Using Deep Learning for Avalanche Detection with Ground-Based Photography

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Abstract

Avalanche detection is becoming more and more vital to the safety of mountain lovers and protection of infrastructure in mountainous regions. This paper explores Artificial Intelligence (AI) as an avenue for avalanche detection, specifically using deep learning and image classification through ground-based photography. Convolutional Neural Networks (CNNs) were used to perform two main tasks, attempting to (1) identify whether each photograph contains any visible avalanches and (2) determine the type of avalanche (i.e., glide, loose, or slab) that is going to occur if detected. For the first task, predicting if an avalanche will occur or not, an accuracy of 77.7% was achieved, and for the second task in predicting avalanche type, an accuracy of 80.6% was achieved, both using DenseNet-201 model architecture. Potential applications of these models include using them as the foundation for real-time webcam avalanche prediction and for a potential mobile application that mountain-goers can use as an additional avalanche safety tool.

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1. Introduction

According to the Federal Emergency Management Agency (FEMA), 28 people every winter in the United States die from being caught in avalanches.[1] Avalanche accidents and fatalities in the United States have been steadily increasing, with the average national annual fatality rate reaching approximately 25 by the late 1990s, which is about 5 times higher than the rate in the early 1950s.[2] Avalanches not only pose threats to human life, but also have serious economic consequences when accounting for property damage, snow removal from highways, and avalanche rescues. The Canadian government estimates that for every hour the Trans-Canada highway is closed due to an avalanche, it costs the Canadian economy $68,000 every hour.[3] With these issues, avalanche detection is becoming more and more vital to the safety of mountain lovers and protection of infrastructure in mountainous regions.

The global Avalanche Detection System market is projected to grow from $146 million in 2024 to $186.9 million by 2030 at a Compound Annual Growth Rate (CAGR) of 4.2% during this forecast period.[4] Currently, avalanche detection mostly exists as a series of sensors, data collectors, georadar, weather monitors, etc. to identify possible avalanches. This technology, however, can be costly, especially with respect to the sensors/instruments that are typically used to record avalanche data. For these reasons, researchers have begun to explore Artificial Intelligence (AI) as an avenue for avalanche detection, specifically using AI to predict avalanches through image classification.[5] **This paper explores its own avenue of avalanche image classification by attempting to accurately predict avalanches, specifically through Convolutional Neural Networks (CNN) and ground-based imagery of avalanche-prone mountains.**

[1] "Protective Actions Research." Fema.gov, 2022, community.fema.gov/ProtectiveActions/s/article/Avalanche-Impact.
[2] Voight et al., "Snow Avalanche Hazards and Mitigation in the United States," National Academies Press, 1990, cited in Cary J. Mock and Karl W. Birkeland, "Snow Avalanche Climatology of the Western United States Mountain Ranges," Bulletin of the American Meteorological Society, 81, no. 10, (2000), 2367
[3] Parks Canada Agency, Government of Canada. "Avalanche Control Program." Parks.canada.ca, 20 Sept. 2023, parks.canada.ca/pn-np/bc/glacier/nature/controle-avalanche-control.
[4] QYResearch. "Global Avalanche Detection System Market Insights, Forecast to 2030." Qyresearch.com, 2024, www.qyresearch.com/reports/3116094/avalanche-detection-system. Accessed 8 Aug. 2024.
[5] "World of Science | CADS - Camera-Based Avalanche Detection System." PowderGuide, 2024, powderguide.com/en/magazine/bergwissen/world-of-science-cads-camera-based-avalanche-detection-system. Accessed 8 Aug. 2024.

2 Literature Review

2.1 Overview

There is a variety of existing literature that has come out over the past few years relating to using neural networks/deep learning for image classification of avalanches. Some of the larger case studies include The Colorado Avalanche Information Center's (CAIC) 2020 paper titled "Predicting Avalanche Field in Images Using Convolutional Neural Networks and Edge Detection" which uses CNNs to detect the location and shape of avalanches from satellite images.[6] The researchers tested different models and found that combining RGB (red, green, blue) data with polygon coordinates further improved avalanche predictions. Other examples of related literature include a 2021 study titled "Snow Avalanche Segmentation in SAR Images With Fully Convolutional Neural Networks" which uses deep learning to identify avalanches through radar images[7] and a 2023 study titled "Combining OBIA, CNN, and UAV photogrammetry for automated avalanche deposit detection and characterization" which uses deep learning to identify avalanches through RGB images taken from unmanned aerial vehicles (UAV).[8]

What is most of most interest, however, is a 2024 study from the University of Innsbruck in Austria titled "Automating avalanche detection in ground-based photographs with deep learning" that uses deep learning to predict avalanches using ground-based photography (pictures that anyone can take, like from a smartphone on the base of mountain, for example).[9] This study is novel in that it is the only publicly-available literature that does avalanche detection with ground-based photography as opposed to satellite, radar, and/or aerial imagery. Additionally, the

[6] Alharbi, Maha, et al. Predicting Avalanche Field in Images Using Convolutional Neural Networks and Edge Detection. 2020.

[7] Bianchi, Filippo Maria, et al. "Snow Avalanche Segmentation in SAR Images with Fully Convolutional Neural Networks." IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 14, 2021, pp. 75–82, https://doi.org/10.1109/jstars.2020.3036914. Accessed 8 Aug. 2024.

[8] Dewali, Sanjay Kumar, et al. "Combining OBIA, CNN, and UAV Photogrammetry for Automated Avalanche Deposit Detection and Characterization." Advances in Space Research, vol. 72, no. 8, 15 Oct. 2023, pp. 3109–3132, www.sciencedirect.com/science/article/abs/pii/S0273117723004714, https://doi.org/10.1016/j.asr.2023.06.033.

[9] James Fox, Anna Siebenbrunner, Sandra Reitinger, David Peer, Antonio Rodríguez-Sánchez,
Automating avalanche detection in ground-based photographs with deep learning,
Cold Regions Science and Technology,Volume 223,2024,104179,ISSN 0165-232X,
https://doi.org/10.1016/j.coldregions.2024.104179.

research team not only approached this study from a classification perspective, but also from a segmentation perspective, which seeks to identify the types of the different "individual" avalanches (i.e., glide, loose, slab) that might make up a larger avalanche. The researchers have the intention of using their findings to develop a real-time, webcam AI that can be used to predict avalanches in Austria from a live camera feed.

For this paper, this ground-based photography approach to avalanche detection will be proposed given how novel of an area of research this topic is. The researchers used a variety of CNN model architectures, along with various segmentation techniques that utilize bounding boxes drawn by avalanche experts. This paper is going to pursue these avenues of research through the applications of these model architectures, along with potentially different architectures. **Simplifying this existing research with the intentions of producing results that do not sacrifice a large amount of model performance is going to be a key point of focus in this paper.**

2.2 Preliminary Methods

With this focus of using deep learning and image classification to predict avalanches through ground-based photography, we can establish two main questions that will be addressed in this paper:

- Can we create a more parsimonious version of the CNN models used in the University of Innsbruck study that has similar performance?
- How well can we classify not just whether an avalanche is going to happen, but also what type of avalanche (i.e., glide, loose, slab)?

By following the University of Innsbruck researchers' work and creating a more parsimonious model with as close to similar performance as possible, we are establishing the foundation for proper avalanche detection AI with less of the computational cost/complexity that the researchers used. Such a feat would offer an easy-to-use skeleton for other researchers to build upon for their own AI avalanche detection models. Also, the fact that this model will only rely on ground-photography, not hard-to-access or proprietary radar or satellite technology, will allow for future explorations into real-time avalanche monitoring and creating temporally continuous avalanche data.

Additionally, being able to classify what type of avalanche threat is present in an image with our parsimonious model will allow further insight into the nature of HOW the avalanche is going to occur. For example, slab avalanches are known to be the most dangerous of the avalanche types with 90% of all avalanche fatalities occurring from slab avalanches.[10] If we are able to successfully identify slab avalanches at a high clip, then theoretically, we should be able to spot avalanche situations that would be most deadly to people on the mountain. Also, if we know what kind of avalanche threat we are looking at, then we will better know the behavior of how the snow might impact any nearby infrastructure and how any avalanche demolition teams might want to approach the snow.

[10] "Avalanche Types." Www.slf.ch, www.slf.ch/en/avalanches/avalanche-science-and-prevention/avalanche-types/#:~:text=Slab%20avalanches%20are%20the%20most.

3 Empirical Design

3.1 Data Gathering and Description

With a high-level outline of the questions we want to address and a rationale for this research, we can begin to look at the data we will use in said research. The same dataset that the University of Innsbruck researchers used will be the data that is used in this paper. The dataset,[11] compiled by UIBK researchers, is comprised of 4,090 labeled avalanche photographs, each categorized by avalanche experts into one of four groups: glide, loose, slab, or none. These categories correspond to different avalanche release mechanisms, with "none" indicating the absence of an avalanche.

To be more detailed, the avalanche photographs in this dataset were taken during the winters from 2000/2001 to 2021/2022 and contain 716 glide, 416 loose, and 1887 slab avalanche photographs and a further 1071 "none" images without visible avalanche regions. This dataset is contained within a 3.4GB zip file that can be downloaded from a website hosted by the UIBK researchers. The zip file contains two folders, one called “images” which contains the images of the avalanches themselves as .jpg files and another called “annotations” which contains polygonal and rectangular bounding boxes for each avalanche image as .json files. These bounding boxes serve as “guides” within the images that specifically mark where an avalanche is forming on the mountain.

The dataset is comprised of 228 labeled avalanches captured in the field, the Alps, using ground-based photography. The photographs have a mean dimension of 3431x2431 pixels, with a standard deviation of 1603x1086 pixels. Each image includes metadata specifying the date and approximate location of capture, totaling 1276 different locations across the Alps.

As enumerated, there are 3 main avalanche types that are captured by the images in this dataset: glide, loose, and slab. Glide avalanches are defined by their mechanism in which the entire snowpack slides downslope, revealing the ground beneath. This type of avalanche often

[11] University of Innsbruck, Lo.La Peak Solutions GmbH, Avalanche Warning Service Tyrol, & Avalanche Warning Service Bavaria. (2023). UIBK Avalanche Dataset (v0.0.1) [Data set]. University of Innsbruck. https://doi.org/10.48323/h07f4-qzd17

begins with the development of full-depth tensile cracks in the snowpack, called glide cracks, as shown in Figure 1.

Figure 1: Three images from the dataset show glide avalanches at various scales. In image (a), glide cracks reveal the terrain beneath the snowpack, while image (b) features a glide avalanche with textured snow runout visible in the lower half. Image (c) displays a large glide crack, part of which has been released as a glide avalanche.

Loose-snow avalanches, seen in Figure 2, originate from a single point and spread out in a triangular shape as they descend, gathering more snow along the way. Depending on the lighting conditions, they may appear either darker or lighter than the surrounding snow.

Figure 2: Images (a) and (b) show loose-snow avalanches with textured runout at the base, while image (c) features several loose-snow avalanches visible as lighter areas of disturbed snow. Each avalanche started at a single point and then spread laterally and downward, gathering more snow as it moved.

Slab avalanches, seen in Figure 3, happen when a weakness within the snowpack spreads, leading to the release of a cohesive slab of snow. The snow above the failed weak layer slides down the slope, creating a distinct line (the crown fracture) at the point of release. This contrasts with glide avalanches, where the entire snowpack slides along the ground beneath, usually over smooth surfaces like vegetation or rock.

Figure 3: Three dataset images showing slab avalanches in a variety of lighting conditions and at different scales. The crown fracture may range from a few meters to many kilometers in width.

Elaborating more on the annotations/bounding boxes, avalanche experts marked each visible avalanche in an image with a polygonal bounding box and classified it into one of three categories: GLIDE, LOOSE, or SLAB, representing glide, loose-snow, and slab avalanches respectively. They were directed to outline the avalanche release area and runout, as both contain important visual features. Each image was then assigned an overall label based on the avalanche release type with the most annotated pixels, or labeled as NONE if no avalanches were identified. Of the 3019 dataset images containing avalanches, 311 contain avalanche regions with at least two distinct labels. An example of these annotations can be found in Figure 4.

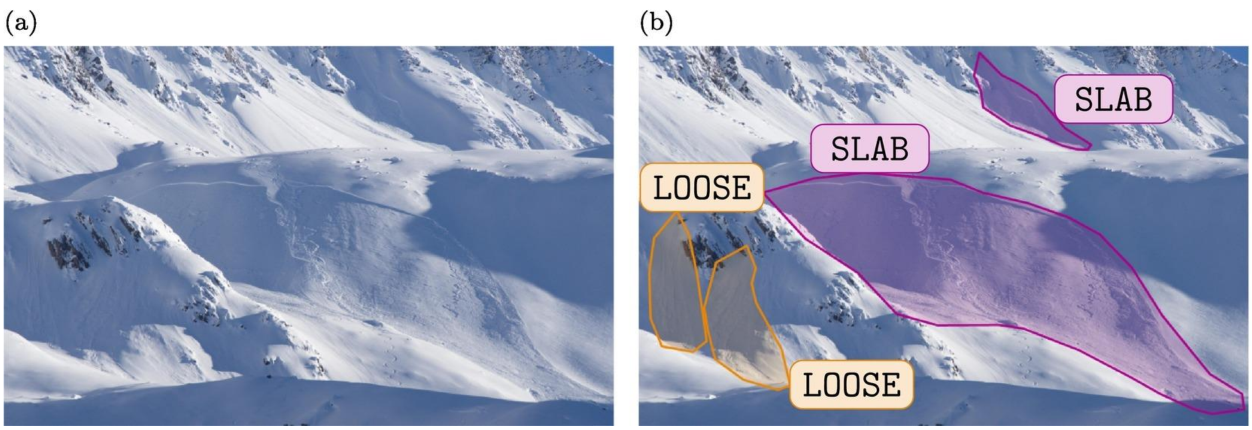

Figure 4: Image (a) from the dataset shows two loose-snow avalanches and two slab avalanches. Each avalanche was outlined by an expert using a polygonal bounding box, as seen in image (b). The image is labeled overall as SLAB because this type of avalanche has this type of avalanche has the most visible pixels.

Overall, this dataset is the only dataset of its kind that contains both this quantity and quality of avalanche photos; there is no other known dataset that contains images with labeled slab, glide, and loose snowpacks at this detail. For this reason, this dataset will be used just like the UIBK researchers but approached slightly differently in the context of CNN model architecture in order to tackle the idea of creating a less computationally complex model (this approach will be discussed in future sections).

3.2 Image Classification Methodology

In this paper, we will be performing two main tasks, attempting to: 1) identify whether each photograph contains any visible avalanches (1 if yes, 0 if no) and 2) determine the predominant type of avalanche present if detected (glide, loose, or slab). We will not concern ourselves with accurately spotting all individual avalanche types present in a picture (which would be an image segmentation task). Sticking to classification of images as a whole instead of looking at all individual avalanches for each image simplifies the task at hand. Being able to identify if an avalanche is likely to happen or not is our most primary concern, especially from a rescue/safety standpoint.

Because we are doing image classification, the images are going to be divided into training and test sets. The researchers provide in the downloadable zip file two .txt files, “test.txt” and “train.txt” which contains indexing information for how they broke up the images into training and test sets. This indexing will also be used in this paper for simplicity’s sake.

The UIBK researchers, in their paper, divided the data into 3612 training images and 478 test images, ensuring that images from the same location were grouped together in each split to prevent data leakage caused by visual similarities among images at the same locations. During training, 10% of the training data was set aside as a validation set for each training run.[12] The test images were completely held out from all training runs and were used solely to assess the model's performance on unseen data. To enhance the model's ability to generalize, they employed data augmentation techniques during training, such as affine transformations, color variations, and random horizontal flips. A similar split will happen in this paper, along with the data augmentation techniques to “clean up” the photos for classification.

It should be noted that the data augmentation step in this paper is one of the first major deviations this work takes from the UIBK researchers’ work. In the UIBK paper, all images were reduced to 900x800 images before they were loaded into their models. In this work, due to the stark computational demands that processing 900x800 images proposes, all images were

[12] In the case of this paper, the validation set will just be added to the testing set.

shrunken to where the shortest side of the image was equal to 224 px and then randomly cropped to create a 224x224 structure that most of the utilized model architectures require. This augmentation of the data does reduce the potential for our models being as accurate as the UIBK models, but it greatly reduces the computational complexity of our tasks, thereby appealing to this idea of “parsimony” that we earlier elaborated upon.

3.3 CNN Architecture Descriptions

For this paper, a variety of deep learning techniques from the convolutional neural network (CNN) family will be used such as AlexNet, VGG, GoogLeNet, ResNet, and DenseNet. Each method has their own advantages which will provide a comprehensive approach into finding the best possible model for avalanche image classification. Descriptions of the utilized architectures can be found below in Table 1.

Architecture	**No. of layers**	**Description**
AlexNet	8	A landmark architecture for deep learning is winning the ILSVRC 2012 challenge.
VGG	16	An architecture that is deeper (i.e., has more layers of neurons) and obtains better performance than AlexNet by using effective 3 × 3 convolutional filters.
GoogLeNet (Inception)	32	This architecture is computationally efficient (using 12 times fewer parameters than AlexNet) while offering high accuracy
ResNet	18, 34, 50, 101, 152	The winning architecture of the 2016 ImageNet competition. The number of layers for the ResNet architecture can be different. We try 18, 34, 50, 101, and 152 layers in this work.
DenseNet	121, 161, 169, 201, 264	This architecture is characterized by its dense connectivity pattern, where each layer receives inputs from all preceding layers and passes its own feature maps to all subsequent layers. We try 161 and 201 in this work.

Table 1: Deep Learning Architectures

3.4 Evaluation Metrics

When training our model that attempts to classify an image as having an avalanche or not (1 or 0), a binary cross entropy loss function will be used as our loss function in which our CNNs are evaluated and trained upon. Similarly, when training our model that attempts to classify an avalanche image as a glide, slab, or loose avalanche, multi-class cross entropy loss will be the basis for our loss function. The cross-entropy loss function, for both binary and multi-class classification, can be generalized as:

$$CE = -\sum_{i}^{C} t_i log(s_i)$$

Where t_i and s_i are the groundtruth and the CNN score for each class i in C. As usually an activation function (e.g., Sigmoid, Softmax) is applied to the scores before the CE Loss computation, we write $f(s_i)$ to refer to the activations.

For this analysis, the following four metrics will be used to help grade our model: accuracy, precision, recall, and F1 score. Each of the scores can be defined as such:

- **Accuracy**: Overall correctness of predictions.
- **Precision**: Proportion of true positives among positive predictions.
- **Recall**: Proportion of true positives identified correctly.
- **F1 Score**: Harmonic mean of precision and recall, balancing both metrics.

In the case of an avalanche detection model, both accuracy and F1 score are critical metrics for evaluating performance. Accuracy provides a straightforward measure of how often the model's predictions are correct, which is essential for understanding the overall effectiveness of the model in identifying avalanches. However, the F1 score, which is the harmonic mean of precision and recall, offers a more nuanced evaluation by balancing the trade-off between false positives and false negatives. This is particularly important in avalanche detection, where missing an avalanche (false negative) could have severe consequences for safety, and unnecessary warnings (false positives) could lead to unnecessary evacuations and resource allocation. Hence, using both accuracy and F1 score ensures a comprehensive assessment of each model's performance.

4 Analysis and Results

4.1 Task I: Binary Avalanche Prediction

As discussed, the results from this project can be broken down into two tasks: Task I, the binary classification case of trying to predict whether an avalanche is going to occur (1) or not (0), and Task II, the multi-class classification case of trying to predict the type of avalanche (i.e., loose, glide, slab) that is going to occur if an avalanche risk is present. We will first take a look at Task I.

Each model was trained for 30 epochs. This number of epochs was chosen for a couple of main reasons. For one, obviously, computational complexity was wanted to be kept at a minimum. 30 epochs was found to be a perfect balance between convergence and computational time. Secondly, it was observed that no major improvements in loss or accuracy were really made across any of the models past 30 epochs. In fact, in many cases, overfitting often occurred once the 30-epoch mark approached. Below, in Figure 5, training and testing loss versus epoch can be observed below in Figure 5.

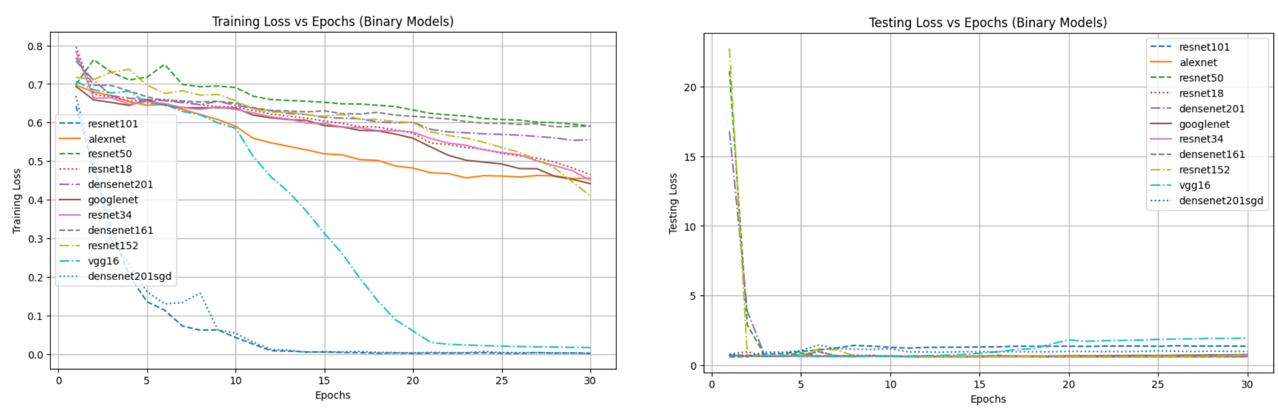

Figure 5: Training and Test Loss vs. Epochs for Task I

The highest reported Accuracy and F-1 Score values for each CNN architecture in Task I can be seen below in Table 2.

Architecture	**Accuracy %**	**F-1 Score %**
AlexNet	66.7	70.6
VGG	65.1	69.0
GoogleNet (Inception)	65.3	69.6
ResNet-18	68.2	71.0
ResNet-34	68.6	72.6
ResNet-50	64.6	68.5
ResNet-101	72.4	74.1
ResNet-152	66.5	71.4
DenseNet-161	67.6	70.9
DenseNet-201	68.8	73.2
DenseNet-201 SGD	**75.7**	**77.7**

Table 2: Accuracy of different models for Task I

The performance metrics for various avalanche detection models show a range of accuracies and F1 scores. DenseNet-201 optimized with a Stochastic Gradient Descent (SGD) instead of an Adam optimizer stands out as the top performer, followed by ResNet-101 and DenseNet-201. It should be noted that all other models were optimized with an Adam optimizer with weight decay (to prevent overfitting) while AlexNet and VGG also used SGD as SGD tends to perform better on these architectures according to literature.[13]

While these values show us the highest accuracy/F1 values, showcasing the potential of these model architectures, a more robust view of our models' performances can be seen in Figure 6 which shows the spread of all accuracy values over all 30 epochs. We can still see, though, that DenseNet-201 optimized with SGD has the highest median accuracy out of all the models, proving it to be the strongest model for Task I.

[13] M. Manataki, A. Vafidis and A. Sarris, "Comparing Adam and SGD optimizers to train AlexNet for classifying GPR C-scans featuring ancient structures," 2021 11th International Workshop on Advanced Ground Penetrating Radar (IWAGPR), Valletta, Malta, 2021, pp. 1-6, doi: 10.1109/IWAGPR50767.2021.9843162.

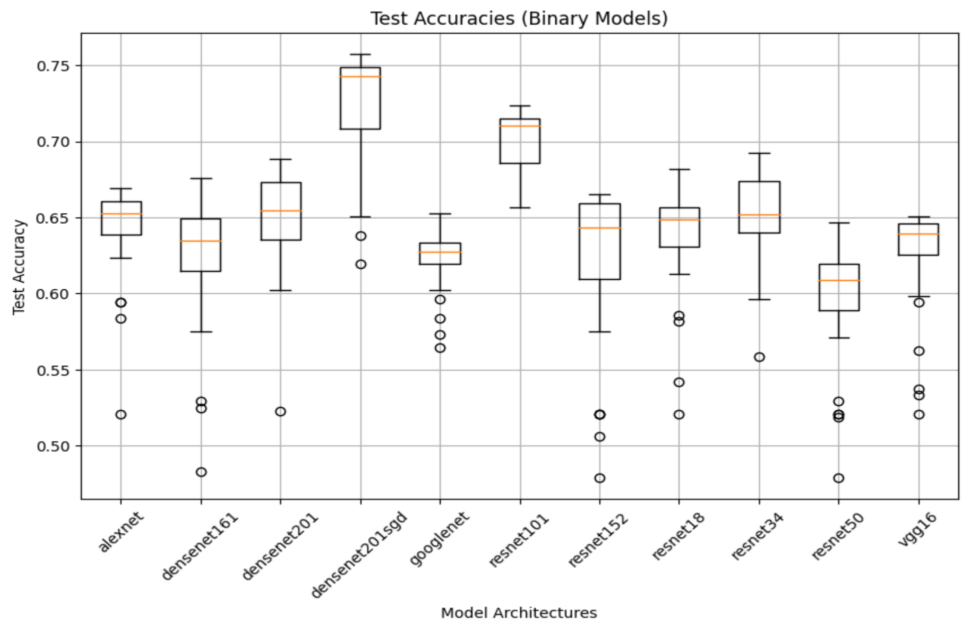

Figure 6: Spread of Test Accuracies for Task I

4.2 Task II: Multi-class Avalanche Type Classification

Once again, this time for Task II, each model architecture was trained for 30 epochs. We can observe that some overfitting occurred past the 15-epoch mark as our training losses for most models saw slight increases from the 15 to 30 epoch range. Once again, all models were trained with an Adam optimizer with weight decay, except for AlexNet, VGG-16, and DenseNet-201 SGD, which were trained with Stochastic Gradient Descent (the same procedures followed in Task I). Even with experimentation to reduce overfitting, namely through weight decay, overfitting remained present past the 15-epoch mark for most model architectures, albeit some less than others. All losses can be observed below in Figure 7.

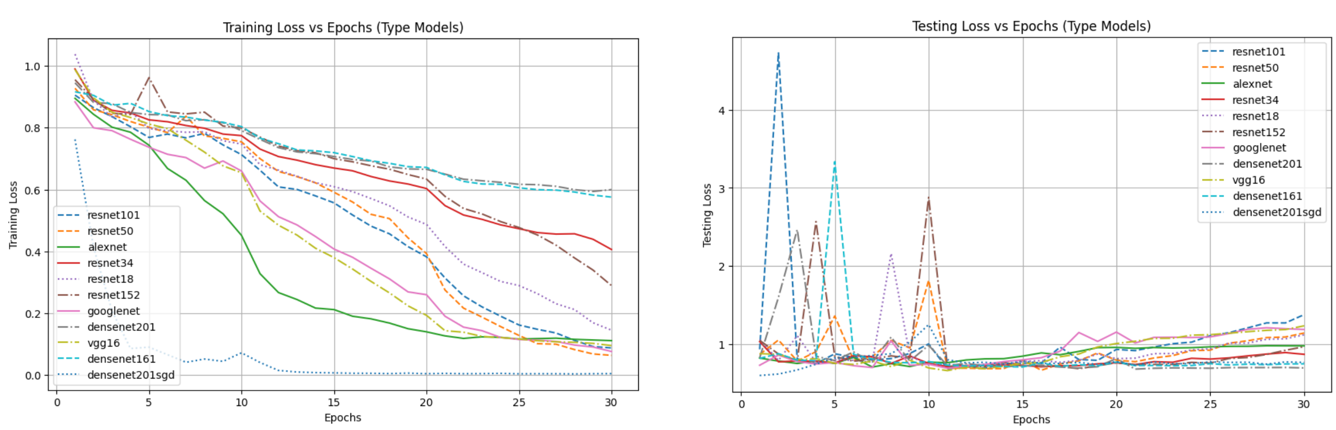

Figure 7: Training and Test Loss vs. Epochs for Task II

The highest reported Accuracy for each CNN architecture in Task II can be seen below in Table 3. It should be noted that F-1 score is not included in the table. The F-1 score is particularly valuable in predicting whether an avalanche will occur or not because it balances precision and recall, which is crucial when dealing with imbalanced datasets and the high stakes of missing an avalanche prediction. However, when predicting the type of avalanche (e.g., slab, glide, loose), the relevance of the F-1 score diminishes because the focus shifts more towards accurately classifying different types, where metrics like accuracy are more appropriate.

Architecture	**Accuracy %**
AlexNet	73.7
VGG	77.0
GoogLeNet (Inception)	74.0
ResNet-18	70.9
ResNet-34	72.6
ResNet-50	72.3
ResNet-101	73.1
ResNet-152	72.0
DenseNet-161	71.2
DenseNet-201	74.2
DenseNet-201 SGD	**80.4**

Table 3: Accuracy of different models on task II

Once again, we can observe that DenseNet-201 optimized with Stochastic Gradient Descent was our best performing model in terms of highest reported accuracy over all 30 of the trained epochs. In fact, this model architecture had an accuracy over 4% higher than the next best reported accuracy in DenseNet-201 optimized with Adam optimizer. This vast difference is likely due to the performance of SGD vs. Adam which will be addressed in a future section.

While these values show us the highest accuracy values, showcasing the potential of these model architectures, a more robust view of our models' performances can be seen in Figure

8, which shows the spread of all accuracy values over all 30 epochs. We can still see, though, that DenseNet-201 optimized with SGD has the highest median accuracy out of all the models, proving it to be the strongest model for Task II, predicting avalanche type.

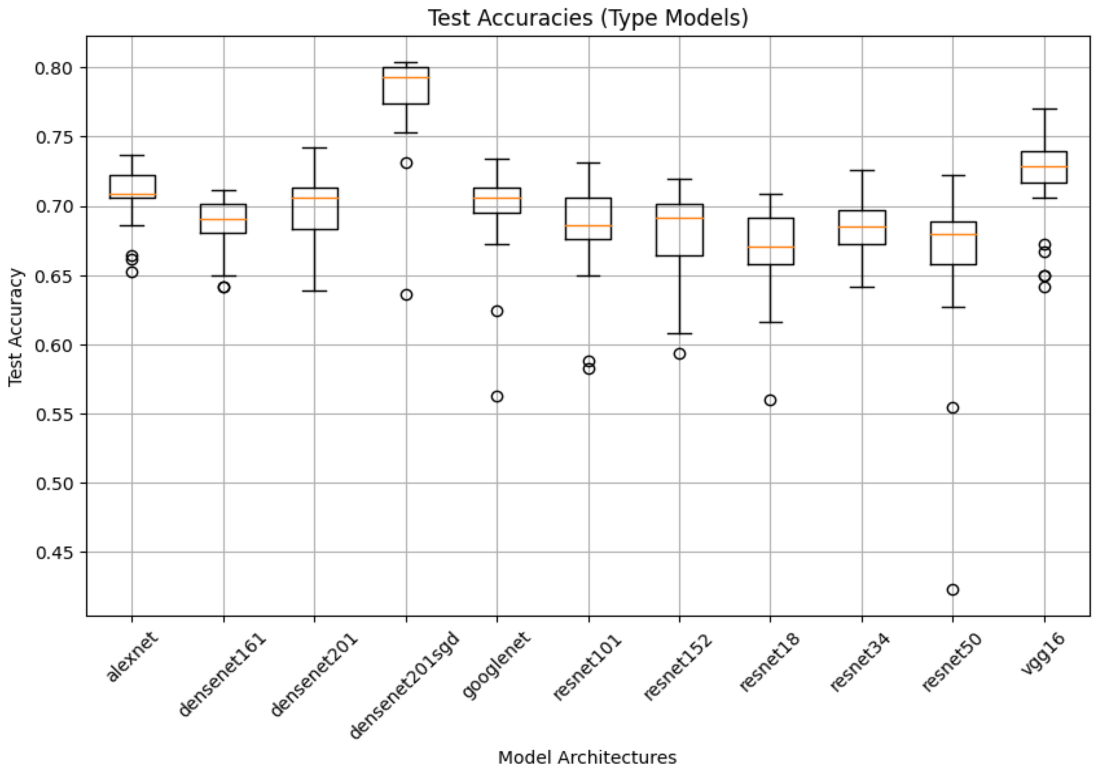

Figure 8: Spread of Test Accuracies for Task II

4.3 Model Comparisons

In summary, our highest reported accuracy scores for Tasks I and II, can be found in Figure 9 and Figure 10, respectively.

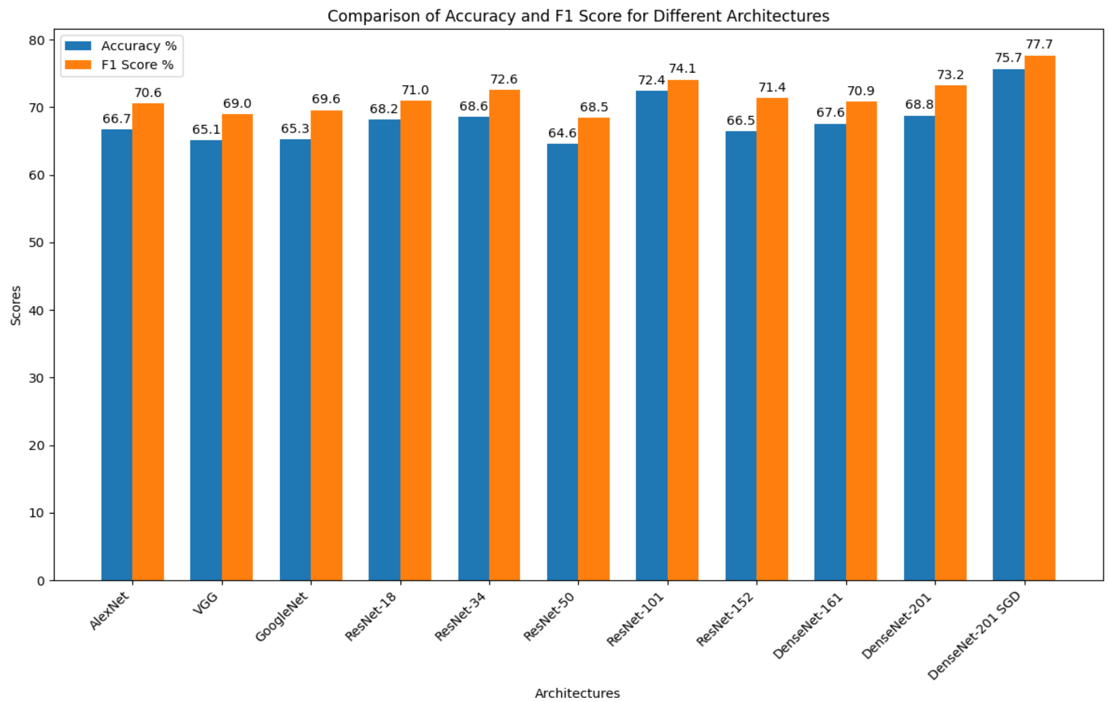

Figure 9: Highest Accuracies by Model for Task I

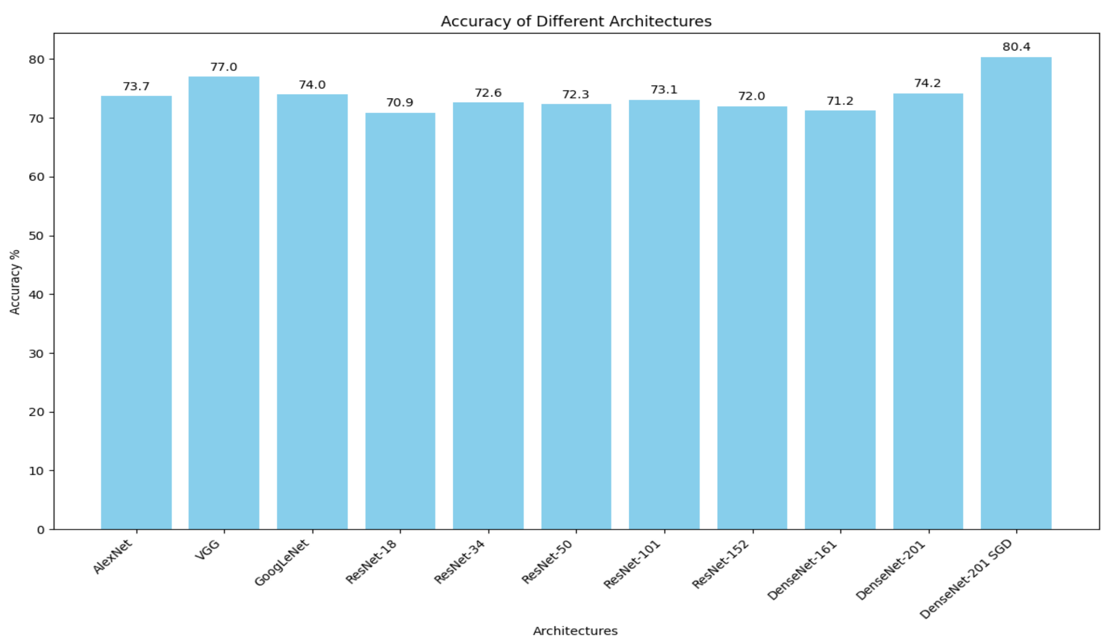

Figure 10: Highest Accuracies by Model for Task II

With all of our models' results, we can say that DenseNet-201 trained with Stochastic Gradient Descent was our best overall model for both Task I and II. With these results, it might be intuitive to think that all "deeper" model architectures (i.e., models with more layers) performed better, but we can see that AlexNet and VGG, our "smaller" models, performed better than many of our deeper architectures like ResNet. Reasoning for this likely comes down to SGD being better suited to optimize these model architectures to our data as opposed to an Adam optimizer. It appears most models trained with Adam produced a lot of models that incurred higher degrees of overfitting. It was not discovered until later on in the experimentation process that SGD produces, overall, better results than Adam. Therefore, in order to avoid runtime issues related to finite computational resources, SGD (outside of VGG and AlexNet) was simply applied to our best model, DenseNet-201. Overall, an optimized model with a very deep network of convolutional layers, DenseNet-201, in our case, produced the strongest results.

Our images in our dataset are very complex images that only extremely trained eyes in the field of avalanche detection would be able to spot. It is impressive, that even as we as we reduce the images to the size of 224x224, a more than 3-fold reduction in image size from the mean dimension of our original images, we have models able to predict avalanches and avalanche types at around an 80% clip. This accuracy is a significant achievement in relation to our goals of creating an accurate avalanche prediction model that does not rely on heavy computational resources or extreme model complexity.

4.4 Fitting the Best Models

With our best model architecture for both Task I and Task II being DenseNet-201, optimized with SGD, the parameters that produced the best accuracy results were saved and used to fit the model to the test data in order to visualize the results more closely. Confusion matrices were produced for both tasks and can be seen in Figure 11 and Figure 12 for each task respectively.

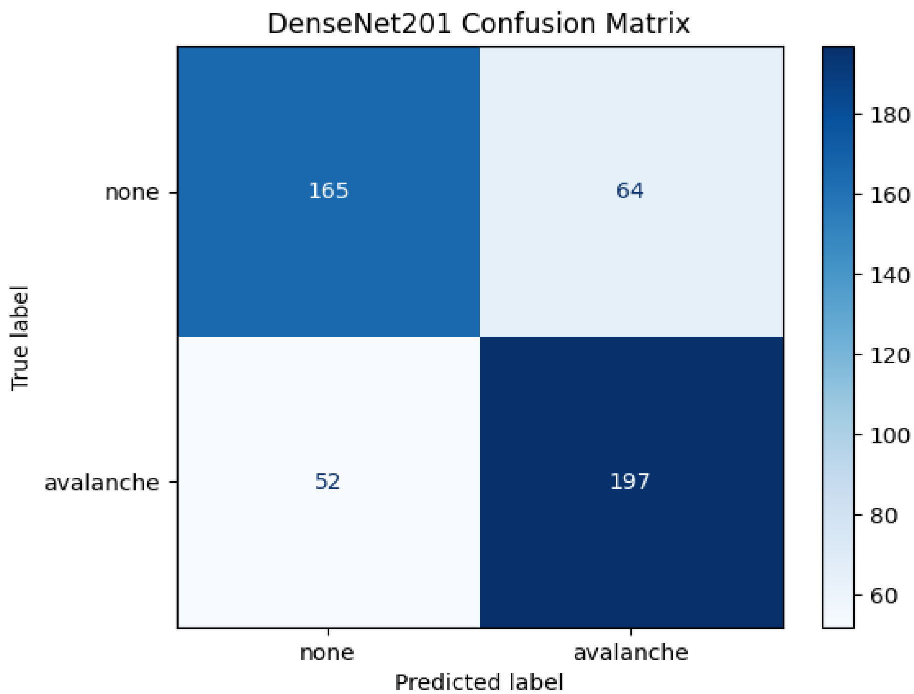

Figure 11: Confusion Matrix for Best Model in Task I

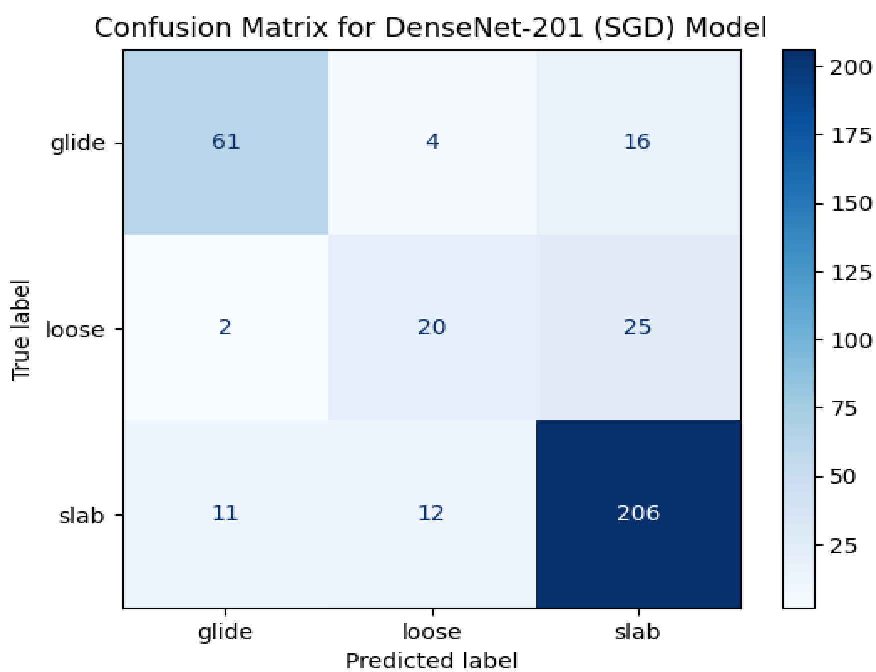

Figure 12: Confusion Matrix for Best Model in Task II

For Task 1, we can see an even distribution of true positives (avalanche) and true negatives (no avalanche) in Figure 11, highlighting our model's ability to successfully pick out if an avalanche is going to happen or not from an image. For Task II, according to Figure 12, we can see our model is very robust in being able to predict the most dangerous avalanches, slab avalanches. This finding is extremely valuable, especially in terms of having a model from the standpoint of safety and rescue. Slab avalanches can be spotted at a high clip, allowing for sufficient warning to be produced from this model regarding the highest impact type of avalanches.

It should also be noted that our best models for both tasks produce strong balances in precision and recall which is especially important to Task I. Having a model that falsely tells you an avalanche is going to happen at a very high rate is extremely unhelpful as it would encourage a misallocation of safety resources from avalanche rescuers and potential unnecessary shutdowns in ski resorts. On the contrary, a model that predicts avalanches (true positives) at a very low rate, poses extreme threats to safety. Our models avoid both of these pitfalls which is extremely valuable.

5 Conclusion

In conclusion, we produced models that are able to predict avalanches with a 77.7% accuracy and the type of avalanche (glide, loose, or slab) with an accuracy of 80.4%. Both of these models were produced from the same DenseNet-201 architecture, optimized with Stochastic Gradient Descent. While previous research from the University of Innsbruck in Austria has been done with predicting avalanches from ground-based photography, this paper produces models with less complexity and require less computational resources and power, with the largest difference being our models only need to process 224x224 images as opposed to 900x800 images. While our models’ accuracy is not quite as strong as the UIBK researchers’, they are still strong achievements given the goals of this paper to produce similar results from more parsimonious data augmentation and model complexity.

There are of course potential improvements that can be made to be our work, including performing more discriminative fine tuning to each of our models, experimenting more with regularization and optimizer choice to reduce overfitting, and even increasing image size so more image detail can be learned by our models. Each of these potential improvements will be considered in future work that follows this paper.

The most powerful part of the models produced from this work is that they only require images created from ground-based photography. Essentially, anyone would be able to take a picture of a mountain face and the models from this paper would be able to tell you fairly successfully whether the mountain is avalanche prone, and if so, what type of avalanche is going to occur. Applications of these models include building the foundations of a real-time webcam avalanche detection system, a mobile application for backcountry mountain enthusiasts to identify avalanches, and supplementary systems for current avalanche detection teams and rescuers. Each of these applications will be pursued after the publication of this paper.

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