



AvalancheGuard

AI-powered Avalanche Observations

About us



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AvalancheGuard was developed as a Capstone project for the Master of Information and Data Science at the School of Information, University of California, Berkeley. We worked under the guidance of our advisors, Joyce Shen and Zona Kostic.

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01

Problem Space





Introductio

Avalanche forecasts save lives. They help people who travel, live, work, and recreate in the backcountry make informed decisions about their activities in snowy mountain environments.

Forecaster Dreams

The executive director of the Sierra Avalanche Center & the former executive Director of AIARE (American Institute of Avalanche Research and Education) want more data.

More data

"We want more people to tell us about avalanche activity they're seeing"

Timely data

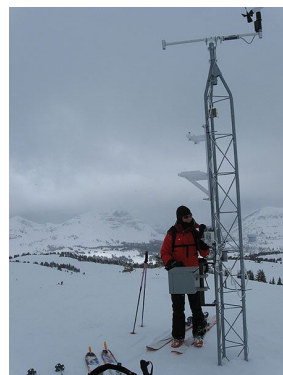
"Especially, if someone triggers an avalanche, we want to know that before the next morning"



The State of Avalanche Forecasting



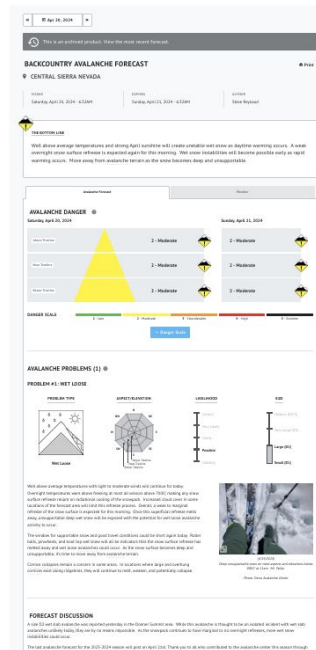
Snowpack Analysis



Weather Information



Field Observations



Opportunity to crowdsource for stronger forecasts

Assemble official forecast

Why crowdsource?

Only 3

Official Forecasters in the entire Tahoe Area

141,000

People who read Avalanche Forecast in
Tahoe Region

642

(<0.5%)

Observations in the Tahoe
area last season.

What Skiers think

Barriers

Recreational skiers don't submit observations because they are **nervous about writing the wrong thing**.

A desire to help

Skiers would happily upload observations to our application if they knew it was **helping the community**. They would need guidance and reassurance on what constitutes a useful contribution.



Our Target Users



Image: <https://www.cntraveler.com/story/how-to-safely-try-backcountry-skiing>

Skiers



Sierra Avalanche Center Facebook Post

Forecasters

Impact



Observations

Number of observations logged.



Accuracy

Observation labeling accuracy of avalanche activity and red flags.



Time

Number of hours saved in an avalanche forecaster typical day

02

Our Solution



Our Solution - Demo

Let us walk through our app from the point of view of our target users.



Image:
<https://www.cntraveler.com/story/how-to-safely-try-backcountry-skiing>

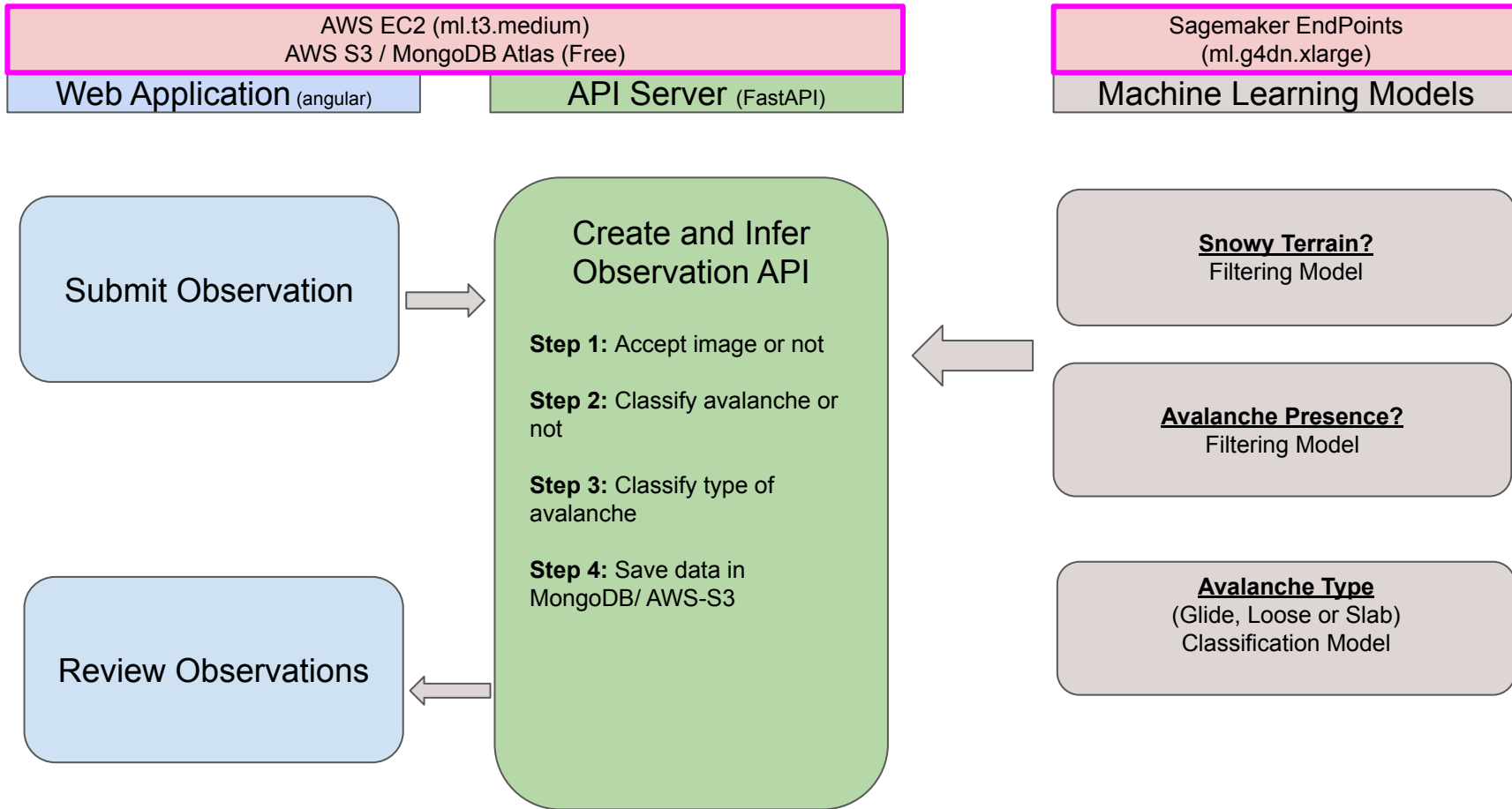
Skiers



Sierra Avalanche Center Facebook Post

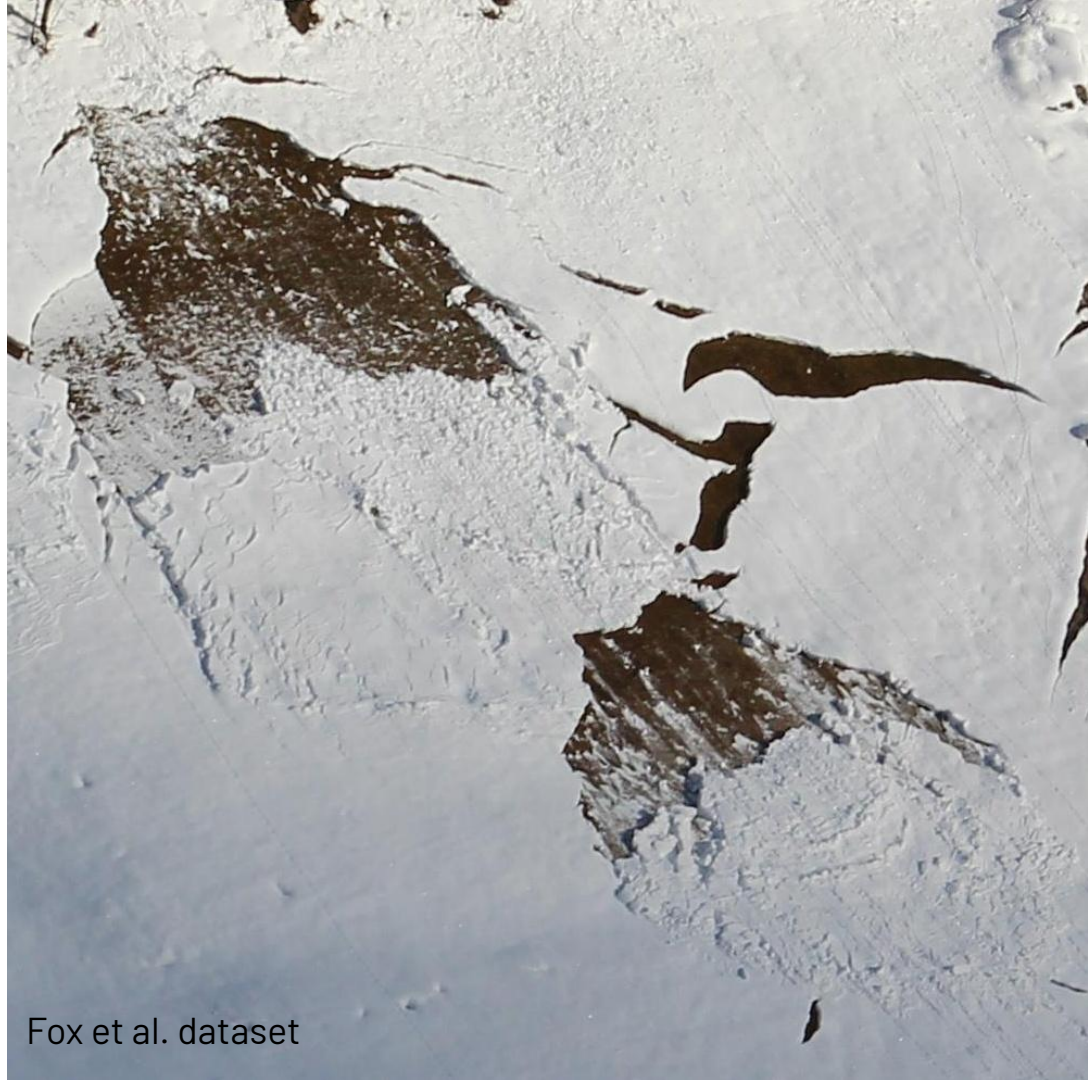
Forecasters

MVP Application Architecture



03

Technical Approach



Fox et al. dataset

A grayscale aerial photograph of a desert landscape. The terrain is dominated by sand dunes and ridges, with some sparse, dark vegetation scattered across the surface. The lighting creates soft shadows, highlighting the contours of the dunes. The overall scene is a vast, open, and arid environment.

Dataset

Datasets Summary

		Snowy Terrain? Filtering Model	Avalanche Presence? Filtering Model	Avalanche Type Classification Model
<u>Imagenet</u> Variety of other types of pictures Stanford University, Princeton University		✓	x	x
<u>Landscapes Dataset</u> Pictures of coast, desert, forest, mountains & glacier Kaggle Dataset, Published by Utkarsh Saxena		✓	x	x
<u>Primary Dataset:</u> Ground-Based images of avalanches University of Innsbruck, Austria github.com/j-f-ox/avalanche-detection	Wide-Angle Original Version	✓	✓	x
	Close-Up Version (Cropped)	✓	✓	✓

Primary Dataset - EDA

- European bias
- Expertly labeled dataset
- High resolution 3-color jpg images
- Wide-angle pictures
- Conflicting labels (8% images have conflicting labels)

Primary Dataset Pipeline

- **Crop** close-ups of avalanches from original wide-angle pictures.
- **Resize** all images to 224x224, consistent w/ many computer vision foundation models.
- **Balance Classes** w/ undersampling

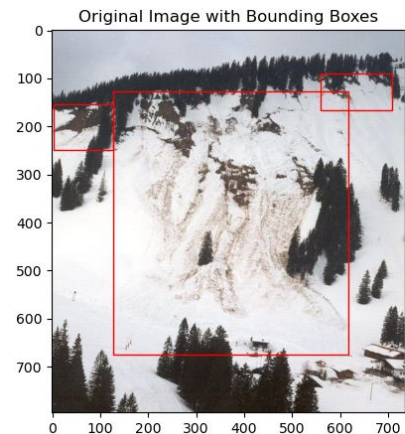


Fox et al. dataset

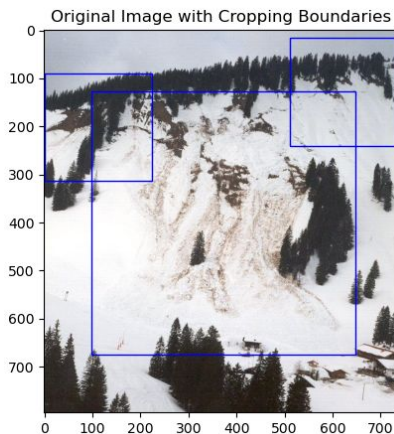
Primary Dataset - Cropping Procedure

Cropping:

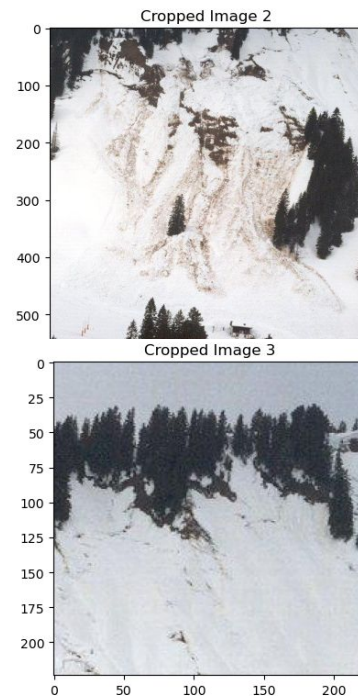
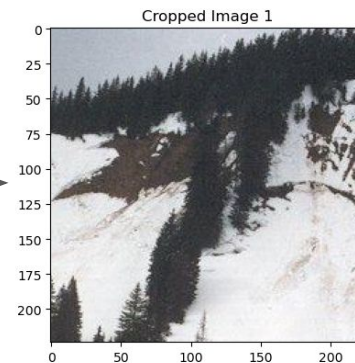
- Simplifies classification w/ close-up shots instead of wide-angle
- Cleans by removing images with conflicting labels
- Augments dataset ~5x



Find
nearest
square



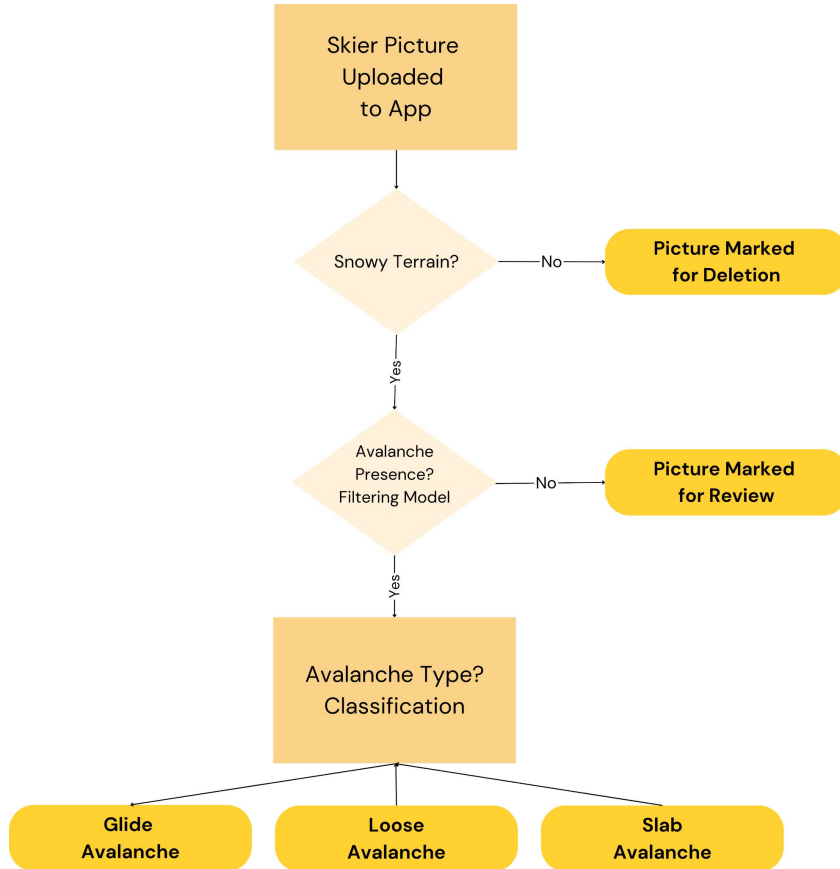
Crop





Modeling Approach

Cascaded Model Architecture



3 Cascaded Models successively take an input picture uploaded by a snow enthusiast and

1. Filter out any pictures that are not a snowy mountain
2. Filter out any pictures that don't feature an avalanche
3. Classify a valid picture of an avalanche into an avalanche type: glide, loose, or slab

Individual Model Architectures

All 3 models are fine-tuned on EfficientNetV2S. Differences in task complexity and nature (binary vs multi-class) drive differences in fine-tuning layers and parameters.

Binary Filtering Models

Input	(224, 224, 3)
Output	Binary
Model	Fine-tune EfficientNetV2S
Finetuning Layers	GlobalAveragePooling2D() Dense(1, activation = 'sigmoid')
Hyperparameters	
Learning Rate	0.001
Optimizer	Adam
Batch Size	32
Epochs	10
Loss Function	binary_crossentropy
Evaluation	accuracy

Avalanche Classification Model

Input	(224, 224, 3)
Output	Glide Avalanche Loose Avalanche Slab Avalanche
Model	Fine-tune EfficientNetV2S
Finetuning Layers	GlobalAveragePooling2D()(x) BatchNormalization()(x) Dropout(0.5)(x) Dense(1024, activation='relu')(x) Dropout(0.5)(x) Dense(num_classes, activation='softmax')(x)
Hyperparameters	
Learning Rate	0.001 to 0.0001 w/ ReduceLROnPlateau & patience 3
Optimizer	Adam
Batch Size	32
Epochs	40 w/ tf.keras.callbacks.ModelCheckpoint
Loss Function	sparse_categorical_crossentropy
Evaluation	accuracy

Model Approach

- We landed on EfficientNetV2S fine-tuning, leveraging a common image classification transfer learning approach for our moderate dataset size.
- Feature extraction of colors and texture was insufficient due to image complexity
- Transformer-based approaches are state-of-the-art but difficult b/c of our small dataset
- Cleaning data, preprocessing, class balancing, fine-tuning layer params were also all tuned

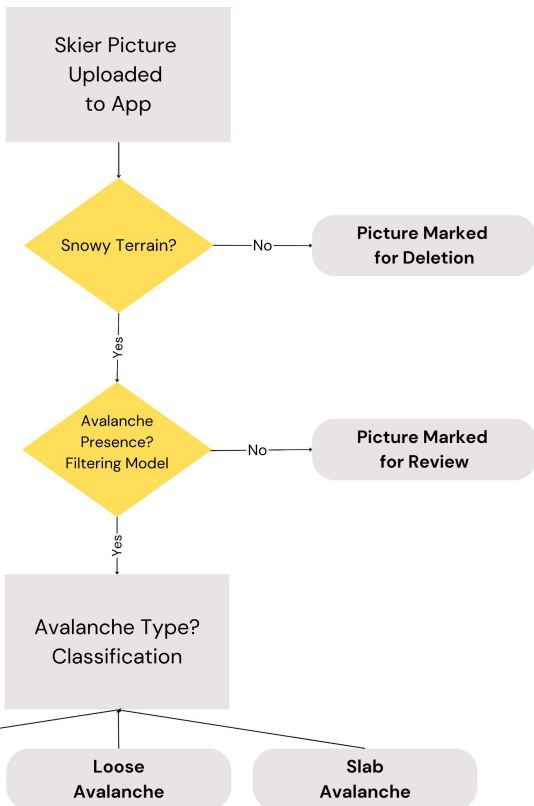
Classification Model Experiment Tracker

Validation Accuracy	Classes	Multiple Labels	Preprocessing	Balancing Approach	Model	Notes
0.3	Glide, Loose, Slide None	yes	equalizeHist GaussianBlur adaptiveThreshold	Undersample	CNN simple	Decisions: 1. Abandon preprocessing 2. Cascade Models
0.4					Resnet Finetune	
0.35					EfficientNetB4	
0.4	removed	Color & Texture Features + Logistic Regression				
0.6	Removed by Cropping, effectively augmenting		none	Augment: - rotate - flip horizontal	Color & Texture Features + Random Forest	Decision: Color & Texture features insufficient despite small improvements
0.56					Color & Texture Features + Logistic Regression	
0.55					Glide, Loose, Slide	
0.7						
0.73			Undersample	EfficientNetB4		
0.79				Undersample	EfficientNetV2S	Winner

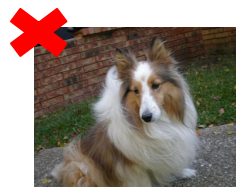


Model Performance

Model Performance - Filtering Models



Amazing at filtering out irrelevant pictures
99% accuracy



Great at detecting presence of an avalanche
False positives often have skier tracks in the image
84% accuracy

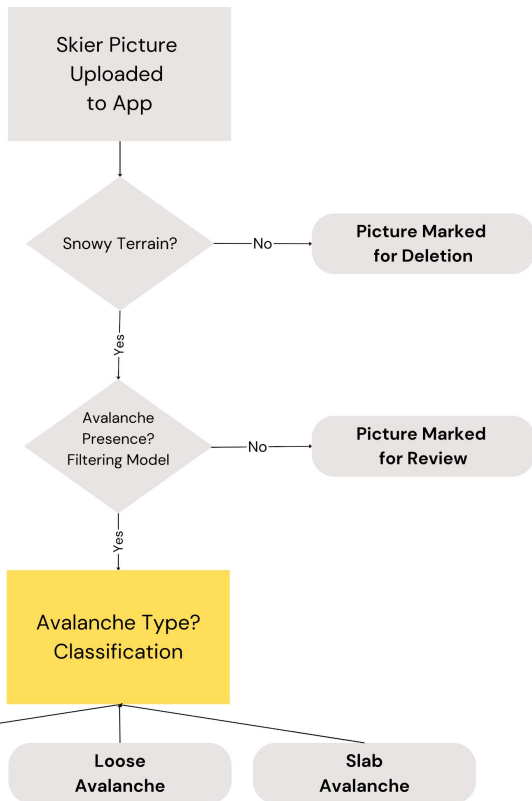


False Positive

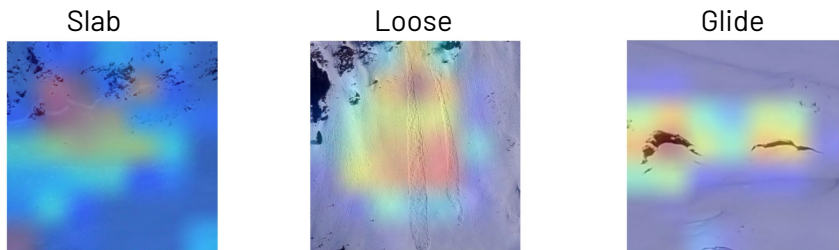
True: 0, Pred: 1



Model Performance - Classification Model



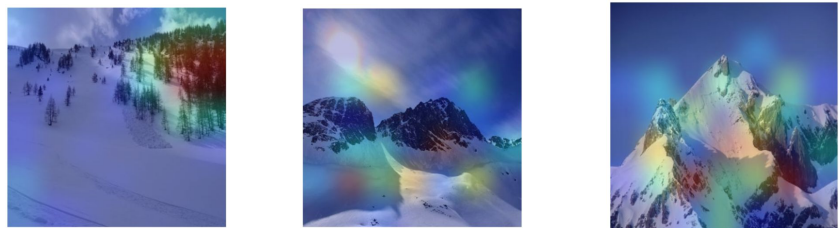
Great at classifying avalanche types for close-up images
79% accuracy



CAM images

Struggles at classifying avalanche types for wide-angle images that include other features such as rocks, trees, clouds
65% accuracy

Sample Complicated Images



CAM images

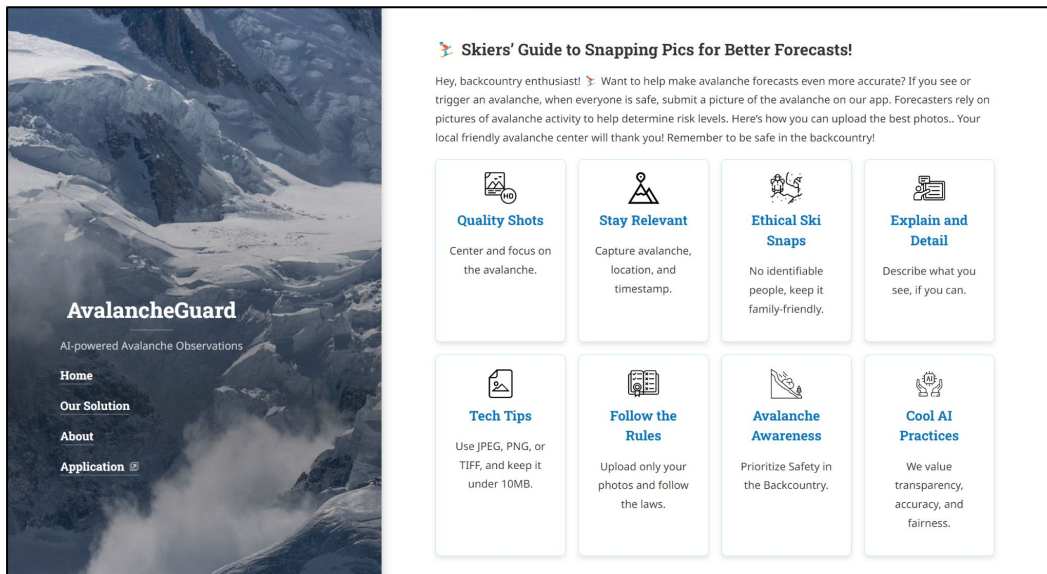
Model Performance - Mitigation

For optimal performance with our model, skier pictures should center and focus on the avalanche.

We provide this guidance (and more fun tips!) on our website.

Close-ups more likely anyway from a skier w/ cell phone camera.

Website - Education Section











AvalancheGuard
AI-powered Avalanche Observations

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- Application

Skiers' Guide to Snapping Pics for Better Forecasts!

Hey, backcountry enthusiasts! Want to help make avalanche forecasts even more accurate? If you see or trigger an avalanche, when everyone is safe, submit a picture of the avalanche on our app. Forecasters rely on pictures of avalanche activity to help determine risk levels. Here's how you can upload the best photos.. Your local friendly avalanche center will thank you! Remember to be safe in the backcountry!

 Quality Shots Center and focus on the avalanche.	 Stay Relevant Capture avalanche, location, and timestamp.	 Ethical Ski Snaps No identifiable people, keep it family-friendly.	 Explain and Detail Describe what you see, if you can.
 Tech Tips Use JPEG, PNG, or TIFF, and keep it under 10MB.	 Follow the Rules Upload only your photos and follow the laws.	 Avalanche Awareness Prioritize Safety in the Backcountry.	 Cool AI Practices We value transparency, accuracy, and fairness.

An aerial photograph of a snowy mountain range. The terrain is covered in snow, with some rocky outcrops and ridges visible. The lighting creates soft shadows, highlighting the contours of the mountains. The text 'Model Evaluation' is centered in the middle of the image in a bold, black, sans-serif font.

Model Evaluation

Model Evaluation

Models were evaluated using a combination of metrics and analysis tools.

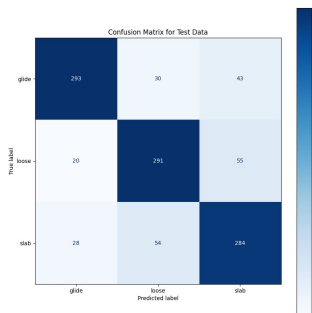
Accuracy was used for model training because the type of misclassification is not important.

Precision, Recall, f1-score

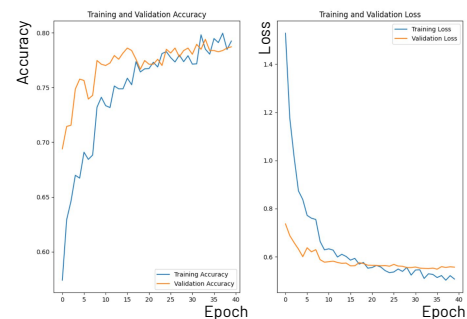
Classification Report:

	precision	recall	f1-score	support
glide	0.86	0.80	0.83	366
loose	0.78	0.80	0.79	366
slab	0.74	0.78	0.76	366
accuracy			0.79	1098
macro avg	0.79	0.79	0.79	1098
weighted avg	0.79	0.79	0.79	1098

Confusion Matrix



Accuracy and Loss Curves



Misclassified Images



Class Activation Maps



Technical Challenges & Takeaways

Architecture Challenge:

Single model to detect and classify an avalanche wasn't working

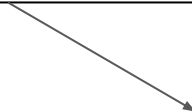


Cascaded models

- Modular
- Future-proof
- Reduce Complexity
- 📌 Explainability

Computer Vision Challenge:

Moderately sized dataset

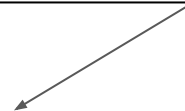


EfficientNet Model Selection

- Feature Extraction insufficient
- Transformer-based models needs more data
- EfficientNet (CNN) fine tuning successful for our dataset size & complexity

Snow Complexity Challenge:

- Avalanches ≠ Objects
- Lack boundaries, color differences.
- Texture variations subtle
- Rocks, trees, dirt looks similar
- Snow & clouds look similar



An aerial, black and white photograph of a mountainous landscape covered in snow. The terrain is rugged, with numerous ridges and valleys. A prominent, wide valley runs diagonally from the upper left towards the lower right. The snow appears to have settled in the lower elevations and along the ridges, creating a textured, uneven surface. The overall scene is serene and desolate.

Closing Remarks

Roadmap

Wide-angle image performance improvements by including a segmentation model

Instagram integration, where many users get their avalanche risk information & already upload images

Expand forecaster-facing observations insight platform to enable sorting and other visualizations

Our Mission

We aim to improve safety in the mountains
by crowdsourcing avalanche observations, and accurately labeling them w/ machine learning,
for avalanche forecasters to obtain
the volume of field data they need to complement their weather and snow pit data
to provide the public with
more accurate and precise avalanche risk forecasts.



Special Thanks

We'd like to thank everyone who advised us and provided feedback throughout our capstone project, especially:

- David Reichel, Executive Director at the Sierra Avalanche Center, for guidance, feedback, and data.
- Richard Bothwell, former Executive Director of AIARE, for guidance, feedback, and avalanche safety insights.
- Jeffrey C, forecaster, for feedback and explaining the forecaster's process.
- David, Arnaud, Zara, and other backcountry skiers for sharing their experiences and insights.
- Jaeyoung Lim from ASL at ETH Zurich and Elisabeth Hafner from WSL SLF for sharing their avalanche research insights in Switzerland.

Resources

PHOTOS

Slide 5: Images and quotes from Sierra Avalanche Center Facebook posts & avalanche.org

Slide 28: Sierra Avalanche Center Facebook page

Slide 25: Adventure Sports Journal

Adrian Tanic, Unsplash

Paul Bill, Unsplash

Krzysztof Kowalik, Unsplash

Slide 4: Nicolas Cool, Unsplash

Matea Nikolina, Unsplash

Lucas Leonel, Unsplash

Jasper Guy, Unsplash

Slide 16, 43: Alberto Restifo, Unsplash

Slide 2: Anders Jilden, Unsplash

Slide 1, 7, 8, 17: Alessio Soggetti, Unsplash

Slides 16, 20, 24, 28: Fox et al

Information and Links

Slide 6, 7 and 8: [Sierra Avalanche Center Annual Report 2020](#)

Datasets

"Automating avalanche detection in ground-based photographs with deep learning". The accompanying dataset of avalanche photographs is available at <https://researchdata.uibk.ac.at//records/h07f4-qzd17>.

Addison Howard, Eunbyung Park, Wendy Kan. (2018). ImageNet Object Localization Challenge. Kaggle. <https://kaggle.com/competitions/imagenet-object-localization-challenge>

Landscape Recognition | Image Dataset | 12k Images, <https://www.kaggle.com/datasets/utkarshsaxenadn/landscape-recognition-image-dataset-12k-images>

Our MVP

Demo 1

The screenshot shows a Google Slides presentation titled "AvalancheGuard final" in a browser window. The slide is titled "MVP Demo" and features two side-by-side images of a skier. The left image is a photograph of a skier in a snowy mountain landscape, with a caption below it: "Image Courtesy: <https://emilypost.com/about/the-emily-post-institute>". The right image is a digital illustration of a skier in a blue jacket and white helmet, with a caption below it: "Generated by Adobe Firefly". The slide navigation pane on the left shows slides 8 through 14, with slide 8 containing a table with the following data:

Why professionals?	
Only 3	642
141,000	(+0.9%)

The name "Amiya Ranjan" is visible in the bottom left corner of the slide.

AvalancheGuard website