Snowstorm Classification Using ResNet-18 CNN for Seal Monitoring Application

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***Abstract*—The reconstruction of Antarctica New Zealand's research centre, namely Scott Base, is set place to start construction at the end of 2022. Previous research has been conducted to measure the surrounding Weddell Seal activity to ensure the population is not disturbed once Scott Base's construction is underway. This research paper proposes a finetuned ResNet-18 Convolutional Neural Network to classify snowstorms in the Seal images taken in the 2019-2020 Summer. The value of a reliable and accurate model is in the ability to distinguish between true and false low counts of the population (where false counts arise from snowstorm induced low-visibility). Evaluation of the proposed model shows encouraging results. The model achieves an accuracy of 97.8%, precision of 99.6%, recall of 95.5% and a F_1-Score of 97.5%. These results outperform alternate non-CNN weather classification approaches (86%) and match that of other ResNet-18 weather classifiers (98.22%).**

***Index Terms*—ResNet-18, Convolutional Neural Network, Snowstorm, Antarctica, Image Classification**

I. Introduction

Antarctica New Zealand has secured a $344 million budget for the redevelopment of its research station Scott Base. The institute will start construction in the 2022-2023 Summer. A research project to monitor the surrounding Weddell Seals is currently being undertaken throughout 2022 by myself. The project is supervised by Professor Richard Green and Postdoctoral Researcher Oliver Batchelor. Both Richard and Oliver are experts in the area of Computer Vision. Monitoring of the nearby Seal colonies is required to ensure that the groups are minimally disturbed by the construction noise.

During the analysis of the Seal's counts in the 2019-2020 summer by Batchelor, the accuracy was affected by severe snowstorms [1]. The object detector performed well in moderate snowstorms where the wind-blown snow added noise to the images. However, heavy snowfall that impacted the visibility of the high-resolution cameras resulted in a cluster of counts of zero seals. In some cases, the camera lens is covered with snow.

Without being able to distinguish if the image is affected by a snowstorm, the validity of low Seal counts is jeopardised. The result could be a true low count or a false count due to the low visibility caused by a snowstorm. The validity of the low counts of the Seals is crucial if a causational relationship between Scott-Base construction noise and disturbed seals can be made.

Generally, sensors have been used for weather observation and detection. However, the installation and maintenance of such sensors are costly. This cost is amplified when considering Antarctica's environment justified as off-the-shelf equipment is rarely suited for dramatic storms.

II. Background

Most research in the field of weather classification originates outside of Antarctica and does not focus on binary classification (e.g. Does the image contain a snowstorm?). Multi-class weather classification models are crucial to Internet-of-Things (IoT) and Cyber-Physical-Systems (CPS). For example, self-driving cars commonly utilise Lidar for their superior angular resolution and highly accurate range measurements. However, the sensors are greatly affected by adverse weather conditions such as snow, fog and rain. Raindrops that fall close to the sensor give a reading similar to close objects on the road [2]. To compensate, the system can use a multi-class weather classification model to identify rain or snow and adjust sensor parameters to better suit the conditions [2].

Weather classification techniques have had great improvement over the recent years, a headway that can be partially explained by the accelerated performance of Convolutional Neural Networks (CNN) [3]. This can be demonstrated by the high levels of accuracy in existing related work.

A. SAID Approach

One approach that forgoes CNN's blends and boosts certain histogram features in an image to maximise the accuracy of a set of classifier algorithms. The classification algorithms are Random Forest, KNN, Naive Bayes and Radial base kernel function Support vector machine (RBF-SVM). The features optimised are Hue, Saturation and Value (HSV), Contrast, Gradient and Local Binary Pattern (LBP). The approach utilises an ensemble of said classifying algorithms which each has accuracy weighted votes on the weather of the input image. This approach resulted in a 86% accuracy on an unseen testing dataset [4]. The reliance on accuracy as a sole metric for the success of a pipeline can be viewed as archaic. The faults with solely using accuracy to quantify the performance of a classifier are well documented [5]. Such metric does not account for the ratio of retrieved documents that are relevant (precision). The accuracy of the positive class (recall) is also obfuscated. Alternative classification metrics should be used such as the F1-score, or the Matthews Correlation Coefficient (MCC) when the cost of low precision and low recall is unknown [5].

B. CNN Approach

One approach utilises a finetuned CNN to produce outstanding results. [6] utilises ResNet-18, a 72-layer architecture with 18 deep layers. The proposed ResNet-18 CNN is pre-trained on the ImageNet database. This large image database currently holds more than 14 million hand-annotated images [7] containing over twenty thousand classes. However, training a model on such a significant number of images with today's technology is not feasible. While the paper fails to specify, the ResNet CNN will have been trained on a subset of the database. The ImageNet Large Scale Visual Recognition Challenge (ILSVRC) is an annual competition held from 2010 to 2017 in which contestants must classify a one million image ImageNet subset containing one thousand object classes. This dataset is commonly used to pre-train CNN models. The proposed ResNet-18 was further finetuned using the Multi-class Weather Dataset for Image Classification (MWDIC) [8]. MWDIC holds 1125 images partitioned into four classes: Sunrise, Shine, Rain and Cloudy. Researchers split the MWDIC into training and testing subsets with a 75% and 25% allocation respectively. Sample images of the four classes in the MWDIC are seen in Fig. 1.

The model achieves an impressive 98.22% on the testing subset. This shows an improvement over the previous approach which refrained from using CNN's. Another improvement from the previous research paper is in the form of model evaluation. Additional metrics used are the precision and sensitivity of the classification. The papers also utilised a Confusion Matrix (Fig. 2) to describe the performance of the multi-class classification model in terms of the number of False Negatives, False Positives, True Negatives and True Positives.

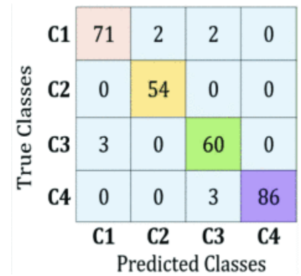


Fig. 2: Confusion Matrix from multi-class weather classification model [6]

III. Solution

A. ResNet-18

Residual neural networks (ResNet) [9] are effective when training deep neural networks. Its architecture adds connections between layers to skip or add shortcuts, namely skip-connections. The two main reasons for this added complexity are:

1) Avoids the vanishing gradient problem.
2) Reduces the severity of Degradation. Due to additional layers increasing training error [9].

Residual Blocks (RB) exist in the ResNet architecture for this purpose. An RB is a stack of layers organised using the output of an earlier layer as an input to a deeper layer in the RB. Therefore, creating a skip-connection by design, shown in Fig. 3.

The ResNet-18 architecture can be broken down into four modules each with four convolutional layers. Additionally, there is a convolutional layer accepting the input and a fully-connected layer making a total of eighteen layers. A softmax layer is added to perform classification tasks. Fig. 4 shows the ResNet-18 architecture along with the skip-connections.

The proposed storm classification pipeline can be abstracted into three components: Preprocessing component, the ResNet-18 finetuning component and the Classification component. The architecture of the proposed model is shown in Fig. 5. The

Fig. 1: Sample images of Cloudy, Rain, Shine & Dawn [6]

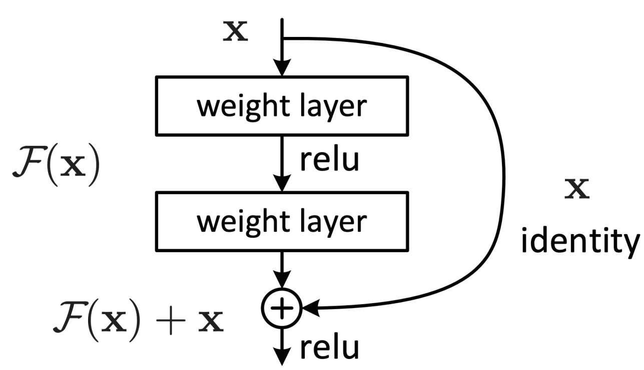


Fig. 3: An example of a skip-connection in the ResNet-18 architecture [9]

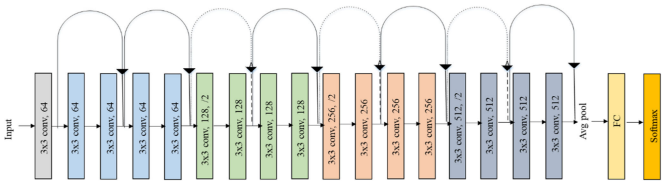


Fig. 4: ResNet-18 Architecture [10]

pipeline starts by processing images taken from the Antarctic Dataset Subset (ADS). The preprocessing stage performs five operations to augment, label, shuffle and partition the images. This stage is necessary to normalise the Finetuning component's inputs for the training, validation and testing phases. The ADS and processing stages are elaborated on in sections III-B and III-C respectively.

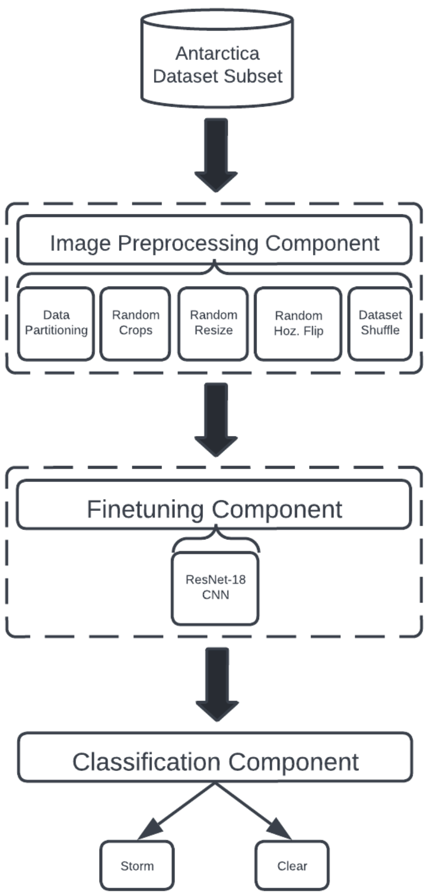
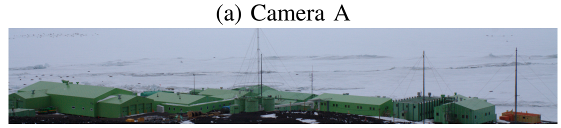


Fig. 5: Architecture of proposed ResNet-18 pipeline

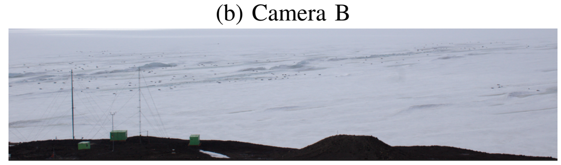
B. Antarctic Dataset

The Weddel Seal Abundance Monitoring Programme, carried out by Antarctica New Zealand, annually monitors the seal population to evaluate any impact the current Scott Base renovations could have on seal counts. A time-series sequence of images was taken over the 2018-2019 Summer showing the Weddell seals surrounding Scott Base, Antarctica. Three DSLR cameras were set up with their viewpoints. The 10-minute interval images were cropped to *5000 x 700* pixels to focus on the colony [1]. Fig. 6 shows example images of the three viewpoints surrounding Scott Base.

(a) Camera A



(b) Camera B



(c) Camera C

Fig. 6: Example images of the three cameras co-located with Scott Base

The 2019 Antarctic Dataset contains a total of 25,275 images split across the three camera angles. With Camera A, B and C possessing 6980, 9113 and 9182 images respectively. It is not feasible for the ResNet-18 architecture (with an input size of *224 x 224*) to train on such a large dataset. Additionally, each image must be manually classified as to whether it contains a snowstorm. It is for these reasons that the Antarctica Dataset Subset (ADS) was created. The ADS contains a smaller total count of 894 images split evenly across the three cameras. The choice to evenly split the dataset across the viewpoints was to avoid an inaccurate precision-recall curve due to class imbalance [11].

C. Image Preprocessing

The aim of preprocessing is to prepare the images to be fed into a neural network. Additionally, augmentations are commonly added to artificially boost the input dataset and to give the model a wider array of scenarios to train on. Augmentations can help to generalise a model, however, due to the static nature of the ADS (fixed size, camera position, lens), only basic augmentations were applied. For the proposed ResNet-18 model the following stages are performed on the images:

Data Partitioning: This stage splits the ADS into three datasets: training (70%), validation (15%) and testing (15%). This partition ratio is recommended for datasets of this size [12]. The model in initially fit to the training dataset to learn the weights of the network. Next, the semi-trained model is tested on the validation set to evaluate the immature model and tune its hyperparameters. The final dataset provides an unbiased evaluation on the final model.

Random Crops: Due to the large nature of the ADS images, the images were unified by cropping them to a *500 x 500* square. The images were cropped at five random locations in the image. Because a storm's decrease in visibility is observed in every location of an image, a random crop would suffice. Having five crops per image also synthetically increased the ADS size by fivefold from 894 to 4470 images. Fig. 7 shows an example of five square crops using Camera A.

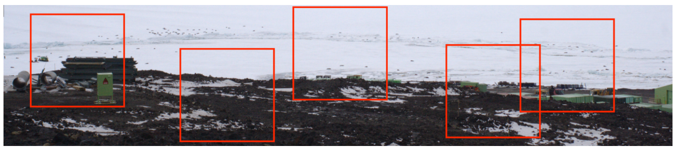


Fig. 7: Image from Camera A with five red squares each representing a *500 x 500* crop

Random Resize: This stage ensures that the input image meets the ResNet-18 input size restriction. The synthetic crops from the previous stage are resized into a *224 x 224 x 3* matrix. This matrix size fits a 224 pixel square RGB image where the three colour channels are each separately encoded as a third dimension. The resize is randomly centered in the image to improve the robustness of the model.

Random Horizontal Flip: This stage will randomly flip an image with a 50% probability. Alike other data augmentations, this improves the performance and outcome of the model by forming a diverse training dataset.

Dataset Shuffling: Every epoch the dataset is shuffled during training. This stage tries to avoid overfitting the model and reducing its variance. For example, by training on the storm before the clear images, we are not providing a dataset representative of the overall distribution of data.

D. Finetuning

Finetuning an existing pre-trained model on a specific dataset can save a developer time and can result in better-performing models [13]. The finetuning component in the proposed pipeline starts with a model with ResNet-18 weights learnt from the ImageNet dataset. Fig. 8 exhibits finetuning by learning the parameters for a generalised CNN and then applying the learnt weights to a specialised CNN (snowstorm classification. Fig. 8 also illustrates the modification in the output layer, decreasing the number of classes to two.

The pre-trained model is then fine-tuned on the ADS to classify snowstorms. During training, the loss (calculated by the Cross-Entropy Loss Function) decreases as the optimisation function modifies the weights and their bias. As mentioned, the Cross-Entropy Loss Function is used to evaluate the model after each epoch. The Cross-Entropy Loss Function is defined as:

$$L = -\frac{1}{N}\left[\sum_{j=1}^{N}[t_j log(p_j) + (1-t_j) log(1-p_j)]\right] \tag{1}$$

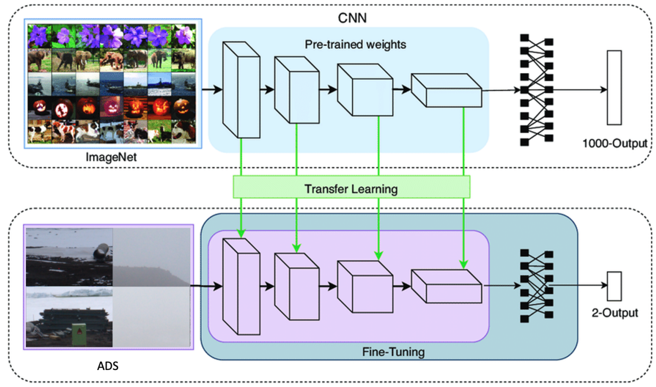


Fig. 8: Finetuning from ImageNet trained model. Figure adapted from [14]

Where N is the number of classes, t_i is the truth value (either 1 or 0) and p_i is the Softmax probability for the ith class.

The optimisation function used was stochastic gradient descent (SGD) with momentum. The popular momentum method was included to aid convergence time. Momentum works by remembering the previous change in weight and using its magnitude to accelerate towards convergence. The formula for SGD with momentum is defined as:

$$\begin{aligned} \Delta w_{t+1} &:= \mu \Delta w_t - \alpha g_{t+1} L \\ w_{t+1} &:= w_t + \Delta w_{t+1} \end{aligned} \tag{2}$$

Where w is the weight, μ is the momentum (between 0 and 1), α is the learning rate, g is the gradient and L is the loss function given by eq. (1). In this paper, $\alpha = 0.001$ and $\mu = 0.9$.

E. Classification

Last in the pipeline is determining which class is best represented by the ResNet-18 output. The results from the final ResNet-18 layer are average-pooled and flattened into a *2 x 1* matrix. Due to the nature of a binary classification task, the Softmax function effectively calculates the probability of the image being a snowstorm. The Softmax function is defined as:

$$\sigma(z_i) = \frac{e^{z_i}}{\sum_{j=1}^{N} e^{z_j}} \quad for\ i = 1, 2, \ldots, N \tag{3}$$

Where N is the number of classes.

F. Ensemble Classification

All the aforementioned techniques have been concerning classifying snowstorms in small *224 x 224* images. Inaccurate classifications can occur if a single crop is used to classify the original *5000 x 700* image. To overcome this, an ensemble of classifications is conducted on the original image, using and ensemble of methods provides a better performing classifier [15]. Akin to the preprocessing stage, the image is cropped five times in random locations. The model classifies each of the five images and combined accuracy is calculated. eq. (4) defines the method for combining the accuracies of the classifications.

$$a_j := \begin{cases} a_j, & \text{if Storm} \\ -a_j, & \text{if Clear} \end{cases}$$
$$a_{combined} := \frac{\sum_{j=1}^{E} a_j}{E} \tag{4}$$

Where a is accuracy and E is the number of crops (five in this case). eq. (5) shows how the final classification is chosen where C is the predicted class. Accuracies can be both positive (Storm) and negative (Clear).

$$C := \begin{cases} Storm, & \text{if } a_j \geq 0 \\ Clear, & \text{if } a_j < 0 \end{cases} \tag{5}$$

IV. Results

Tab. I illustrates a summary of the development environment itself and its configurations when training the ResNet-18 model.

TABLE I: Development Environment Details

Item	Description
OS	Linux Mint 20.3
CPU	Intel Core i7-8700 @ 3.20GHz
GPU	Nvidia GeForce RTX 2070
IDE	JetBrains Gateway Beta 2022.1
Language	Python 3.8.10
Camera	Panasonic Lumix DC-S1R (47MP)
Model	ResNet-18
Loss Function	Cross-Entropy
Optimiser	Stochastic Gradient Descent
Epochs	15
Batch Size	8
Learning Rate	0.001
Momentum	0.9

To quantify the model's performance, four well-known metrics have been used. Namely, accuracy, precision, recall and F1-score. Each metric is briefly described below with True Positive, True Negative, False Positive and False Negative respectively abbreviated to TP, TN, FP and FN:

Accuracy: The ratio of the number of correct classifications to the total number of classifications.

$$accuracy = \frac{TP + TN}{FP + FN} \tag{6}$$

Precision: The number of correct snowstorm classifications to the total number of snowstorms seen.

$$precision = \frac{TP}{TP + FP} \tag{7}$$

Recall: The number of correct snowstorm classifications to the total number of snowstorms classified.

$$recall = \frac{TP}{TP + FN} \tag{8}$$

F1-Score: A measure of the classification's accuracy when accounting for the models precision and recall.

$$F_1Score = 2 \times \frac{recall \times precision}{recall + precision} \tag{9}$$

To measure the model's performance during training, the loss and the F1-score were calculated. The loss function — defined by eq. 1 — showed improvement in the model as the pre-trained model has a loss of 0.3004 and the final fine-tuned model has a loss of 0.0774. A history of the best F_1-Score — defined by eq. 9 — was also tracked during the 15 epochs. Fig. 9 shows the progression of the model starting at $F_1 = 0.926$ and finishing at $F_1 = 0.9692$.

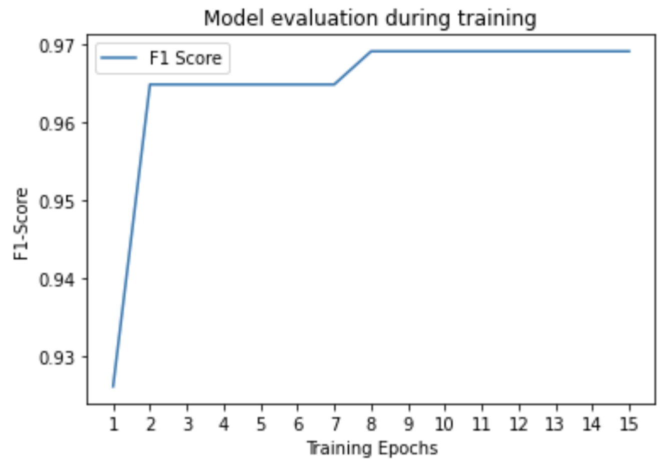


Fig. 9: Best F_1Score over 15 epochs

The performance of the proposed model can be illustrated by a confusion matrix. This shows the distribution of the True Positive, True Negative, False Positive and False Negatives. Fig. 10 illustrates the final snowstorm classifiers confusion matrix.

Digesting Fig. 10, the proposed model performs excellent with $< 2.5\%$ of images being incorrectly classified. The proposed model is quantifiably evaluated below using the aforementioned metrics.

$$\boldsymbol{accuracy = 97.8\%} \quad eq. (6) \qquad \boldsymbol{precision = 99.6\%} \quad eq. (7)$$
$$\boldsymbol{recall = 95.5\%} \quad eq. (8) \qquad \boldsymbol{F_1Score = 97.5\%} \quad eq. (9)$$

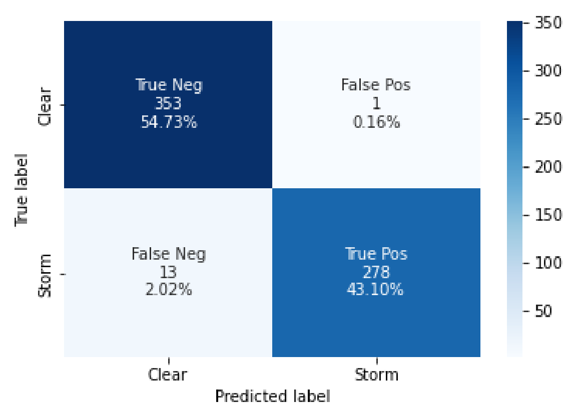


Fig. 10: Confusion Matrix or proposed ResNet-18 model

The proposed model offers a reliable snowstorm classifier with high accuracy in the trained environment. Other metrics — namely the $F_1 Score$ at 97.5% — back this claim with their encouraging results. However, the praises of the proposed model cannot be celebrated without considering its limitations of such. The model has only been trained and tested on a relatively narrow dataset (ADS). This can restrict the performance of the model in environments that even slightly differ to that of Cameras A, B & C. Fortunately, this was foreseen and can be treated as a non-issue due to the application of the model aligning (down to the viewpoint) with the trained dataset. It is therefore noted, as a constraint and warning, that the proposed model is not generalised but specialises in classifying snowstorms in the three cameras surrounding Scott Base.

V. Conclusion

Antarctica New Zealand's Scott Base redevelopment is set to start after the planning and design are finalised at the end of 2022. Previous research, conducted by Oliver Batchelor [1], commenced monitoring of nearby Weddell Seal colonies to ensure the population is not disturbed. This research paper proposed a ResNet-18 CNN to classify snowstorms in the Seal images taken in the 2019-2020 Summer. A reliable and accurate model empowers researchers to distinguish between true and false low counts of the population (where false counts arise from snowstorm induced low-visibility).

The final CNN model was finetuned from an ImageNet pretrained model to save time and increase performance. Specifically, the model was finetuned using a subset of previously captured images from Antarctica. This dataset was chosen for its near-identical viewpoints to its application. A random 70%, 15%, 15% partition was applied to split the images into training, validation and testing data loaders respectively. Finally, the proposed model shows encouraging results in comparison to existing weather classification research. The accuracy of the proposed model (97.8%) outperforms the SAID ensemble approach [4] (86%) by 12.84% while it falls short by only 0.429% of an alternative ResNet-18 weather classification CNN [6] (98.22%).

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VI. Appendix

A. Source code

The Jupyter Notebook containing the image preprocessing, finetuning and classification stages are hosted online at https://github.com/fletcherd3/Antarctic-Snowstorm-Classification/blob/master/storm_detection.ipynb.

B. Dataset

The random cropped images created from the Jupyter Notebook are organised into their classes (Storm & Clear) and the datasets (train, validation & testing). The images are hosted online at https://github.com/fletcherd3/Antarctic-Snowstorm-Classification/tree/master/data.