowed for consistent mapping across a large, remote area where field studies are challenging. The resulting inventory provides valuable baseline data on rock glacier distribution, morphology, and kinematics that can inform further research on permafrost, climate change impacts, and water resources in this high mountain region.

Thus, as can be seen from the reviewed works dedicated to inventorying and mapping glaciers, traditional ML classifiers such as RF, SVM, KNN, DT, GB, and MLP were applied. These methods mostly rely on structured data and use algorithmic approaches for classification. In contrast, CNNs and their variants, such as U-Net, DeepLabv3+ with ResNet, DRN, MobileNet, GlacierNet, Mobile-Unet, Res-UNet, FCDenseNet, R2UNet, GLNet, Channel Attention U-net, and ENVINet5, are DL models designed for image processing and segmentation tasks. The difference lies in their architecture: CNNs leverage convolutional layers to automatically extract features from input images, whereas traditional ML classifiers use predefined features. Some works are considered hybrid models, like RF-CNN and ANN with U-Net, as they combine elements from both traditional ML and DL learning to leverage their respective strengths. Methods like Relief-F and Pearson correlation are feature selection techniques that can be used to preprocess data for either traditional ML classifiers or CNNs, enhancing the performance by selecting the most relevant features.

3.2. AI for Monitoring of Glacier Evolution

Monitoring of glacier evolution becomes crucial for understanding the environment as glaciers worldwide respond to the effects of global climate change. AI offers tools for continuously tracking glacier dynamics, providing insights into changes in glacier extent, volume, and behavior over time. By leveraging AI algorithms in conjunction with satellite imagery and remote sensing data, researchers analyze trends, detect patterns, and forecast future glacier evolution with sufficient accuracy and efficiency. In this section, we delve into the innovative applications of AI in monitoring glacier evolution.

Bolibar et al. [56] simulated the annual glacier-wide surface mass balance (SMB) using a novel algorithm based on deep ANN. This was integrated into an open-source model for mapping selected regional glaciers. They evaluated the nonlinear deep learning SMB model and compared it with standard linear statistical methods using data obtained from French Alpine glaciers. ALPGM is an open-source Python glacier model mainly structured into: (i) a glacier-wide SMB simulation and (ii) an update module for glacier geometry. The SMB simulation component utilizes ML algorithms for predictive modeling, while the geometry update module produces glacier-dependent functions for annual geometry adjustments. The workflow (shown in Figure 22) execution is configurable via the model interface, where users are allows to deploy or skip specific steps, including preprocessing meteorological forcings, training SMB models, evaluating model performances, and updating glacier geometries.

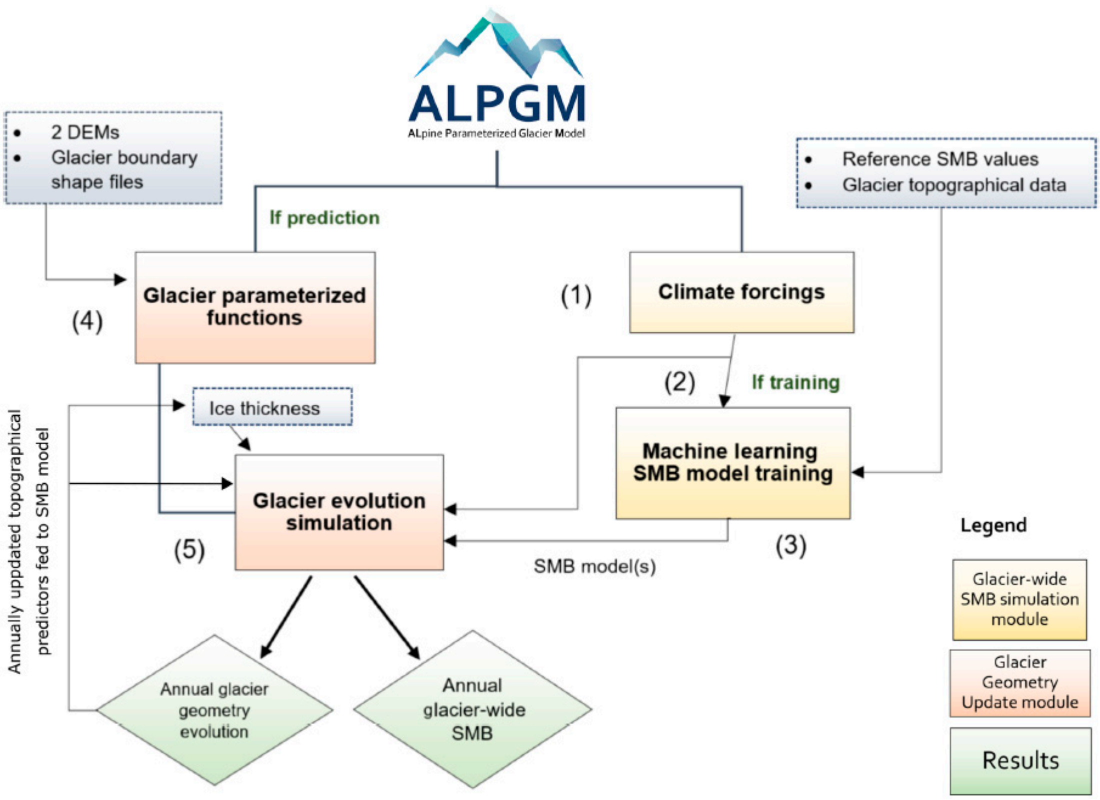

Figure 22. Structure and workflow of the ALPGM by Bolibar et al. [57].

The machine learning SMB model production workflow involves selecting relevant topographical and climatic predictors based on literature reviews and sensitivity analyses. To generate the SMB model, algorithms such as OLS, Lasso, and deep ANN may be selected, with ALPGM employing popular Python libraries like stats models, scikit-learn, and Keras with a TensorFlow backend. The presented approach showcases the potential of DL for the simulation of SMB, capturing nonlinearities not only in spatial, but also in temporal dimensions. The developed method showed explained variations of 64% for spatial and 108% for temporal, and accuracy values of 47% and 58% for spatial and temporal, respectively. This resulted in an r^2 value of about 0.7 and an RMSE (root-mean-square error) of 0.5 m of water equivalent.

Ambinakudige and Intsiful [58] assessed the accuracy of three ML algorithms (SVM, RF, and MLC) for area classification and estimated the glacier volume change of Columbia Icefields from 1985 to 2020. All three algorithms classified images with over 99% accuracy and kappa coefficients of over 0.993, with SVM performing slightly better in identifying debris. The authors found that 10.4% of the ice/snow area was lost over the study period, which is consistent with other studies in the same region.

Utilizing Landsat satellite imagery from various years, the study revealed a significant decline in glacier area and volume in the Columbia Icefield between 1985 and 2020. SVM classification consistently showcased over 99% accuracy in classifying glacier features across different years, enabling accurate estimation of glacier changes over time. The observed trends align with broader global patterns of glacier retreat and volume loss attributed to climate change-induced warming. Moreover, the study underscores the importance of continued research leveraging ML methodologies, particularly in assessing glacier changes on a global scale. The findings not only reiterate the efficacy of ML techniques for glacier classification, but also emphasize the urgent need for comprehensive studies in order to understand the impacts of climate change on glacier dynamics. As glaciers continue to retreat worldwide, the integration of advanced ML approaches with remote sensing data holds promise for developing reliable records of glacier changes, which are essential for informing climate mitigation and adaptation strategies.

The study by Rajat et al. [59] applied U-Net to identify and map glacier evolution in the Himachal Pradesh province of India, leveraging Indian Remote Sensing (IRS) and Landsat satellite data spanning from 1994 to 2021. The results demonstrated a high identification accuracy of 95%, with a significantly reduced processing time compared to traditional methods. The findings revealed a concerning trend of glacial retreat in the region, with the glaciated area decreasing at a rate of approximately 67.84 km^2 per annum over the past three decades.

Utilizing Landsat satellite imagery from different years, the study evaluated changes in glacier area and volume, highlighting a substantial loss of approximately 1822 km^2 in glacier area from 1994 to 2021. This decline in glacial coverage underscores the urgency of understanding and mitigating the impacts of climate change on Himalayan glaciers, which are crucial water sources for the region.

The U-Net network model employed in the study effectively learns glacier characteristics and enhances feature extraction, leading to improved accuracy in glacier identification. By integrating deep learning with remote sensing data, the study offers a valuable tool for monitoring and assessing glacial changes, essential for water resource management and hydropower planning in the region. Furthermore, the paper suggests avenues for future research, including exploring the integration of additional variables such as thermal bands and precipitation data to enhance the machine learning model's accuracy. Incorporating in situ observations and debris glacier data could provide valuable insights into the relationship between glacier changes and climate change, facilitating more precise predictions of future glacier dynamics.

Yang et al. [60] conducted a study on glacier changes using remote sensing (RS) data and applied a DL technique to assess the risk of glacier debris flow in the region of the great bend of the Brahmaputra River in the Tibet Plateau, focusing particularly on the

Zelongnong ravine. Thus, they evaluated the glacier regions in the Zelongnong ravine using an automated semantic segmentation method trained using remote sensing data and the DL technique. They proceeded by computing variations in glacier elevation and volume between 2000 and 2016, examining the nature of changes within the research site.

Subsequently, they partitioned the Zelongnong ravine into five sub-basins, applied the glacier correction coefficient to enhance the initial geomorphic information entropy theory, and assessed the susceptibility of glacier debris flow in the Zelongnong ravine. Furthermore, glacier ablation is influenced by various factors, including slope, aspect, elevation, and climatic conditions such as sunlight exposure. These factors play crucial roles in determining the rate of glacier ablation. Therefore, the assessment of the susceptibility of debris flow can be obtained from the indicator—the ablation volume of the glaciers. Thus, by categorizing susceptibility grades based on the ablation volume, accurate predictions regarding glacier debris flow susceptibility can be made. The overall workflow and schematics of the developed method are shown in Figures 23 and 24.

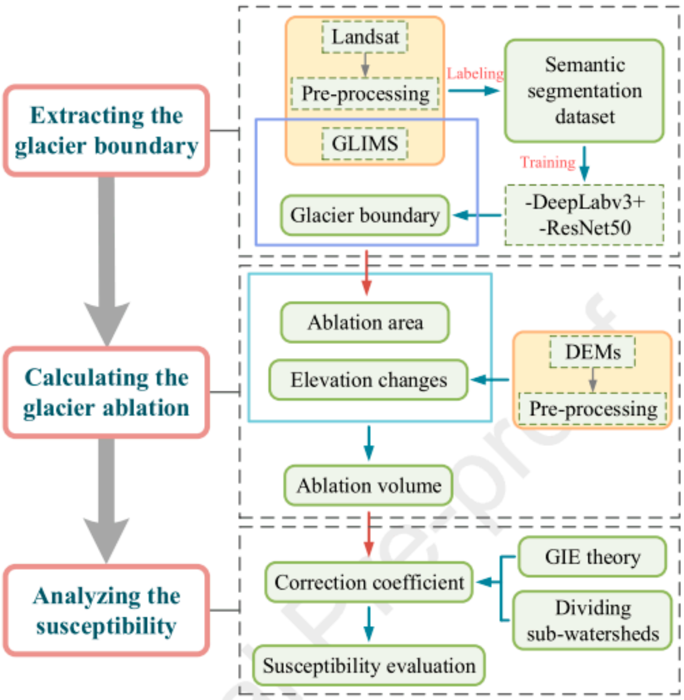

Figure 23. Workflow of this study by Yang et al. [60].

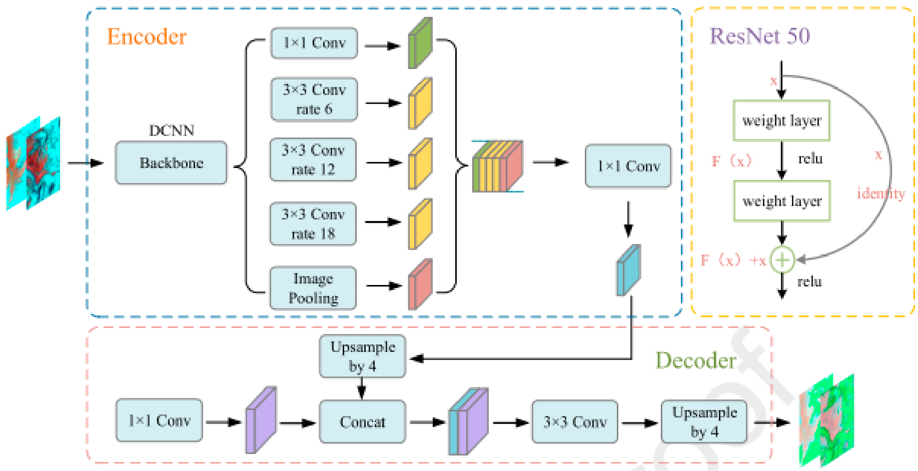

Figure 24. DeepLabv3+ semantic segmentation model and ResNet-50 residual unit [60].

Thus, the monitoring of glacier evolution using AI methods is advancing. It is more complex compared to mapping and inventory studies due to the inclusion of temporal changes in glaciers. Therefore, the development and testing of such methods require more time and effort. Nevertheless, it can be considered one of the main areas for future research in glacier studies using AI.

3.3. AI for Snow/Ice Differentiation

Another opportunity for AI applications arises in the area of snow and ice discrimination, which represents an innovative solution for optimizing the accuracy and optimization of remote sensing analysis. Through extensive training on a variety of datasets including satellite imagery and ground-based observations, AI models can quickly learn to discern the subtle spectral and textural nuances characteristic of snow and ice, overcoming the limitations of traditional manual interpretation or spectral analysis methods. This capability not only speeds up the processing of extensive remote sensing data, but also facilitates rigorous quantification of the extent of snow and ice, which is fundamental for climate research, hydrologic modeling, and environmental monitoring initiatives.

In their study, Prieur et al. [61] created an automated procedure that allows snow lines on glaciers to be identified from remote sensing images. It was tested on temperate glaciers located in the Alps of Europe. A feed-forward NN, SVM with Gaussian and linear kernels, and RF were selected as ML methods, and they used data from Landsat 8, especially data that considered the glacier inventory of the Alps in 2015 and the Copernicus DEM (Figure 25). The algorithms were designed to systematically categorize each glacier within the research region, employing a step-by-step binary classification approach. This process involves identifying and removing shadowed areas and eliminating leftover ice or snow pixels to eventually create a map that delineates ice and snow coverage on the glacier. The resulting map may be presented as either a binary map or a probability map, depending on the chosen method of map extraction. Since glaciers often have ice- and snow-covered areas devoid of clouds, the developed procedure suggests two techniques to identify the snow lines on the glaciers. If these methods fail, the mapping of the glacier is stopped. The initial method involves a modified version of automatic snow mapping on glaciers (ASMAG) bin decomposition detection process. This approach utilizes the snow line produced by ASMAG's procedure as an initialization vector for the detection of active contours. The alternative approach involves calculating the gradient of the snow cover map and then applying a threshold to this gradient based on elevation. This is intended to eliminate the gradient caused by patches of snow in the ablation region of the glacier. Both approaches provided good accuracy in identifying the lines between snow and glaciers, but discontinuous snow lines and steep sections of glaciers led to the failure of the methods.

3.4. AI for Ice Dynamics Modeling

AI also has the potential to transform the efficiency and accuracy of calculations in modeling ice dynamics, presenting another prospective application in this research domain. By leveraging vast amounts of observational data, satellite imagery, and remote sensing datasets, AI-based models can capture the nuanced interactions that include ice flow, mass balance, and calving dynamics. This capability not only speeds up the modeling time, but also allows researchers to gain a deeper understanding of the multifaceted drivers of glacier dynamics and their responses to environmental changes.

With this purpose, Jouvet et al. [62] introduced a glacier model (IGM), a novel approach to simulating ice dynamics, mass balance, and their combination, to estimate the evolution of glaciers and icefields. Central to the novelty of the model was its utilization of a convolutional neural network (CNN) to model ice flow, optimized using the data developed by means of a hybrid Shallow Ice Approximation (SIA) + Shallow Shelf Approximation (SSA) or Stokes ice flow model. This substitution of the computationally intensive ice flow component with a cost-effective emulator enabled IGM to model mountain glaciers up to 1000 times faster than traditional Stokes models on central processing units (CPUs), with accuracy levels surpassing 90% in terms of ice flow solutions and nearly identical transient thickness evolution. Leveraging graphics processing units (GPUs) further enhanced speed-ups, especially for emulating Stokes dynamics or modeling at high spatial resolutions. IGM is an open-source Python code designed for 2D gridded input and output data, facilitating effective and user-friendly glacier and icefield simulations.

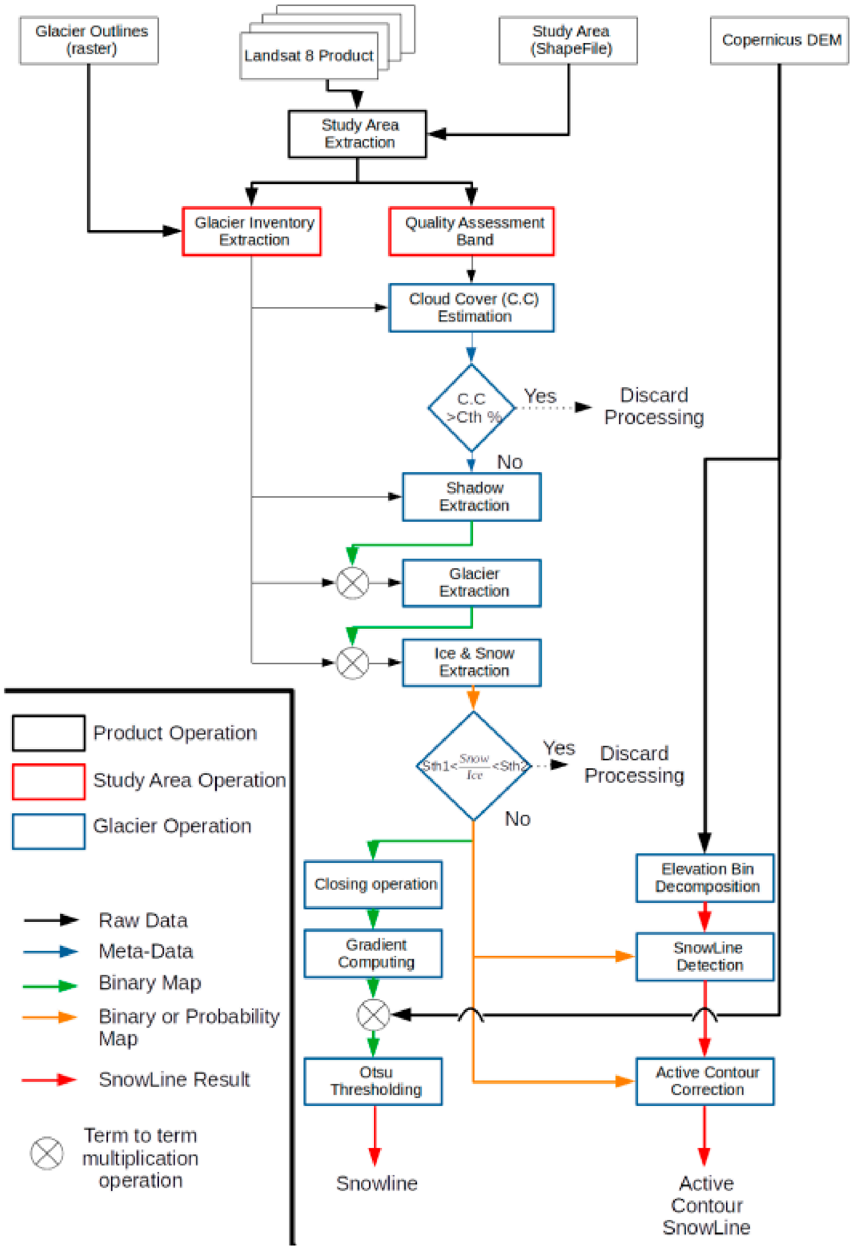

Figure 25. General flowchart of the proposed method [61].

The approach applies DL to ice flow modeling, employing CNN to predict ice flow using topographic properties as well as basal sliding parametrization in a generic manner. Unlike previous methods that emulated specific glacier dynamics from small-sized ensemble parameters, the neural network emulator in this study is trained from a large dataset generated from ice flow simulations obtained from state-of-the-art models—PISM and CfsFlow—equipped with hybrid SIA/SSA and Stokes mechanics at varying spatial resolutions. Integration of surface mass balance (SMB) and the conservation approach with the ice flow simulator yields the IGM, facilitating highly efficient and mechanically advanced ice flow simulations (Figure 26).

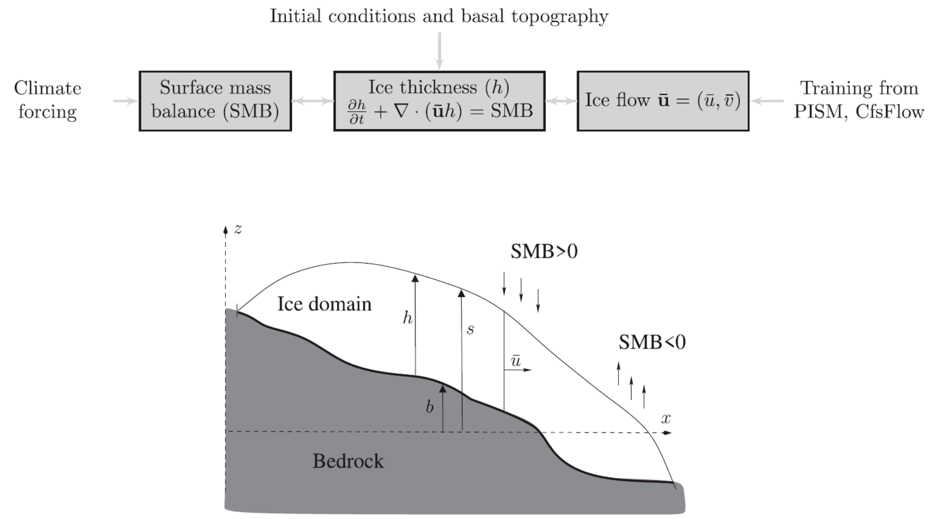

Figure 26. Connections between the model elements and the input data of IGM by Jouvet et al. [62].

However, IGM's limitations include dependency on the training dataset's representativeness, assumptions of isothermal ice, limitations in boundary conditions, and compatibility only with regular gridded data. Despite these limitations, IGM's computational efficiency opens new opportunities in paleo ice flow modeling, with applications in reconstructing glacial cycles, studying landscape evolution, inferring paleo climatic patterns, and improving global glacier modeling by reducing uncertainties associated with simplified models. Overall, IGM presents a promising advancement in glacier modeling, with potential applications in both paleo and modern ice sheet simulations.

The latest two areas of research, snow/ice differentiation and ice dynamics modeling, are relatively new and have not matured yet compared to the first two classified research areas. However, researchers have already begun working in these directions, and they are expected to become areas of greater interest in the near future.

4. Discussion

The most common type of AI-based glacier study consists of mapping and glacier inventory. In fact, mapping and glacier inventory are crucial for evaluating glacier sizes and keeping track of them, providing essential data for understanding climate change impacts and predicting future water resources. These activities help scientists assess glacier health, contributing to global efforts in managing ecosystems and mitigating natural hazards. Thus, as can be noticed in the main section above, the earliest methods were classification methods such as random forest (RF), K-nearest neighbor (KNN), support vector machines (SVMs), decision trees (DTs), and gradient boosting (GB). In their work, Zhang et al. [40] selected the number of trees in RF as 100, but there was not any information on how the number of trees affected the accuracy of the RF in mapping glaciers, nor in testing or training sample sizes. Alifu et al. [45] compared these classification methods among each other and showed that RF was the best-performing and most robust ML method by carrying out hyperparameter analysis optimization. Khan et al. [43] also confirmed that RF performed better than the neural network method (i.e., ANN) when tested and compared using 26,688,723 pixels (391,907 labeled as debris-covered glacier, 1,354,622 as glacier, and 942,194 as non-glacier areas). The authors also mentioned that the computational complexity to train ANN is relatively higher. During the model parameter selection, only the learning rate and momentum were optimized, with fixed settings for other parameters (1000 iterations, sigmoid activation, and 200 hidden neurons), resulting in optimal accuracy with a learning rate of 0.1 and momentum of 0.8. Although tuning additional parameters such as the number of hidden layers, units per layer, batch size, and regularization techniques (e.g., dropout, weight decay) could have led to a better performance of ANN, it was not explored in this study.

The earliest studies of glaciers using CNN were conducted in 2019. Mohajerani et al. [41] and Baumhoer et al. [42] developed modified U-net models. The U-Net architecture by Mohajerani et al. [41] consists of 29 layers with three downsampling steps, increasing feature channels from 32 to 256, and uses custom sample weights to address class imbalance. In contrast, Baumhoer's [42] modified U-Net processes larger 780 $\times$ 780-pixel tiles with four input channels, includes four downsampling and upsampling units, and features 7.8 million trainable parameters. Both architectures use 3 $\times$ 3 convolutions, ReLU activations, 2 $\times$ 2 max pooling, and dropout layers, but differ in the number of layers, input size, and approach to handling class imbalance. Neither works performed thorough hyperparameter optimization to fine-tune parameters such as the learning rate, batch size, number of layers, and dropout rate, which could be used to evaluate the robustness of the models and potentially enhance their performance.

In other works [47–53], the authors proposed the combination of two methods into a hybrid AI approach to map glaciers, hoping for better accuracy compared to non-hybrid methods. For example, Lu et al. [47] combined RF with CNN and showed that the hybrid approach performs better than RF-only and CNN-only approaches in terms of user accuracy. However, in terms of producer accuracy, RF showed a better accuracy. Thus, the author clearly stated that due to the limited size of the glacier dataset in their experiment, the advantages of hybrid RF-CNN over traditional ML methods (i.e., RF and CNN) were not evident. In fact, the accuracy of the models depends on the testing data. For example, Kaushik et al. [17], in their study, showed that their developed GLNet method performed with an accuracy of 0.99 for site 1, while for site 2, this was reduced to 0.80, which is significantly low. They described this reduction in accuracy as being due to the presence of frozen and partly frozen lakes in the testing data, which was not accounted for during the training of GLNet.

The development of CNN-based models for glacier studies further continued and was actively studied by the authors, Xie, Asari, and Haritashya [48,49]. They initially developed the so-called GlacierNet and CNN segmentation model, and performed comparative analyses of their model with Mobile-UNet, Res-UNet, FCDenseNet, R2UNet, and DeepLabV3+. Based on their comparative analysis, DeepLabV3+ was the most effective for regional and large-scale glacier mapping due to its high intersection over union (IOU) and overall performance. During their study, they explored that the challenge lies in estimating the glacier terminus, which requires additional studies on the network's architecture, implementation of automated post-processing techniques, and incorporating additional terminus data. Peng et al. [14] also confirmed that DeepLabV3+ performed with higher accuracy; however, their proposed model with the LGT encoder and multiple LGCB layers was able to map both the complete glacier area and clear edges, making it potentially suitable for glaciers with accurate terminus mapping. Collectively, these studies illustrate the evolving landscape of AI techniques in glacier mapping, where various models are combined to improve the accuracy and address diverse challenges.

Another area of glacier studies where AI models have started to be actively applied is the monitoring of glacier evolution. Compared to glacier mapping, which focuses on spatial changes, monitoring glacier evolution also considers temporal variations, making it more complex than mapping studies. Bolibar et al. [56,57] studied the evolution of glaciers in the French Alps in the 21st century. Their comparative study showed that nonlinear DL models outperformed linear models by 94% to 108% in variance and 32% to 58% in accuracy, indicating that DL maintains a consistent performance across spatial and temporal dimensions, whereas linear methods struggle with the increased complexity of temporal SMB variations. Similarly, Ambinakudige and Intsiful [58] studied the glacier volume changes of Columbia Icefields from 1985 to 2020, but they used classification models such as SVM and RF. The latter models provided about 99% accuracy in classifying glacier features in 1985–2020. Furthermore, Rajat et al. [59] used U-Net to identify and map glacier evolution in the Himachal Pradesh province of India, but their timeline was from 1994 to 2021, and the accuracy of the model was around 95%. Yang et al. [60] clearly outlined and acknowledged limitations in their approach in their study, including the assumption that all melted glacier ice converts to water, which overlooks the potential formation of new ice bodies and does not fully address variability or errors in glacier changes. Thus, because of the complexity of modeling dynamic glacier changes over time and space, AI models face notable challenges, highlighting the need for more advanced approaches. This presents an intriguing opportunity for exploring new AI techniques in order to better address these challenges. Moreover, the availability and time-frequency of data are crucial for the accuracy of AI models. Given that glacier monitoring spans several decades, consistent data throughout the measured and evaluated periods are essential for training AI models effectively.

Some other studies have pioneered new areas of study, such as snow/ice differentiation and ice dynamic modeling. In fact, snow/ice differentiation is indeed very important, because identifying the boundaries between snow and ice allows the size and volume of glaciers to be estimated. Prieur et al. [61] applied ML methods and showed good accuracy. However, their pre-processing algorithm (CFMask) might have compatibility problems with other multi-spectral products like Sentinel. They also mentioned another limitation, which was the need to retrain classifiers for new multi-spectral products, because different imaging systems offer varying spectral information. Therefore, training AI models for snow/ice differentiation using different types of images with varying spectral information is crucial. This is especially true for all image-based glacier studies using AI, particularly when developing advanced AI tools that can be applied to any glacier location once trained. In terms of ice dynamics modeling, Jouvet et al. [62] developed the instructed glacier model (IGM). In fact, ice has been modeled as a viscous, non-Newtonian fluid as described by computationally expensive Stokes equations. The authors explained that their IGM provides near-Stokes accuracy with high computational efficiency; operates on 2-D regular grids, simplifying data management; and requires only basic topographic inputs without the need for catchment or flowline identification. However, IGM's applicability is limited by its training dataset; it cannot model ice flow beyond the training data's scope; assumes isothermal ice; and only supports regular gridded data, excluding unstructured meshes.

5. Conclusions

Understanding changes in glaciers, evaluating their current conditions, inventorying, and predicting future scenarios based on climate change effects are highly crucial endeavors. Glaciers serve as vital sources of drinkable water, agricultural irrigation, and energy generation. Therefore, monitoring their status and forecasting their future behavior are important tasks in the face of ongoing environmental transformations.

As methods requiring less human interaction to deliver computational results evolve, the possibility of their application towards monitoring and forecasting glacier layers becomes feasible. Compared to conventional methods based on remote sensing, such methods, which mostly rely on artificial intelligence (AI) techniques, are highly accurate, cost-effective, and reliable once they are trained with accurate and sufficient datasets. With the rise of AI, the number of works dedicated to the application of ML and DL methods on glacier mapping and evaluation has notably increased. Therefore, within the scope of the current state-of-the-art review work, the available research works in AI-based glacier studies are studied and classified, and relative data are collected and tabulated for comparative purposes.

Thus, from the collected number of research papers, the following conclusions are obtained:

- All the reviewed works are classified by the purpose of their research. Among them, glacier mapping is the most studied area, followed by glacier evolution, ice/snow differentiation, and ice dynamic modeling.
- For AI-based glacier evolution studies, the availability of glacier data in terms of time-frequency and overall measured duration is highly important to accurately capture the temporal evolution of glaciers.

- Ice/snow differentiation and ice dynamic modeling are in their early stages regarding AI-based studies. However, the methods developed so far show promising accuracy and require further advancements.
- Methods such as random forest (RF), K-nearest neighbors (KNN), support vector machines (SVMs), and decision trees (DTs) have been foundational. Among them, RF often outperforms other traditional methods in accuracy and robustness, especially for glacier mapping studies.
- Recent studies in glacier mapping have developed CNN-based models, notably U-net and DeepLabV3+, which showed enhanced accuracy in glacier mapping. However, the robustness of these models needs to be tested with appropriate methods, such as hyperparameter optimization, to fine-tune parameters like the learning rate, batch size, number of layers, and dropout rate.
- Hybrid methods that combine two ML and/or DL methods generally show better performance compared to single methods. However, the compatibility and integrability of different methods in hybrid solutions have not been thoroughly studied yet, and comparative studies among hybrid methods are lacking.
- Overall, AI-based glacier research has notably been gaining the attention of scientists and requires more detailed studies. The consistency of AI-based methods needs to be further evaluated, particularly when training on one glacier dataset and testing on a different dataset. Additionally, the impact of training and testing dataset sizes, as well as the remote sensing technologies used to obtain these datasets, should be assessed.
- More generalized AI-based glacier assessment tools, particularly for worldwide glacier mapping and inventory, appear to be a promising direction for future research.

Overall, the integration of AI technologies holds enormous promise for improving glacier mapping and analysis, offering new insights into the complex dynamics of these vital components of the Earth's cryosphere. As researchers continue to explore and improve artificial intelligence methodologies, the potential for greater understanding and better management of glaciers in the context of climate change is becoming increasingly accessible.

The importance of the current state-of-the-art review is significant because it will serve as a guideline for future research works in AI-based glacier studies. As the first review paper in this area, the authors are confident that its results will provide notable value in this research field.

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