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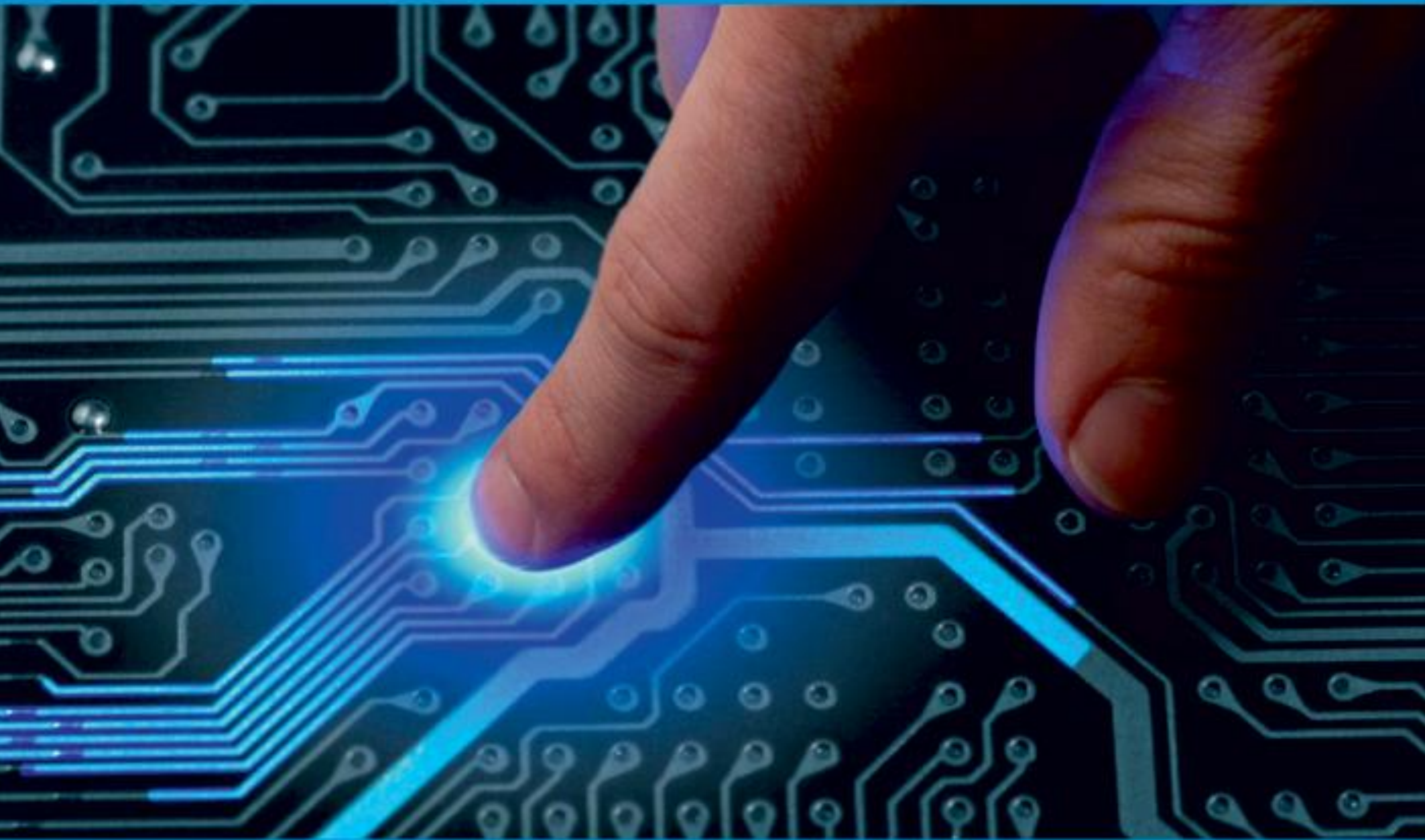

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Improving Glacial Lake Extraction in Higher Mountain Areas using GRD data and Deep Learning

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ABSTRACT: Finding Glacial Lakes (GL) is crucial for understanding how glacial lakes react to changing climates and evaluating the risk of glacial lakes. Extracting GLs accurately remains tough because of their small size compared to surrounding objects. U-Shaped Network (U-Net), a deep learning approach, has shown significant promise in removing GLs because of its intricate encoding-decoding structure and robust bypass connections. Bypass connections transfer excessive information unrelated to GLs from essential visual characteristics to advanced semantic characteristics, resulting in ineffective use of the fundamental factors. This research proposed a Deep Learning-based Glacial Lakes Extraction Model (DL-GLEM) for GL extraction using Ground Range Detected (GRD) data. The research introduced a method for mapping GLs in high alpine regions using Remote Sensing (RS) techniques and an enhanced Deep Learning (DL) system. It efficiently reduces the effects of clouds, glacier debris, viscosity, and freezing variables on identifying GLs. The work offered a practical method for detecting GLs in higher mountain regions with intricate topology and contributed to technological improvements in identifying GL risks.

KEYWORDS: Glacial Lake, Extraction, Deep Learning, Ground Range Detected

I. INTRODUCTION TO GLACIAL LAKE DETECTION

Glacial lakes in Higher MountainAsia (HMA) have significantly increased in size during the last 30 years due to global climate warming [1]. The ongoing growth of the lake's surface area will increase the likelihood of Glacial Lake (GL) outburst floods, severely damaging downstream settlements, hydropower facilities, and other infrastructures.GLs also significantly reduce glaciers that end in lakes [2]. GLs are significant in local hydrological dynamics and the cryosphere catastrophe chain. A listing of GLs is essential to uncover these lakes' geographical dispersion and temporal changes to enhance the comprehension of glacier-lake interactions and identify potentially dangerous lakes.

GLs are often present in regions impacted by warming glaciers and are seen as a notable outcome of glacier mass reduction. More than 1500 GLs in the Himalayas have areas greater than 0.03 km^2, and 208 are considered very dangerous. The eastern Himalayas have the most significant risk of GL outburst floods, with a risk level at least double that of other areas. A recent GLin the Chamoli area resulted in over 1000 fatalities and extensive property damage worth millions of dollars. GLs are essential for indicating climate change and lead to calamities associated with glaciers. They are crucial in cryosphere technology, climatic change studies, and mountain disaster sequences. Scholars have dedicated considerable time and effort to studying GLs and their effects.

In optical satellite imagery, images from Sentinel-2 [3], Landsat-8 [4], and Ground Range Detected (GRD) [5] data are used for surface water modeling. Sentinel-2A and 2B have the most significant spatial accuracy of 10 meters and a five-consecutive days revisit duration among these information sources [6]. Cloud cover hinders good imaging for an extended period, limiting the ability to monitor GLs regularly. The GRD CubeSat array by Planet Labs offers daily worldwide coverage with a 3 m spatial accuracy, making it a crucial data source for tracking and mapping glacier lakes [7].

This research created a methodology for measuring GLs in elevated mountain environments, addressing issues such as cloud cover, observing, turbid lake water, glacier debris, and freeze-thaw situations using GRD data. The structure has been created using several satellite imagery sources and an enhanced Deep Learning (DL) model to record and track dynamic GLs in challenging terrains. It offers technical assistance for studying and recognizing dangers related to GLs. The following sections are arranged: Section 2 explains the history and procedures used to find glacial lakes. The proposed Deep Learning-utilised Glacial Lakes Extraction Model (DL-GLEM) model uses Deep Learning to extractGLs from GRD information. This section analyzes the simulation results of the proposed technique and compares them with current DL models. Section 5 covers the study's result and its future scope.

II. BACKGROUND AND RELATED WORKS

Several researchers have used Remote Sensing (RS) technology to conduct mapping of glacier lakes in higher mountainous and polar locations. Contemporary RS studies on mapping GLs mostly use semi-automatic approaches that use spectral enhancing methods such as Normalized Difference Water Indicator (N-DWI) and topographic factors such as altitude and slopes. Retrieved GLs are then reviewed and adjusted manually [8]. However, using semi-automated approaches for mapping GLs is restricted to certain areas due to the need for human correction after extraction. The rise in both the dimension and the incidence of GLs requires the creation of automated techniques for surveying GLs. Therefore, many computerized methods have been suggested for mapping GLs employing multi-threshold or Machine Learning (ML) techniques [9]. The GL mapping research primarily focused on polar or local areas. The higher mountain terrain is known for its intricate topography, including clouds, darkness, glacial particles, freeze-thaw circumstances in lakes, GLs with varying turbidity stages, periodic snow cover, and rock detritus. Landscapes in higher mountain locations have spectral or radar backscattering properties similar to GLs, which makes traditional ML-based approaches ineffective for automatically extracting glacier lakes. Ahmedet al. created an automated approach to identify GLs in mountainous areas using various RS information and a random forest classification system, with a precision of 82.14% [10]. However, the method's efficacy in identifying lakes with N-DWI values below 0.6 is restricted due to its dependence on radar backscattering, N-DWI thresholds, and the lag in Synthetic Aperture Radars (SARs) [11].

DL methods have recently succeeded in several study areas, especially in RS image categorization of field coverage utilizing Fully Convolutional Neural Networks (FCNNs) based on an encoding-decoding architecture [12]. The proposed methods used and showed remarkable success, mainly because of their strong learning capacities. DL techniques can dynamically learn the characteristics of GLs at different levels and sizes, a capability that traditional GL imaging approaches lack. Yet, the DL-based method for extracting GLs is constrained by the absence of dependable GL label information. U-shaped networks (U-Net) and their enhanced iterations have encoding-decoding architectures that are effectively used in mapping GLs [13]. U-Net's effectiveness lies in its skip connections, merging lower-level data with higher-level characteristics, enhancing the accuracy of pixel-wise segmented masks.

Regarding the smaller size of GLs related to the surrounding land area, bypass connections send excessive and unimportant data from lower-level to higher-level characteristics, resulting in ineffective usage of the lower-level characteristics. Attention processes are now a leading area of study in convolution and recurrence because of their substantial capacity to utilize relationships of characteristic mapping and allow ML to grasp universal context-specific data [14]. The dot-product attentiveness is beneficial for capturing long-range relationships and is frequently employed in computer visualization and language-related assignments [15]. Due to its high computing costs, the dot-product attention technique must work on fulfilling the requirements of DL-based satellite extracting features. The squeezing-and-exciting component adjusts channel-specific feature reactions by considering band relationships [16].

III. PROPOSED DEEP LEARNING-BASED GLACIAL LAKES EXTRACTION MODEL

The study used the Landsat 8-based Operational Land Imager (OLI) detector to collect information in the Himalayan region. The National Aeronautics and Space Administration (NASA) [17] and the United States Geological Surveys (USGS)[18] fund the RS detector. The RS offers lasting and genuine documentation of a specific region at a particular moment, which is used for validation and evaluation. The RS captures 750 scenarios daily using the World Referencing System-2 (WRS-2) [19]. The altitude slope and pixel position vary across photos acquired in various years. Thus, visually interpreting the collected picture to map the Glacier Lakearea is challenging. The GL area has been plotted using geographical coordinates from a Landsat 8 picture, designated using the Universal Transverse Mercato (UTM) [20] and World Geodetical Systems (WGS) [21]. RS offers 11 channels of multispectral information labeledL_1

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throughL_{11}. The photos were obtained at 7500 × 7500 pixels, with every pixel containing 32 bits and a spectralgranularity of 25 meters. Every spectral band picture is in Tagged Image File Format (TIFF) style. The study utilizes Landsat 8 GRD data from 2018 to 2022 to delineate the area occupied by glacier lakes. Ice melting fluctuates periodically, with a significant quantity melting during summer. Thus, in this study, Landsat 8 GRD data are obtained throughout the ice-melting periods to define the boundaries of the glacier lakes region. Changes in climatic conditions and rising temperatures lead to fluctuations in the dimension and quantity of glacier lakes in higher alpine areas. Thus, manually labelingextensiveGRD information for the GLs area is challenging.
Nevertheless, the DLalgorithms needed substantial data for practical training. Waterbody coverings are generated using established water index algorithms and outlined manually using Google Maps. In addition to 30-meter resolution databases, Google Earth photos are used in the suggested strategy to create a comprehensive dataset. The Google Earth photos of every specimen are captured based on its central coordinates (latitudes, longitudes) and a specified zoom range. The glacier lake's region for large-scale information is generated by Environment for Visualizing Images (ENVI) technology and confirmed using high-resolution Google Maps pictures to verify its accuracy [22]. The RShas11spectrumbands categorized according to their wavelengths. Green, Red, Near-Infrared (NIR), and Short-Wave Infrared (SWIR) wavelengths evaluate N-DWI and Modified Normalized Difference Water Indicator (MN-DWI). The working process of the DL-GLEM is shown in Fig. 1.

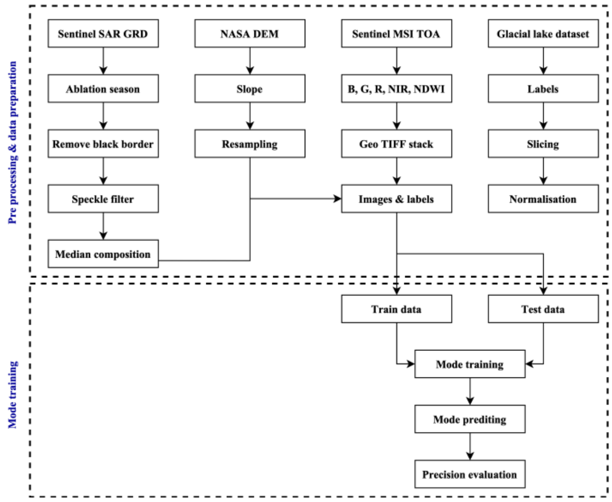

Fig. 1. Working process of the DL-GLEM system

N-DWI and MN-DWI are successfully employed for water body research. The reflectance values for red, green, and blue light are 0.5 - 0.8µm, 0.4 – 0.7µm, and 0.3 to 0.6µm. The reflection value of water bodies is higher in the blue spectrum channel compared to the red and green wavelengths. Clean water had the maximum level of blue reflection in the visible range. As a result, the majority of water bodies seem blue. N-DWI is computed based on the spectral reflection of the green and NIR groups. A limit is employed to isolate the NDWI picture near water bodies. The MNDWI method removes the prominent artificial structures and enhances the efficiency of extracting reservoirs. The suggested DL-GLEM system involves the following stages: 1. Image pre-processing. 2. Extracting the GL's area using Glacial Lake Extraction U-Net [23] and other semantic segmenting approaches. Pre-processing is crucial for identifying the GL's area to mitigate the impact of reflection from dark surfaces.

3.1 Data Pre-Processing
Data preparation is essential in DL since it eliminates unnecessary or untrustworthy data, ultimately enhancing training models' effectiveness. Data pretreatment and preparation include the given procedures.

1) Data Stacking: The SAR photos from the abatement period were first chosen. Image preparation methodsincluded black border elimination, enhanced Lee speckle filtration, and average composing. Slope information was derived and then adjusted to a 10m cell dimension. The information, slope information, and pictures from Sentinel-2 (red, green, blue, NIR, and N-DWI) were combined to form a 7 channel database.

2) Label Data Production: The databases of GLs linked in 2018 and 2022 were chosen. The research combined these two databases first. The study concentrated on improving GLs significantly impacted by glacier activity, including supraglacial ponds and lake-terminating icebergs, using SAR and Sentinel-2 data gathered in 2020 and 2023. The research converted the GL geometries into a raster format. The label database contains pixels representing GLs classified as 1, while the backdrop has been designated as 0.

3) Data Slicing: The research used a sliced window of 512 × 512 pixels to split the band-merged information and related indicators into picture portions of identical size to meet the input specifications for the DL algorithm. The picture patches were configured to overlap by 16 pixels. Image areas without lake pictures were eventually removed.

4) Normalization: Standardizing picture patches enhances the model's converging rate. This research utilized the average-standard deviation approach to equalize the picture units using the standard technique.3000 picture patches and the associated labels were created and separated into a training database (75%) and a testing database (25%).

3.2 DL-based Architecture

The Residual Attention U-Net (RA-U-Net) is a modified version of the U-Net that incorporates elements from the Residual Network (Res-Net) and an enhanced attention component. It was explicitly designed for segmenting pictures of cataract surgical tools. The encoding component of the RA-U-Net architecture was substituted with the Res-Net construction, and the enhanced attention component was modified with the Convolutional Block Attention Module (CBAM) as the attention method for the RA-U-Net modeling [24]. The decoding phase retained the initial U-Net network topology, including skip links to restore the spatial intricacies omitted during the encoding phase progressively. The RA-U-Net algorithm utilizes 7-band information (RGB, NIR, N-DWI, slopes, and SAR) as sources and produces projected outputs that match the size of the input databases (256 × 256 pixels).

3.2.1 Network Backbone

Adding more layers to a neural network will result in quicker convergence. Numerous layers lead to network congestion or reduced efficiency. RA-U-Net tackles this problem by using bypass connections, which include adding a characteristic mapping from a particular layer to a deeper level in the system. This approach enhances the quality of distinct maps and boosts the efficiency of more profound levels.

3.2.2 Attention Modules

GLs in satellite photos are often more minor in the area than other features like glaciers, barren terrain, and vegetation. This makes it challenging to identify GLs utilizingdeep learning algorithms. The RA-U-Net, which operates attention gates, was used to enhance the training of model performance by allowing the system to concentrate on a particular area and disregard irrelevant regions while processing images. Thiscomponent was chosen as the attention mechanism for the RA-U-Net system in this investigation.

IV. SIMULATION ANALYSIS AND FINDINGS

Three distinct area databases are obtained to extract the glacier lake's area and evaluate the suggested system's efficacy. The three area databases were obtained from the OLI detector covering the Imja area, Chandra basins, and Bhaga glaciers. The GL is located in latitudes 27°54’51’’N, 33°7’18’’N, 32°31’54’’N and longitudes 86°52’17’’E, 79°17’21’’E, 078°3’53’’E correspondingly. The Landsat 8 GRD data shows the GL area in Nepal, the Chandra valley, and the Bhaga glacier in Himachal Pradesh.

The study utilizes Landsat 8 GRD data from 2018 to 2022 to delineate the area of the glacier lake. Ice melting fluctuates periodically, with a significant portion melting during summer. Thus, Landsat 8 GRD data are obtained throughout the ice-melting periods to define the boundaries of the glacier lakes region. Three glacier lake area specimen databases are verified using high-resolution Google Maps pictures to confirm accurate labeling.
Testing data was assessed using Precision (P), Recall (R), F-Score (F), and Kappa Coefficients (K). The following metrics are used to calculate the results: True Positivity (T^+), False Positivity (F^+), and False Negatiity (F^-) derived from the confusion matrices.

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$$P = \frac{T^+}{T^+ + F^+} \quad (1)$$

$$R = \frac{T^+}{T^+ + F^-} \quad (2)$$

$$F = 2 * \frac{P * R}{P + R} \quad (3)$$

$$K = \frac{N * \sum_{i=0}^{N-1} c_i - \sum_{i=0}^{N-1} c_{i+} c_{+i}}{N^2 - \sum_{i=0}^{N-1} c_{i+} c_{+i}} \quad (4)$$

The Kappa Coefficient was computeddepending on the confusion matrices, with N representing the entire pixels strength, $c_i$denoting the diagonal components of the confusion matrix, and c_{i+} and c_{+i} representing the total of the rows and columns of the confusion matrices. The assessment measures are calculated by considering all the pixels in the 1300 tiles of the testing dataset. A single confusion matrix is created by considering all pixels in the testing information, and the assessment metrics are then calculated based on this confusion matrix.

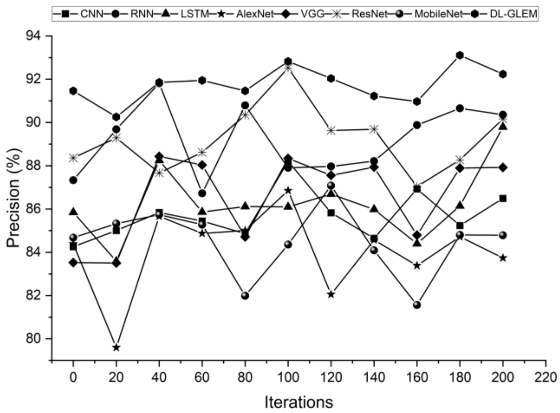

Fig. 2. Precision result analysis for the GL detection

Fig.2shows the accuracy results of several DL models of different iterations. DL-GLEM regularly surpasses other models, achieving a higher accuracy of 91.46% at iteration 0 and increasing to 92.233% at iteration 200. The method's success is due to its efficient use of several remote sensing GRD data sources and sophisticated DL methods, which help overcome difficulties in mapping glacier lakes. The accuracy values fluctuate with iterations, demonstrating the model's capacity to adapt to changing situations. DL-GLEM has a significant influence by improving accuracy and aiding in the correct extraction of GLs, which is crucial for climate change research and identifying risks of GLs.

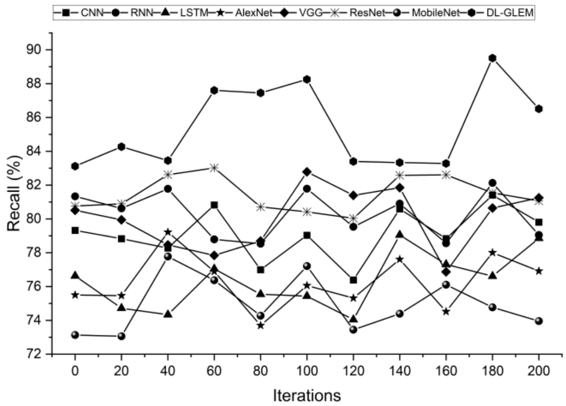

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Fig. 3. Recall result analysis for the GL detection.

Fig. 3 indicates the recall results for multiple DL models at different iterations. DL-GLEM regularly surpasses other methods, with a higher recall rate of 83.117% at iteration 0 and increasing to 86.511% at iteration 200. The effectiveness of the DL-GLEM approach is due to its skillful use of multisource remote sensing GRD data and DL algorithms to tackle obstacles in mapping glacier lakes. The changes in recall levels over iterations show the model's flexibility to changing environments. DL-GLEM has a substantial influence by improving recall rates and aiding in the accurate extraction of GLs, which is essential for climate change research and identifying the risks of GLs.

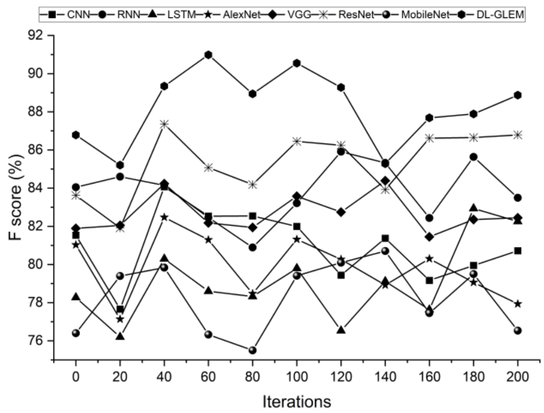

Fig. 4. F score result analysis for the GL detection

Fig.4 displays the F score results for several DL models across many iterations. DL-GLEM regularly surpasses other approaches, earning an F score of 86.787% at iteration 0 and increasing to 88.872% at iteration 200. The DL-GLEM approach stands out for its efficient use of multisource remote sensing GRD data and DL algorithms to tackle issues in glacier lake mapping. The variability in F scores during iterations demonstrates the model's capacity to adjust to different environments. DL-GLEM significantly improves F scores and accuracy in extracting GLs, which is crucial for climate change research and identifying GLrisks.

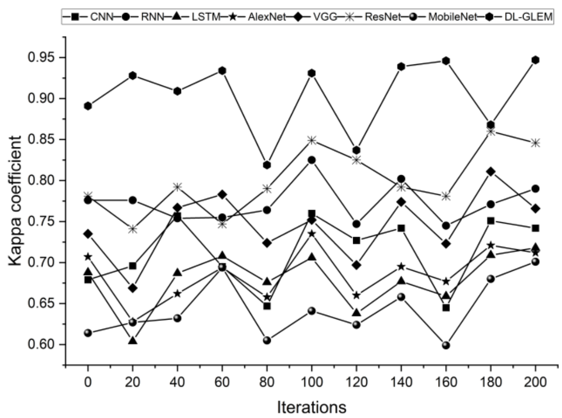

Fig. 5. Kappa coefficient result analysis for the GL detection

Fig.5 displays the Kappa coefficient findings for several DL models over iterations. DL-GLEM regularly surpasses other approaches, with a Kappa coefficient of 0.891 at iteration 0 and increasing to 0.947 at iteration 200. The effectiveness of the DL-GLEM approach is due to its skillful use of multisource remote sensing data and sophisticated DL algorithms to tackle obstacles in mapping glacier lakes. The variability in Kappa coefficients over iterations illustrates the model's capacity to adjust to different circumstances. DL-GLEM significantly improves the Kappa coefficients and enhances the reliability of GL extraction, which is essential for climate change research and identifying GL risks.

V. CONCLUSION AND FUTURE SCOPE

The research introduced a glacier lake extraction frameworkcalled the Deep Learning-based Glacial Lakes Extraction Model (DL-GLEM),using DL to map glacial lakes from several RS resources for GRD data. An enhanced deep-learning RA-U-Net model minimizes training time and quickly merges with several training iterations. Various datasets from many sources were utilized to guarantee the relevance of the system and enhance the precision of lake identification. Factors including clouds, darkness, glacier debris, GL size, and lake water turbulence have been extensively studied for their influence on GL mapping. The DL-GLEM approach shows outstanding results with a mean accuracy of 92.07%, recall of 85.73%, F score of 87.87%, and Kappa value of 0.914 in different iterations. It efficiently reduces the influence of cloud cover, shadows, debris, turbidity, tiny glacier lake size, and freeze-thaw conditions on identifying GLs. The structure demonstrates remarkable precision and durability. It can accurately identify GLs in geographically intricate mountainous areas, minimizing the impact of human subjectivity. The system provides a precise method for mapping GLs in high alpine regions with complex topography using the growing accessibility of satellite images. The system complexity can be reduced, and the same design can be tested for different locations and application areas in the future.

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