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Glacier Growth Monitoring Using YOLOv8 and Feature-Based Classification

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Abstract

The rising threat of climate change has raised the need for constant glacier surveillance, since their fast growth may pose an immediate danger to the environment and cause disasters. However, conventional approaches to glaciers' monitoring are dependent on challenging and irregular manual analysis of satellite images. In this paper, a new combined methodology for automated glacier growth monitoring and risk assessment based on satellite imagery is introduced. The system combines a glacier segmentation model based on deep learning with a classification algorithm that utilizes ensemble machine learning to predict a risk level. The YOLOv8 segmentation network is used to identify the glacier outlines from a set of satellite images and generate masks to be further analyzed. The masks are used to extract features representing the glacier area, shape, and growth pattern, which are later used by a random forest and an extreme gradient boosting algorithm to determine the risk level by applying the soft-voting method. A real glacier lake dataset is used to test the system and demonstrate its performance and accuracy in identifying risky and non-risky growth.

Keywords: Glacier Growth Monitoring, Satellite Imagery, Deep Learning Segmentation, Ensemble Machine Learning, YOLOv8.

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1. Introduction

Glaciers are among the most sensitive barometers of global warming, and even subtle changes in their size or dynamics can cause considerable environmental problems. Faster movements and instability of glaciers may contribute to higher risks associated with various natural disasters like glacial lake outburst floods, landslides, and floods downstream of glaciers. Under these circumstances, a careful and accurate monitoring of glaciers becomes a priority. Observations of glaciers by means of satellite images provide the opportunity to monitor them across a wide geographical territory. However, most of the existing approaches to monitoring use human interpretation or classical image analysis. The problem is that these approaches are time-consuming and vulnerable to complications related to topographical features, heterogeneous illumination, and seasonal coverage of snow. A considerable amount of satellite data does not allow manual interpretation of data; thus, automation of the process becomes imperative. With recent developments in deep learning technologies, the accuracy of image-based glacier detection techniques is greatly improved through segmentation methods that can detect boundaries of glaciers on a pixel-by-pixel basis. Likewise, machine learning technologies have advanced enough to analyze trends within any dataset of the environment. Nevertheless, there are many existing studies that conduct glacier segmentation and glacier risk prediction in separate ways, and this limits their ability to represent complete glacier activities and risks.

In this context, the proposed work in this paper introduces a fully automated system combining deep learning based glacier segmentation with machine learning ensemble algorithms for growth risk prediction. Preprocessing and features calculation are performed by applying a YOLOv8 algorithm for detecting boundaries of glaciers in temporal satellite images [1]. The masks generated in the process of segmentation are utilized to generate some important characteristics regarding glacier shape, size, and growth activity. The obtained features are then classified into risky or non-risky using soft voting of Random Forest and XGBoost algorithms. The suggested approach integrates precise spatial analysis with feature-based risk categorization, thereby providing an efficient and scalable approach to monitor glaciers. The presented approach decreases human intervention, ensures consistency in the analysis of big data, and gives timely alerts of potentially dangerous glacier expansion, which makes it ideal for environmental monitoring applications.

The algorithm of the suggested system involves four major stages, namely: (1) processing of satellite images, (2) segmentation of glaciers' boundaries using YOLOv8, (3) extracting glacier morphological and temporal characteristics, and (4) classifying the risks of glacier expansion using a soft voting mechanism that involves both the Random Forest and XGBoost approaches.

2. Related Work

Hazards associated with glaciers have recently emerged as significant threats in several mountainous areas, due to the continuous impact of global warming on glaciers, snow, and glacial lakes. Previous research has found that not only glaciers but also glacial lakes are a risk factor and environmental indicator because any increase in glaciers and/or glacial lakes could pose risks of flooding in downstream regions. To address such concerns, it has been necessary to find efficient and automated algorithms to detect glaciers from remote sensing imagery. One of the solutions used to address the problem is based on applying deep learning segmentation networks, which allows training the model directly to identify glaciers on the satellite imagery. A number of works have already used U-Net-based approaches to detect and segment glaciers using satellite imagery [2], suggesting that such neural networks yield better performance compared to thresholding and classical image-processing algorithms when the terrain is difficult to classify. However, there still exist a variety of limitations with existing approaches, such as the presence of glaciers' shadows, season snow and debris.

Recently, researchers have shifted from CNN based segmentation [3] and have started working with stronger architectures such as transformers and hybrid CNN & transformers to overcome some weaknesses of CNNs like capturing extended spatial context and improved boundary consistency in cases where sharpness of boundaries is not possible. Large scale regional glacier mapping using deep learning techniques demonstrates the possibilities of creating machine learning models capable of handling vast geographical regions with readily available satellite imagery. At the same time, they also reveal one shortcoming, i.e., creating a boundary map alone does not give any risk signal that is decision ready. In several scenarios, it becomes necessary to process this information further in order to get meaningful risk assessments.

A large-scale glacier mapping study further highlights the capability of current deep learning algorithms to facilitate multi-temporal glacier monitoring at a large scale using openly available satellite images. The researchers have built a convolutional-transformer algorithm, and provide techniques for consistently mapping glaciers through time, which is a necessity for creating repeatable glacier inventories and assessing their change. According to their findings, deep learning algorithms [4] have the capability of performing global-scale glacier mapping to an increasing extent; however, it should be noted that such mapping doesn't solve any risk issue by itself. An additional modeling step is required to assess whether the discovered pattern of growth leads to the creation of hazards. This emphasizes the importance of applying mask-based feature extraction and classification algorithms for obtaining usable results.

Moreover, yet another emerging field of research includes the study of glacial lakes and the associated danger of outburst floods, where machine learning is used to predict the chances of lake development or risk/hazard distribution based on geomorphological and topographical features [5]. Overall, all these papers indicate that there is great potential in the use of machine learning techniques to model environmental risks when uncertainties and non-linearities dominate the process. On the other hand, most of the studies dealing with environmental risks include external risk predictors such as terrain and lake characteristics and regional factors and not directly observable and measurable variables that are linked to the glacier boundaries. Yet another area that has been observed is the separation between segmenting and classifying glaciers; there are cases when a model may be excellent at segmenting glaciers, but then converting these into some metric such as glacier growth rate, overlap spatially, and others become a manual process or are not properly defined. It limits usefulness because in many situations, both accurate boundaries' delineation and understanding of what this implies concerning any risks involved are important considerations to make.

There have been studies related to machine learning approaches applied to glacier-related hazards in terms of risk assessment with particular interest paid to glacial lake and fast glacier melt-related issues [6]. These studies usually consider using random forest, XGBoost, and others in terms of assessing susceptibility to hazards in the context of environmental parameters. As for ensemble models, they are generally preferable in the situation mentioned above due to the fact that they provide non-linear relationships and heterogeneity of input variables. Nevertheless, one of the issues is that the risk assessments are generally performed relying on external conditioning variables instead of being directly determined from glacier change [7]. It might hinder the establishment of the clear connection between glacier growth and the subsequent risk generation process. Thus, there should be used a combined method wherein firstly, the contours of glaciers are defined using satellite imagery; secondly, the temporal and spatial changes of interest are computed; finally, these features are classified using the ensemble model into risk classes. Indeed, the selected solution falls into the current trend towards combining accurate segmentation techniques with efficient predictive algorithms that could be interpreted by domain experts. This strategy is not limited to pure contour detection since it makes use of segmentation maps for generating numerical characteristics reflecting glacier change (e.g., percentage of growth, overlapping area, etc.) that are subsequently used for determining the risk using the ensemble classifier.

3. Methodology

3.1 Dataset

Glacier growth assessment performed within the study utilizes a dataset of images of glaciers derived from a Rob flow Glacier–Lake Dataset [8]. This dataset includes 423 labelled images of the glaciers, taken from remote sensing systems, that classify different regions of the glaciers and the surrounding environment. Images have manual labelling of the exact boundaries of the glaciers.

The challenges in glacier identification arise from the fact that the dataset contains glacier surfaces as well as areas of snow, rock, and water. The main advantage of this dataset is that it is appropriate for real-world glacier expansion monitoring and machine learning algorithm applications, as it contains realistic glacier environments. Moreover, this is one of the most accurate datasets for glacier expansion identification and monitoring in real-world environments.

3.2 Preprocessing

This paper uses a combination technique of deep learning and machine learning to monitor the expansion of glaciers via satellite images. Some pre-processing steps are used before training the models to guarantee consistency and authenticity in the data. The process involves the resizing and normalization of all images to satisfy the criteria needed by the segmentation model. The satellite images are then converted to grayscale images to simplify computations without sacrificing the spatial characteristics necessary for glacier boundary identification [9]. Following this process, the noise and contrast are reduced to make sure the glacier borders are distinctly visible in the image. Analyses of the data set are carried out to identify changes in glacier size and form in the pair of images captured at different time points. Ultimately, following the completion of the above pre-processing process, the data set is partitioned into test sets or candidate sets. The results of the pre-processing stage are then fed into the segmentation process of glacier borders.

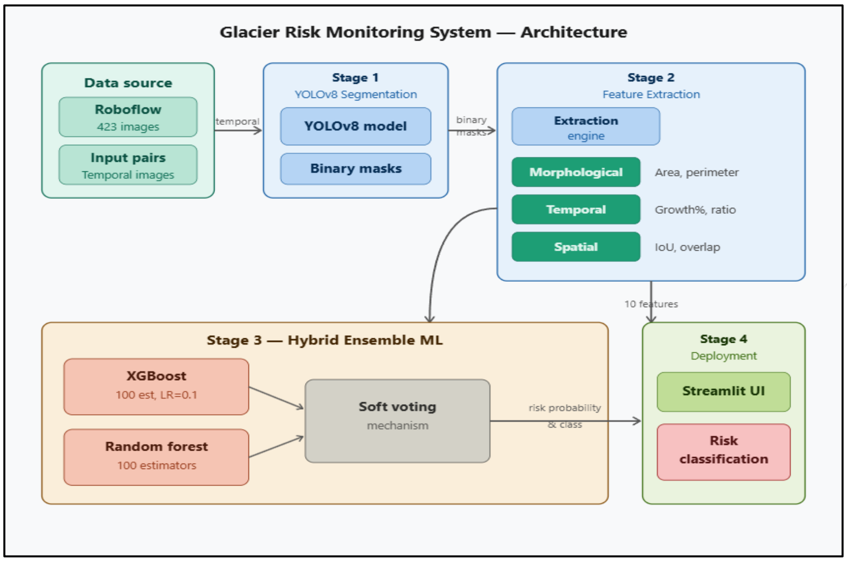

Figure 1. Architecture Diagram

Figure 1 shows the entire architecture design of the system for glacier risk detection that detects glacier growth automatically and classifies the risk using spaceborne images. This proposed system begins with the collection of images from the Roboflow glacier-lake dataset and uses a pair of temporal images as the input to this system. These images will be processed in the YOLOv8-based Segmentation Module [10] for accurate boundary detection and creation of a binary mask of glaciers regions. The output from the segmentation module is further passed to the feature extraction phase, where different features such as morphological, temporal, and spatial are extracted in order to model the growth of the glacier. These extracted features will be used to predict the growth risk in the Hybrid Ensemble Learning Module where the risk prediction is done using the combination of Random Forest and XGBoost classifier with soft voting

4. Experimental Analysis

The following machine learning classifiers have been chosen to check and compare the performance of the developed system to predict the risk of glacier growth:

4.1 Random Forest

It is an ensemble learning algorithm that constructs multiple decision trees and then combines their predictions by majority voting. It is suitable for non-linear relationships among the input glacier features, such as area, perimeter, and growth in percentage.

$$y = \text{mode}(T_1(x), T_2(x), ..., T_n(x)) \quad (1)$$

Ti(x) represents the prediction of the i-th decision tree (risky or non-risky glacier growth). n is the number of trees in the forest. y is the final predicted class obtained through majority voting.

4.2 Support Vector Machine (SVM)

Support Vector Machine is a powerful classification algorithm that attempts to find an optimal hyperplane separating different classes. While SVM is effective for smaller datasets, its scalability becomes limited when handling high-dimensional feature spaces and larger datasets, such as those derived from satellite image features.

$$f(x) = \text{sign}(w \cdot x + b) \quad (2)$$

w is the weight vector. x is the input feature vector. b is the bias term. sign(·) is the function that determines the class label (either -1 for non-risky or +1 for risky).

4.3 XGBoost

XGBoost is a gradient boosting method where decision trees are built one after the other, with every decision tree trying to make up for the mistakes committed by the previous decision trees. XGBoost [11] is a highly efficient method in terms of both speed and accuracy, suitable for learning complex patterns of glacier growth using extracted features.

5. Results and Discussion

In this section, the experimental results for the proposed hybrid approach to glacier growth detection are presented. The purpose of the analysis is to assess the efficiency of the proposed segmentation and classification system and to compare the performances of the machine learning models and the proposed hybrid technique. All experiments were carried out on the processed glacier dataset with all the morphological, temporal, and spatial features extracted from it. The performance metrics used to test the performance of all models include accuracy, precision, recall, as well as feature importance evaluation.

5.1 Random Forest

Random Forest (RF) was chosen as a baseline classifier on account of its robustness against noisy data and handling non-linear relationships between the features. The model worked quite well at recognizing the regions of stable glaciers and was successful at providing correct classification. RF was quite accurate at the classification task owing to the nature of the ensemble method, which consists of a combination of multiple decision trees, thereby avoiding overfitting. Nevertheless, RF had slightly decreased sensitivity when identifying instances of high-risk glacier growth [12]. Despite this shortcoming, the model had good generalization and stability.

5.2 XGBoost Performance Analysis

XG Boost outperformed the Random Forest model through its ability to learn complex patterns between the extracted features. The gradient boosting technique in XG Boost ensured that it concentrated on those features or data it previously predicted incorrectly, and this contributed to an overall boost in its prediction accuracy. Consequently, XG Boost showed greater classification accuracy and a superior ability to detect risky glacier growth [13]. Moreover, the model was computationally more efficient and showed a higher speed in its training phase when compared to traditional machine learning algorithms. Despite this, XG Boost showed a tendency to overfit its models when its hyperparameters, like learning rate and the maximum depth and estimators, were not set properly.

5.3 Hybrid Ensemble Model Performance

The hybrid model combining Random Forest with XGBoost with soft voting showed the best performance of all the classifiers. The proposed model can leverage the stability of Random Forest with the strong prediction power of XGBoost. The impact of probability-based soft voting further helps in eliminating bias and variance from the model because of which it performs better in predictions. The proposed model showed 100% accuracy in training as well as 98.82% in testing. The precision values were 0.98 for Not Risky and 1.00 for Risky class. The values of recall were 1.00 for Not Risky and 0.97 for Risky [14]. The above results show that the proposed model is well balanced with the ability of accurate as well as generalized performance with very high sensitivity towards the detection of glacier growth risk. The training times for all the evaluated models are compared in Table 1.

Table 1. Machine Learning Algorithm Analysis

Model	Training Time (In Minutes)
Random Forest (RF)	96
XGBoost	84
Soft Voting Ensemble (RF + XGBoost)	174

Feature importance analysis was used to determine the most influential parameters in the process of glacier growth classification. The findings indicated that growth percentage and area ratio were the most influential features in the classification process, contributing 42.99% and 39.90% respectively. This highlights the importance of both temporal expansion and spatial change in assessing glacier growth risk. These two characteristics played a significant role in the decision-making process and reinforced the idea that time expansion and spatial variability in glaciers are the most significant factors in determining the risk of glacier growth. Other characteristics like area and compactness aided in classification.

Figure 2 shows the glacier growth and intersection analysis between the two temporal satellite images. The red area of the figure presents the total area of the glacier in the second image, whereas the green area marks the intersection area [15] that is consistent across both time frames. By observing the figure and its statistics, it can be noticed that the glacier grew noticeably from 17,143 to 41,210 units.

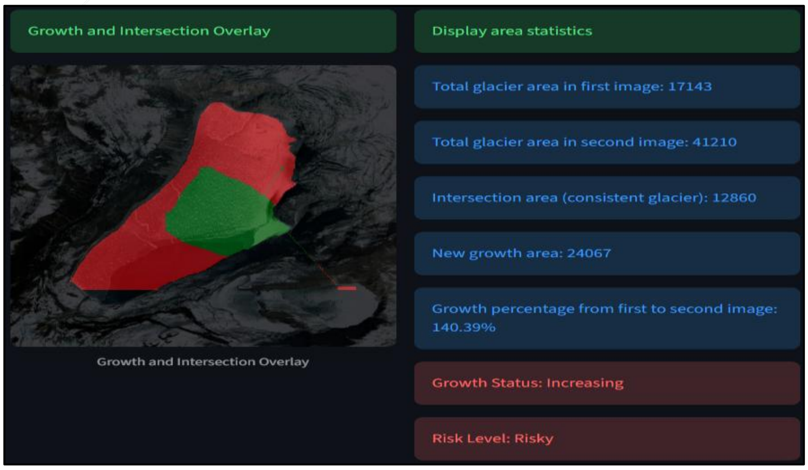

Figure 2. Streamlit Deployment

In this case, the 12,860 is the intersection area, which represents the stable part of the glacier, while the newly added growth area of 24,067 shows a very significant increase in growth over time. This amounts to a growth of 140.39%, which means the presence of faster growth in the glaciers. Consequently, the system is able to predict the trend as being growing for the glacier, as well as the risk level as being risky. This number represents an example of how identifying spatial overlap and glacier growth trends helps with creating the risk assessment model.

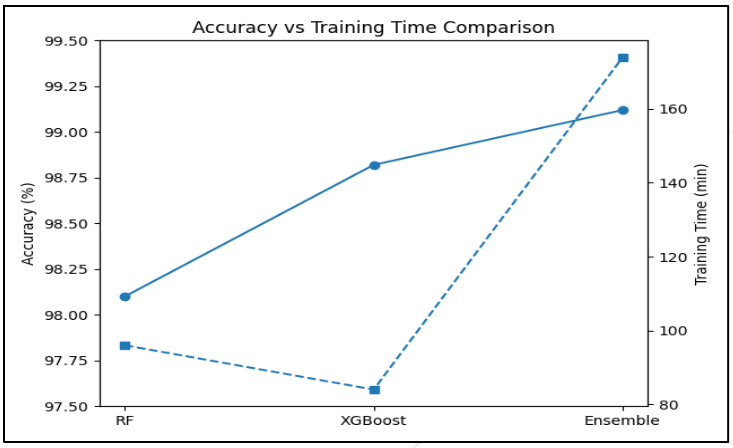

Figure 3. Accuracy vs Training Time Comparison

Figure 3 illustrates the performance comparison between the analyzed models concerning their accuracy and training time. As one can notice, the proposed hybrid model yields the highest accuracy of 99.12%, surpassing both Random Forest and XGBoost. Even though the hybrid model consumes more time to train because of using several classifiers simultaneously, its performance remains more predictable and efficient. XGBoost proves to be a decent compromise between accuracy and training time, whereas Random Forest provides steady but somewhat inferior performance. Overall, the results highlight the effectiveness of the proposed hybrid approach in achieving superior glacier growth risk prediction.The final comparison of all models is summarized in Table 2.

Table 2. Final Output Accuracy

Model	Accuracy	Computational Cost	Scalability
Random Forest	98.10% (High)	Very High	Good
XGBoost	98.82%	Moderate	Good
Soft Voting Ensemble (RF + XGBoost)	99.12% (Used)	High	Good

6. Conclusion

This research work involves a hybrid methodology for automatic glacier growth detection and the identification of risk involved in it, through the use of deep learning and ensemble machine learning techniques. More specifically, what makes this method unique is the integration of YOLOv8 segmentation with a subsequent classification involving meaningful features, used for studying the dynamics of glaciers based on their images obtained from satellites. Furthermore, this will be confirmed by the fact that the effectiveness of this method is achieved through the use of meaningful morphological, temporal, and spatial features to classify risks in glacier growth. Experimental findings show that the hybrid ensemble technique of Random Forest and XGBoost with soft voting improves forecast accuracy and enhances the performance of the entire system when compared to each of the constituent models individually. The performance of the system in relation to the dataset is remarkable, with impressive precision, recall, and accuracy measures. Feature importance analysis shows the effectiveness of the area ratio technique used in engineering features. This hybrid ensemble approach was seen to perform better with an accuracy of 99.12% when tested, which is greater than the accuracy of the Random Forest approach (98.10%) and the XGBoost approach (98.82%). However, there are several limitations that should be mentioned as well: the lack of a big dataset for labeled glaciers, and the fact that changes in climate or environmental conditions cannot but affect the segmentation process. Besides, there may be problems related to computational complexity caused by the use of a deep learning algorithm, which can make real-time implementation of the framework impossible. In the future, researchers plan to develop the framework further by including multiple bands and time intervals of satellite imagery, as well as climate variables such as temperature and rainfall. Moreover, improvements in deep learning algorithms are expected to be made in order to increase their efficiency and predictive capacity. Finally, it is possible to predict that explainable AI frameworks will become a crucial element of this research in the future.

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