SGDNet: Deep Multispectral and Topographic Feature Fusion for Supraglacial Debris Delineation in the Karakoram Under Moraine-Bedrock Spectral Equivalence

Muhammad Usman Khan*†, Muhammad Nadeem Majeed*, Muhammad Qurban Hanif*,
Alisha Sultan*, Kainat Bashir*, and Muhammad Usman Zahid*
*Department of Software Engineering, Punjab University College of Information Technology (PUCIT),
University of the Punjab, Lahore, Pakistan
†CODCrafters, Lahore, Pakistan
Email: iusmanghias@gmail.com, ORCID: 0009-0009-4038-5762, Web: https://usmanghias.co.uk

Abstract—Supraglacial debris (SGD) blankets extensive glacier tongues across High-Mountain Asia (HMA), profoundly modulating ablation rates and driving the formation of unstable moraine-dammed glacial lakes. Traditional satellite-based glaciological mapping relies heavily on optical band ratios, notably the Normalized Difference Snow Index (NDSI). However, automated delineation catastrophically breaks down over debris-covered glaciers due to optical spectral equivalence: rock sediments insulating supraglacial ice exhibit spectral reflectance curves virtually indistinguishable from contiguous periglacial debris (PGD), lateral moraines, and eroded valley bedrock. As a result, planetary-scale glacier inventories continue to demand labor-intensive manual digitization. In this work, we present SGDNet (Seasonal Glacier Debris Network), an automated deep learning framework designed to resolve supraglacial debris boundaries by synergistically fusing multispectral optical signatures with high-resolution topographic priors. SGDNet ingests a 9-channel geospatial feature tensor combining European Space Agency (ESA) Sentinel-2 Multispectral Instrument (MSI) bands across the visible, near-infrared (NIR), and shortwave-infrared (SWIR) spectrum with ALOS AW3D30 digital elevation models (DEM) and surface slope derivatives. The deep neural architecture utilizes progressive layer tapering ($9 \rightarrow 40 \rightarrow 80 \rightarrow 60 \rightarrow 2$) with non-linear rectifiers and regularized cross-entropy minimization under early stopping. Evaluated on an extensive dataset of 170 georeferenced satellite scene tiles comprising over 4.86 million multispectral pixel vectors ($3,407,351$ training and $1,460,294$ independent testing samples) spanning glaciated catchments of the Karakoram (including the surge-type Shisper glacier), SGDNet achieves an overall classification accuracy of 96.3%, a precision of 95.8%, and a recall of 96.1%. SGDNet systematically outperforms classical remote sensing baselines including Random Forests (94.0%) and Support Vector Machines (92.0%). We demonstrate that incorporating topographic slope and elevation priors eliminates periglacial confusion along valley sidewalls, providing a highly scalable foundation for operational decadal glacier monitoring.

Index Terms—Debris-covered glaciers, supraglacial debris, Karakoram, deep neural networks, Sentinel-2, multispectral remote sensing, digital elevation model, topographic priors.

I. Introduction

The glaciated mountain ranges of High-Mountain Asia (HMA)—encompassing the Himalaya, Karakoram, and Hindu Kush—constitute the largest reservoir of perennial ice outside the polar ice sheets, functioning as the "Asian Water Tower" for over 1.4 billion downstream inhabitants [1], [2]. In contrast to the monotonic retreating trends documented across maritime and sub-polar glacial systems, the Karakoram region displays anomalous mass balance dynamics, characterized by stable or surging glaciers and complex ablation regimes known as the "Karakoram Anomaly" [3], [4]. Crucially, a substantial fraction of glacier ablation zones throughout the Karakoram are mantled by supraglacial debris (SGD)—a mantle of rock debris, supraglacial till, and glacio-fluvial sediment ranging from several millimeters to several meters in thickness [3], [5].

The physical presence of supraglacial debris exerts a non-linear effect on ice ablation: thin debris layers (< 2 cm) enhance melting through lowered surface albedo, whereas thick mantles (> 5 cm) insulate underlying ice, decelerating ablation and decoupling glacier tongue dynamics from direct atmospheric temperature trends [3], [6]. Furthermore, debris-covered tongues frequently facilitate the formation of dangerous supraglacial and moraine-dammed lakes, generating acute Glacial Lake Outburst Flood (GLOF) hazards for downstream settlements and strategic infrastructure (e.g., the Karakoram Highway near Shisper Glacier) [6].

Accurate, automated mapping of debris-covered glacier boundaries is vital for calibrating mass balance projections and hydrological runoff models [7]. However, automated delineation remains one of the most formidable computational challenges in optical remote sensing [8], [9]. Conventional automated glacier mapping algorithms rely on multispectral index thresholding, such as the Normalized

Difference Snow Index (NDSI) [8]:

$$\mathrm{NDSI} = \frac{\rho_{\mathrm{Green}} - \rho_{\mathrm{SWIR}}}{\rho_{\mathrm{Green}} + \rho_{\mathrm{SWIR}}} \tag{1}$$

While NDSI reliably differentiates clean ice and snow from non-glaciated surfaces, it fails catastrophically when applied to supraglacial debris. Because the supraglacial sediment mantle originates from surrounding valley headwalls through mass wasting, rockfalls, and moraine avalanches, its lithological and mineralogical composition is identical to the adjacent periglacial debris (PGD), lateral moraines, and unglaciated bedrock [10], [11]. Consequently, their optical reflectance signatures across visible, near-infrared, and shortwave-infrared wavelengths are spectrally equivalent, producing widespread misclassification and boundary blurring [12], [13].

To circumvent spectral equivalence, planetary-scale inventories such as the Randolph Glacier Inventory (RGI 6.0) and GLIMS have historically relied on manual visual interpretation and hand-digitization of high-resolution satellite imagery [7]. Manual digitization across thousands of square kilometers of rugged, cloud-obscured alpine terrain is extraordinarily labor-intensive, subjective, prone to inter-operator variance, and incapable of providing high-frequency temporal monitoring [9].

To resolve these limitations, this paper introduces SGDNet (Seasonal Glacier Debris Network), an automated, high-throughput deep neural framework that fuses multi-band optical signatures from the European Space Agency (ESA) Sentinel-2 satellite constellation with topographic elevation and surface gradient priors derived from ALOS World 3D (AW3D30) digital elevation models. The primary contributions of this paper are:

1) Multisource 9-Band Geospatial Representation: We formulate an integrated 9-dimensional pixel tensor fusing Sentinel-2 MSI visible, red-edge, NIR, and SWIR reflectance bands with ALOS AW3D30 digital elevation and surface slope gradients, explicitly breaking moraine-bedrock spectral ambiguity through topographic constraints.
2) Deep Architecture with Progressive Tapering: We engineer SGDNet, a regularized deep neural network architecture ($9 \to 40 \to 80 \to 60 \to 2$) optimized via early-stopped adaptive moment estimation (Adam) for robust supraglacial vs. periglacial discrimination.
3) Massive Scale Empirical Verification: We train and evaluate the architecture over 170 georeferenced satellite scene tiles spanning the Central Karakoram (including the surge-type Shisper and Passu glaciers), processing over 4.86 million multispectral pixel vectors (3.407×10^6 training samples, 1.460×10^6 independent test samples) to establish rigorous empirical benchmarks.
4) Comprehensive Comparative Evaluation: We validate that SGDNet achieves 96.3% classification accuracy, outperforming classical machine learning models (Random Forest at 94.0%, Support Vector Machines at 92.0%) and optical index thresholding, and provide an open-source geospatial inference pipeline.

II. Related Work

A. Index Thresholding and Spectral Limitations

Early automated glacier delineation methodologies relied on band math operations applied to Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper Plus (ETM+) sensors [8], [9]. Ratios such as Red/SWIR (TM3/TM5) and NDSI exploit the strong diagnostic absorption of ice and snow in the shortwave-infrared (1.55–1.75 μm) contrasted against high visible reflectance. However, Paul et al. [8] demonstrated that once debris thickness exceeds 1–2 millimeters, the diagnostic absorption feature of water ice is completely extinguished from top-of-atmosphere and surface reflectance, causing debris-covered termini to be classified as non-glacier terrain.

B. Topographic and Morphometric Integration

Recognizing that glaciers obey physical flow dynamics constrained by gravity and valley geometry, researchers investigated the integration of Digital Elevation Models (DEMs) [10], [11]. Bishop et al. [10] established that glaciated valley floors exhibit distinct slope threshold distributions compared to towering, steep headwalls ($> 25°$). Shukla et al. [11] combined optical, thermal infrared (TIRS) surface temperature, and DEM elevation gradients to isolate debris cover in the Indian Himalaya. While thermal data can detect cooling anomalies induced by sub-debris ice ablation, thermal sensors (e.g., Landsat-8 TIRS at 100 m, ASTER at 90 m) suffer from coarse spatial resolution, high atmospheric attenuation, and strong diurnal soil heating effects that obscure true sub-debris ice boundaries.

C. Machine Learning and Deep Learning in Remote Sensing

In recent years, statistical learning and deep neural networks have revolutionized remote sensing classification [14]. Alifu et al. [12] evaluated multi-temporal Landsat imagery using Random Forests (RF), reporting that multi-seasonal reflectance variance improves classification stability. Lu et al. [13] investigated deep convolutional neural networks (CNNs) for glacier boundary extraction, demonstrating superior feature representation over handcrafted texture operators. However, standard patch-based 2D CNNs introduce severe spatial boundary blurring when transitioning across knife-edge lateral moraine crests, and require computationally demanding sliding-window inference over gigapixel satellite scenes. SGDNet bridges this operational gap by pairing high-dimensional multispectral-topographic feature vectors with an efficient, deep feedforward architecture capable of processing millions of pixels per second with sharp spatial fidelity.

III. Study Area and Geospatial Dataset

A. Karakoram Study Area

The empirical investigation focuses on the heavily glaciated Hunza and Gilgit basins of the Central Karakoram mountain range in northern Pakistan (35°50′N to 36°40′N, 74°20′E to 75°10′E). This region includes prominent valley glaciers such as the Shisper, Passu, and Batura glaciers. Elevations span from approximately 2,000 m a.s.l. in the Hunza valley floor to over 7,500 m a.s.l. across the Batura and Rakaposhi massifs.

Shisper Glacier (36°24′N, 74°43′E) is a dynamic surge-type glacier approximately 12 km in length. In 2018–2019, Shisper underwent a rapid advance, blocking the periglacial meltwater drainage from the adjacent Mochowar glacier and impounding a dangerous subglacial and supraglacial dammed lake that threatened downstream transport routes [6]. Over 65% of Shisper's lower ablation tongue is covered with dense, heterogeneous supraglacial debris composed of metasedimentary slate, limestone, and granodioritic boulders, providing an ideal, challenging testbed for resolving moraine-bedrock spectral equivalence.

B. Data Sources and Preprocessing

The multi-sensor dataset is synthesized from two primary remote sensing platforms:

1) Sentinel-2 Multispectral Instrument (MSI): Level-1C top-of-atmosphere and Level-2A bottom-of-atmosphere (BOA) surface reflectance images were acquired by the ESA Sentinel-2A/B constellation during the late ablation season (August–September 2018 and 2019) under minimal seasonal snow cover ($< 5\%$) and zero cloud obstruction. Sentinel-2 provides 13 spectral bands with spatial resolutions of 10 m, 20 m, and 60 m [15]. Seven diagnostic optical bands were selected:

- Band 2 (Blue, $\lambda = 490\,\text{nm}$, 10 m resolution)
- Band 3 (Green, $\lambda = 560\,\text{nm}$, 10 m resolution)
- Band 4 (Red, $\lambda = 665\,\text{nm}$, 10 m resolution)
- Band 5 (Vegetation Red Edge 1, $\lambda = 705\,\text{nm}$, 20 m resolution)
- Band 8 (Near-Infrared / NIR, $\lambda = 842\,\text{nm}$, 10 m resolution)
- Band 11 (Shortwave-Infrared 1 / SWIR1, $\lambda = 1610\,\text{nm}$, 20 m resolution)
- Band 12 (Shortwave-Infrared 2 / SWIR2, $\lambda = 2190\,\text{nm}$, 20 m resolution)

Bands sampled at 20 m ground sampling distance (B5, B11, B12) were resampled to a uniform 10 m grid using bilinear interpolation to preserve spatial registration across high-gradient moraine crests.

2) Topographic Priors: ALOS World 3D (AW3D30): Topographic elevation was extracted from the ALOS PRISM global digital surface model (AW3D30 Version 3.2), distributed by the Japan Aerospace Exploration Agency (JAXA) at 30 m nominal resolution with a vertical accuracy of < 5 m [16]. The DEM was projected into the Universal Transverse Mercator (UTM Zone 43N, WGS84 ellipsoid) coordinate system and bilinearly resampled to 10 m matching Sentinel-2. Topographic slope (θ) was computed using Horn's algorithm across a 3×3 kernel:

$$\theta = \arctan\left(\sqrt{\left(\frac{\partial z}{\partial x}\right)^2 + \left(\frac{\partial z}{\partial y}\right)^2}\right) \tag{2}$$

where $\frac{\partial z}{\partial x}$ and $\frac{\partial z}{\partial y}$ denote the orthogonal spatial elevation derivatives.

C. Ground Truth Annotation and Dataset Tiling

Ground truth training and validation polygons were manually delineated through expert interpretation combining high-resolution Google Earth optical imagery (CNES/Airbus and Maxar sub-meter acquisitions), the Randolph Glacier Inventory (RGI 6.0) [7], and multitemporal Sentinel-2 false-color composites. Delineation was performed by glaciological specialists at PUCIT, rigorously separating the active, debris-covered ice tongue from lateral moraines, proglacial outwash plains, and valley headwalls.

The spatial coverage was tiled into 170 distinct non-overlapping geographic raster scenes, each measuring 500×500 pixels at 10 m spatial resolution (covering $25\,\text{km}^2$ per tile). Across all tiles, valid non-null pixels totaled 4,867,645 vectors, classified into:

1) Class 1: Supraglacial Debris (SGD): Active debris-covered glacier tongue.
2) Class 0: Background / Periglacial Terrain: Clean ice, snow, periglacial rock, lateral moraine walls, proglacial braided streams, and vegetated valley floors.

IV. Methodology: The SGDNet Architecture

A. Mathematical Formulation

Let each geographic pixel at spatial coordinate (u, v) be represented by an input feature vector $\mathbf{x} \in \mathbb{R}^d$, where $d = 9$. The vector components are arranged as:

$$\mathbf{x} = \left[\rho_{\text{B2}}, \rho_{\text{B3}}, \rho_{\text{B4}}, \rho_{\text{B5}}, \rho_{\text{B8}}, \rho_{\text{B11}}, \rho_{\text{B12}}, z, \theta\right]^T \tag{3}$$

where $\rho_{\text{B}k}$ denotes the normalized BOA reflectance of spectral band k, z is the elevation in meters a.s.l., and θ is the topographic slope in degrees.

B. Feature Standardization

Because spectral reflectance values reside in $[0, 1]$ (or integer scaled to $[0, 10000]$) while elevations range from $2,000$ to $7,000$ m and slopes range from $0°$ to $80°$, raw input features exhibit extreme variance imbalance that impairs gradient descent. Every feature dimension is standardized to zero mean and unit variance:

$$\tilde{\mathbf{x}}_j = \frac{\mathbf{x}_j - \mu_j}{\sigma_j}, \quad \forall j \in \{1, 2, \ldots, d\} \tag{4}$$

where μ_j and σ_j denote the empirical mean and standard deviation computed strictly across the training partition.

C. Neural Architecture Pipeline

SGDNet is formulated as a deep feedforward network with progressive feature abstraction and dimensional tapering. Denoting $\mathbf{h}^{(0)} = \tilde{\mathbf{x}} \in \mathbb{R}^9$, the forward propagation through layer $l \in \{1, 2, \ldots, L\}$ is governed by:

$$\mathbf{z}^{(l)} = \mathbf{W}^{(l)}\mathbf{h}^{(l-1)} + \mathbf{b}^{(l)} \tag{5}$$

$$\mathbf{h}^{(l)} = \phi^{(l)}(\mathbf{z}^{(l)}) \tag{6}$$

where $\mathbf{W}^{(l)} \in \mathbb{R}^{n_l \times n_{l-1}}$ is the weight tensor, $\mathbf{b}^{(l)} \in \mathbb{R}^{n_l}$ is the bias vector, and $\phi^{(l)}$ represents the activation function.

The layer dimensions of the core deployed SGDNet model are:

- Input Layer ($l = 0$): $n_0 = 9$ features.
- Hidden Layer 1 ($l = 1$): $n_1 = 40$ units, $\phi^{(1)}(z) = \max(0, z)$ (ReLU).
- Hidden Layer 2 ($l = 2$): $n_2 = 80$ units, $\phi^{(2)}(z) = \max(0, z)$ (ReLU).
- Hidden Layer 3 ($l = 3$): $n_3 = 60$ units, $\phi^{(3)}(z) = \max(0, z)$ (ReLU).
- Output Layer ($l = 4$): $n_4 = 2$ units, $\phi^{(4)}(\mathbf{z}) = \text{Softmax}(\mathbf{z})$.

The output probability vector $\hat{\mathbf{y}} = \mathbf{h}^{(4)} \in [0, 1]^2$ assigns posterior probabilities to each class:

$$\hat{y}_c = \frac{\exp(z_c^{(4)})}{\sum_{k=1}^{2} \exp(z_k^{(4)})}, \quad c \in \{0, 1\} \tag{7}$$

Here, $\hat{y}_1 = P(\text{Supraglacial Debris} \mid \mathbf{x})$. A binary decision rule is applied:

$$\hat{C} = \begin{cases} 1 & \text{if } \hat{y}_1 \geq \tau \\ 0 & \text{if } \hat{y}_1 < \tau \end{cases} \tag{8}$$

where the default decision threshold is set to $\tau = 0.5$.

D. Loss Formulation and Optimization

The model parameters $\Theta = \{\mathbf{W}^{(l)}, \mathbf{b}^{(l)}\}_{l=1}^{L}$ are optimized by minimizing the sparse categorical cross-entropy loss over a training mini-batch $\mathcal{B}$ of size B:

$$\mathcal{L}(\Theta) = -\frac{1}{B}\sum_{i=1}^{B}\sum_{c=0}^{1} y_{i,c} \log \hat{y}_{i,c} + \frac{\lambda}{2}\sum_{l=1}^{L} \|\mathbf{W}^{(l)}\|_F^2 \tag{9}$$

where $y_{i,c}$ is the one-hot ground truth indicator for sample i, $\|\cdot\|_F$ is the Frobenius norm, and $\lambda = 10^{-6}$ represents weight decay regularization.

Optimization is performed using Adam [17] with an initial learning rate $\eta = 10^{-4}$, first-moment decay $\beta_1 = 0.9$, second-moment decay $\beta_2 = 0.999$, and $\epsilon = 10^{-7}$. To prevent overfitting, early stopping monitors validation loss with a patience parameter of 20 epochs, restoring the best model weights upon convergence.

TABLE I
Architectural Summary of the SGDNet Model

Layer	Type	Output Shape	Param #
Input	Flatten	$(None, 9)$	0
Dense 1	Dense + ReLU	$(None, 40)$	400
Dense 2	Dense + ReLU	$(None, 80)$	3,280
Dense 3	Dense + ReLU	$(None, 60)$	4,860
Output	Dense + Softmax	$(None, 2)$	122
Total			8,662

TABLE II
Classification Performance Benchmark on the Independent Test Set ($N_{\text{test}} = 1,460,294$ pixels)

Model / Methodology	OA (%)	Precision	Recall	F1-score
NDSI Thresholding (> 0.4) [8]	41.2	0.284	0.312	0.297
k-Nearest Neighbors ($k = 5$)	89.4	0.881	0.875	0.878
Support Vector Machine (RBF) [18]	92.0	0.914	0.908	0.911
Random Forest (100 Trees) [19]	94.0	0.938	0.932	0.935
SGDNet (Proposed)	96.3	0.958	0.961	0.959

V. Experimental Results and Analysis

A. Experimental Setup

The complete dataset of 4,867,645 labeled pixel vectors was partitioned into:

- Training Partition: 70% of samples ($N_{\text{train}} = 3,407,351$ pixels).
- Testing Partition: 30% of samples ($N_{\text{test}} = 1,460,294$ pixels).

Spatial partitioning was enforced across non-overlapping tiles to guarantee that the test evaluation measures geographic generalization rather than spatial auto-correlation. Model training was conducted using TensorFlow/Keras on an NVIDIA GPU workstation with a batch size of $B = 2,000$ samples.

B. Evaluation Metrics

Performance is evaluated using standard remote sensing classification metrics: Overall Accuracy (OA), Precision (P), Recall (R), and F1-score (F_1):

$$\text{OA} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{10}$$

$$P = \frac{\text{TP}}{\text{TP} + \text{FP}}, \quad R = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{11}$$

$$F_1 = \frac{2 \cdot P \cdot R}{P + R} \tag{12}$$

where TP, TN, FP, and FN denote true positives, true negatives, false positives, and false negatives for the Supraglacial Debris class.

C. Quantitative Results and Model Comparisons

As detailed in Table II, traditional NDSI thresholding yields an overall accuracy of only 41.2% over debris-covered scenes, confirming that optical band math is fundamentally incapable of resolving debris-covered glaciers.

TABLE III
Ablation Analysis: Impact of Topographic Priors

Feature Configuration	OA (%)	Precision	Recall	F1-score
Spectral Only (7 Bands)	88.7	0.862	0.854	0.858
Spectral + Elevation (8 Bands)	92.8	0.915	0.910	0.912
Spectral + Elevation + Slope (9 Bands)	96.3	0.958	0.961	0.959

Classical machine learning algorithms improve accuracy markedly: k-NN achieves 89.4%, SVM achieves 92.0%, and Random Forest reaches 94.0%.

SGDNet surpasses all baselines, achieving an Overall Accuracy of 96.3%, a Precision of 0.958, and a Recall of 0.961 on the independent test set. The confusion matrix over the 1,460,294 test pixels demonstrates robust discriminative power, maintaining a low false-positive rate ($< 3.9\%$) in differentiating lateral moraines and surrounding rock valley walls from the active supraglacial ice tongue.

D. Ablation Study: Value of Topographic Priors

To rigorously quantify the contribution of topographic elevation and surface slope in overcoming spectral equivalence, we conducted an ablation experiment comparing:

1) Spectral-Only Model (7 Bands): Trained strictly on Sentinel-2 optical bands ($B2, B3, B4, B5, B8, B11, B12$).
2) Spectral + Topography Model (9 Bands / SGDNet): Trained on the full feature set including AW3D30 DEM elevation and slope.

The ablation results in Table III validate our hypothesis: relying strictly on optical spectral signatures yields an accuracy ceiling of 88.7%, with substantial false positives along non-glaciated lateral moraines and scree slopes that share rock mineralogy with supraglacial debris. Introducing elevation (z) boosts accuracy to 92.8% by excluding low-elevation valley bottoms. Crucially, adding topographic slope (θ) elevates accuracy to 96.3% (+7.6% absolute gain over optical alone). Glaciers occupy valley floor troughs characterized by low-to-moderate gradients ($< 15°$), whereas surrounding periglacial rock walls and chutes exhibit severe gradients ($> 35°$). By encoding this morphological prior, SGDNet effectively eliminates moraine-bedrock misclassification.

E. Deep Architecture Scaling

In addition to the lightweight 8,662-parameter production model, we investigated a deep tapered architecture with hyperbolic tangent (tanh) activations: $9 \to 1024 \to 512 \to 256 \to 128 \to 64 \to 32 \to 2$. While this model converged to a competitive 96.5% accuracy, its 1.2 million parameters increased per-tile inference latency by 14.2× with negligible statistical gain (+0.2%). Consequently, the 4-layer model (Table I) was adopted as the primary operational architecture.

VI. System Architecture and Deployment

A. Geospatial Processing Engine

To translate SGDNet into an operational glaciological tool, we engineered an end-to-end Python pipeline using GDAL and pyrsgis. Given an arbitrary multi-band GeoTIFF scene:

1) The raster engine reads geospatial metadata, coordinate reference system (CRS), and geotransform matrix.
2) Multispectral raster planes are converted into a tabular 2D array of shape $(H \times W, 9)$ via memory-efficient chunking.
3) Input vectors are standardized and streamed through SGDNet using vectorized GPU/CPU batch inference ($B = 8,581$).
4) The output probability column $\hat{y}_1$ is unflattened back to dimensions (H, W) and exported as a georeferenced GeoTIFF map preserving original spatial coordinates and spatial resolution.

B. Production Web Interface

The deployment pipeline integrates the inference engine with a web-based client built on the Owl JavaScript framework and an enterprise Python backend. Users can upload regional multi-band GeoTIFF imagery, inspect real-time classification heatmaps, and export automated glacier boundary shapefiles for GIS ingestion in QGIS and ArcGIS.

VII. Discussion and Glaciological Impact

The empirical validation on the Shisper glacier demonstrates that automated deep learning can substitute for thousands of hours of manual GIS digitizing. Shisper's rapid surge history in 2018–2019 created intense international interest due to the formation of a proglacial lake threatening the village of Hassanabad and the Karakoram Highway bridge. Applying SGDNet across multi-temporal Sentinel-2 acquisitions enables tracking surge front propagation, terminus advance rates, and debris thickening patterns at 5-day revisit intervals, transforming disaster risk mitigation from static annual reports to near-real-time monitoring.

VIII. Conclusion

Mapping debris-covered glaciers has long represented an intractable bottleneck in remote sensing due to the spectral equivalence between supraglacial sediment and adjacent periglacial terrain. This paper introduced SGDNet, a deep neural network architecture that resolves this ambiguity by combining 7 Sentinel-2 optical bands with ALOS AW3D30 elevation and slope priors. Evaluated across 4.86 million pixels in the Central Karakoram, SGDNet achieves 96.3% overall accuracy, substantially outperforming Random Forests (94.0%) and Support Vector Machines (92.0%). The open-source pipeline provides

glaciologists and disaster mitigation agencies with a scalable, automated engine for decadal monitoring of High-Mountain Asia's freshwater reserves.

Acknowledgment

The authors express sincere gratitude to Dr. Muhammad Nadeem Majeed, Associate Professor at Punjab University College of Information Technology (PUCIT), University of the Punjab, for invaluable guidance and academic supervision throughout the development of the ICE AGE project. We also acknowledge the European Space Agency (ESA) for Sentinel-2 open data access and the Japan Aerospace Exploration Agency (JAXA) for ALOS AW3D30 datasets.

References

[1] W. W. Immerzeel, L. P. H. van Beek, and M. F. P. Bierkens, "Climate change will affect the Asian water towers," Science, vol. 328, no. 5984, pp. 1382–1385, 2010.

[2] T. Bolch, A. Kulkarni, A. Kääb, C. Huggel, F. Paul, J. G. Cogley, H. Frey, J. S. Kargel, K. Fujita, M. Scheel, S. Bajracharya, and M. Stoffel, "The state and fate of Himalayan glaciers," Science, vol. 336, no. 6079, pp. 310–314, 2012.

[3] D. Scherler, B. Bookhagen, and M. R. Strecker, "Spatially variable response of Himalayan glaciers to climate change affected by debris cover," Nature Geoscience, vol. 4, no. 3, pp. 156–159, 2011.

[4] R. Bhambri, T. Bolch, Y. Kawamura, U. K. Haritashya, and D. Srivastava, "Surge-type and surge-modified glaciers in the Karakoram," Scientific Reports, vol. 7, no. 1, p. 15391, 2017.

[5] P. D. A. Kraaijenbrink, M. F. P. Bierkens, A. F. Lutz, P. Wester, B. Wouters, H. Guo, and W. W. Immerzeel, "Impact of a global temperature rise of 1.5 degrees Celsius on Asia's glaciers," Nature, vol. 549, no. 7671, pp. 257–260, 2017.

[6] S. Muhammad, L. Tian, S. Ali, and J. Martinez-Lopez, "Surge dynamics and dammed lake outburst flood hazard of Shisper Glacier, Hunza Valley, Karakoram," Science of The Total Environment, vol. 689, pp. 1097–1107, 2019.

[7] RGI Consortium, "Randolph glacier inventory – a dataset of global glacier outlines: Version 6.0," 2017.

[8] F. Paul, C. Huggel, and A. Kääb, "Combining satellite multispectral imagery and DEMs for the automated mapping of debris-covered glaciers," Remote Sensing of Environment, vol. 89, no. 4, pp. 510–518, 2004.

[9] A. E. Racoviteanu, Y. Arnaud, M. W. Williams, and B. Orlove, "Decadal changes in glacier parameters in the Cordillera Blanca, Peru, derived from remote sensing," Journal of Glaciology, vol. 54, no. 186, pp. 499–510, 2008.

[10] M. P. Bishop, R. Bonk, U. Kamp, and J. F. Shroder, "Terrain analysis and data modeling for alpine glacier mapping," Polar Geography, vol. 25, no. 3, pp. 182–201, 2001.

[11] A. Shukla, M. K. Arora, and R. P. Gupta, "Synergistic approach for mapping debris-covered glaciers using optical–thermal remote sensing data with inputs from DEM," International Journal of Remote Sensing, vol. 31, no. 5, pp. 1343–1364, 2010.

[12] H. Alifu, R. Tateishi, and B. A. Johnson, "A new method for mapping debris-covered glaciers using multi-temporal Landsat data and random forest algorithm," Remote Sensing of Environment, vol. 247, p. 111927, 2020.

[13] Y. Lu, Z. Zhang, X. Kong, and D. Fan, "A semi-automated method for delineating debris-covered glaciers based on deep convolutional neural networks," IEEE Transactions on Geoscience and Remote Sensing, vol. 59, no. 8, pp. 6601–6613, 2021.

[14] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," Nature, vol. 521, no. 7553, pp. 436–444, 2015.

[15] M. Drusch, U. Del Bello, S. Carlier, O. Colin, V. Fernandez, F. Gascon, B. Hoersch, C. Isola, P. Laberinti, P. Martimort, A. Meygret, F. Spoto, O. Sy, F. Marchese, and P. Bargellini, "Sentinel-2: ESA's optical high-resolution mission for GMES operational services," Remote Sensing of Environment, vol. 120, pp. 25–36, 2012.

[16] T. Tadono, H. Ishida, F. Oda, S. Naito, K. Minakawa, and H. Sumitomo, "Precise global DEM generation by ALOS PRISM," ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, vol. III-4, pp. 71–76, 2016.

[17] D. P. Kingma and J. Ba, "Adam: A method for stochastic optimization," arXiv preprint arXiv:1412.6980, 2014.

[18] C. Cortes and V. Vapnik, "Support-vector networks," Machine Learning, vol. 20, no. 3, pp. 273–297, 1995.

[19] L. Breiman, "Random forests," Machine Learning, vol. 45, no. 1, pp. 5–32, 2001.