1. Introduction

In order to estimate the snow percentage of parking road images, a novel algorithm is proposed in this article. Through data augmentation and feature extraction, a regression model is trained. After several experiments, the results demonstrate that the algorithm is able to estimate roughly the covered snow ratio of each image.

2. Data preprocessing

Since the exact snow coverage rate of given images is unavailable from the training data, annotating manually snow coverage rate for all images is time-consuming but necessary for supervised learning. The CAD, a famous design software is applied to label the snow area of images and compute its rate. An annotated sample is shown in the following figure:

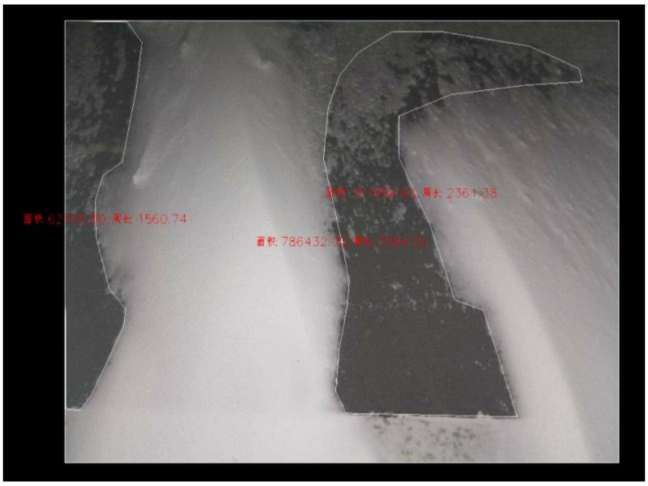

Fig.1. Annotation sample

Additionally, the given dataset is unbalanced with significantly different number of each categorial image. The experiment with original data shows unsatisfactory performance on the images with a snow coverage of more than 50% because of inadequate images. Therefore, data augmentation is necessary for the images with snow cover. Before that, the first 100 images in each category, a total of 300 images are picked to consist of the testing images, the rest images are applied to train and generate new images. Through randomly rotate, shear, shift and flip the training images, new images are numerously generated. Specifically, the number of images in the second category has doubled, and the number of images in the third category has enlarged 6 times. Detailed information is displayed in the table below:

Snow category	Original image	Test image	Train image	Generated images	New train images
0	1695	100	1595	0	1595
<0.5	934	100	834	834	1668
>=0.5	300	100	200	1200	1400
Total	2929	300	2629	2034	4663

Tab.1. The number of images in each category

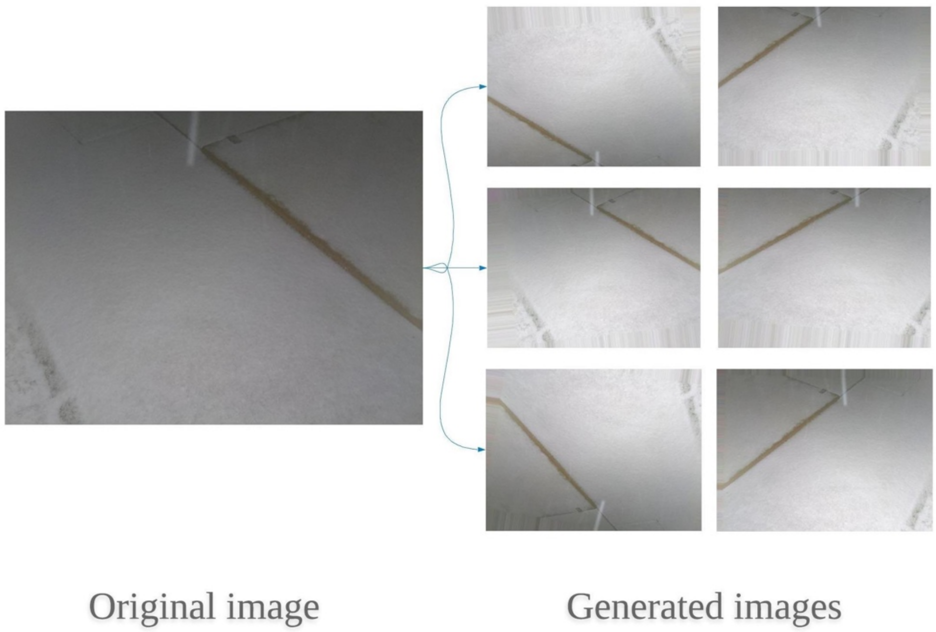

Fig.2. Data augmentation sample

The figure above exhibits the newly generated images sample based on the images with a snow coverage greater than 50%. Evidently, the new images are near to the original image on the snow coverage. Thereby, original snow rate data is used in those new images without extra annotation. Through data augmentation, an almost equal number of images in every category is fed into model for training.

3. Algorithms

The challenge is obviously a regression question as the exact snow coverage rate of each image is required to estimate. As is shown in the flow chart below, the image is firstly input into the base model for extracting feature, then extracted feature is fed into regression model for predict the exact snow percentage.

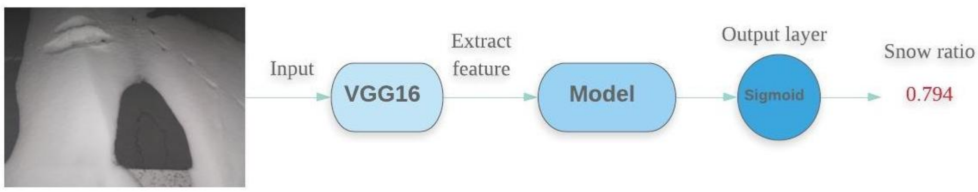

Fig.3. Algorithm flow chart

The selected base model is vgg16, which is a very famous and widely used deep convolutional neural network. Before feeding images into the vgg16 model, implement some preprocessing operations on the images, including standardization and rescale. Subsequently, the extracted feature is input into the regression model, which consists of one global average pooling layer, five dense layers with relu activation function, and an output layer with a sigmoid activation function. Finally, the prediction result between 0 and 1 will be output through the sigmoid function in the last layer.

4. Experiments and Result

At the very beginning, the original training images (2629 images) are utilized to train. Despite the trained model performing well on the images without any snow cover, the estimation result on other images is terrible. When the newly generated images (2034 images) through data augmentation are added to train, the newly trained model outperforms the former one.

To evaluate the model, a new metric function named sAcc is defined following the request of the exam. When the estimation result falls within 20% up and down of the ground truth snow coverage rate is taken as the correct answer, then computing the average accuracy with the validation images. The highest accuracy model will be adopted to test the final dataset. Besides, the mean squared error (MSE) and mean absolute error (MAE) are also taken as the metrics of model performance.

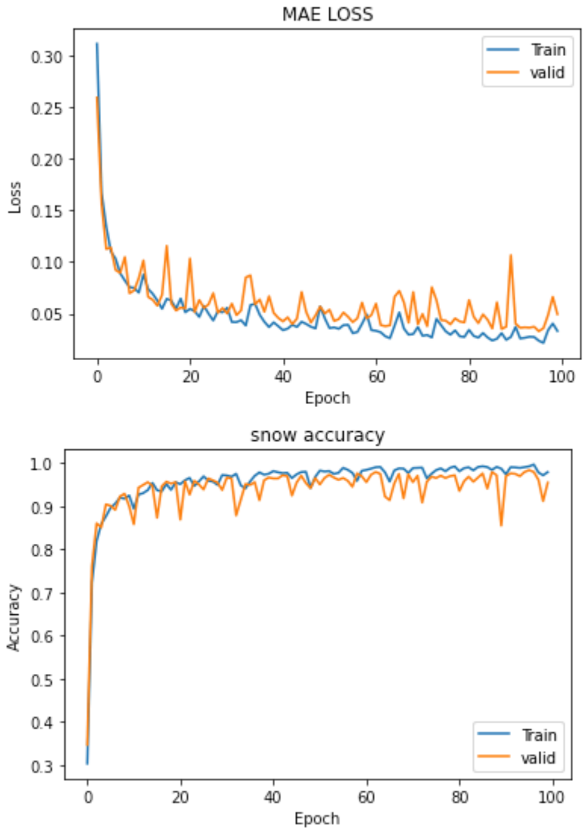

Fig.4. The variations of training and validation loss and accuracy

The new training data (total 4663 images) is split into train and valid subsets images with a ratio of 8:2. Namely, 3731 images are used in training and the rest 932 images are applied to validate model's performance at every epoch. The figure above displays the variation of accuracy and MAE loss during the 100 training epochs. Obviously, the MAE loss has generally decreased and the valid accuracy has generally grown.

Eventually, both curves stabilize and the valid accuracy has reached 0.984, demonstrating the model is capable of estimating the images' snow coverage ratio. When the test images are fed into trained model, the average accuracy rate is 93.3%, greater than the former model. The detailed information is shown in the table below:

Category	Snow = 0	0 < snow <0.5	0.5<=snow<=1	Total
MSE	0.0049	0.0138	0.049	0.049
MAE	0.0136	0.0592	0.097	0.0564
Accuracy	99%	92%	89%	93.3%

Tab.2. The experiment result on test dataset

The test dataset includes 300 images, which is equally divided into three categories as mentioned before. In spite of the MAE on the images of second and third category is comparatively large, the model exhibits high accuracy on overall images. Actually, the estimation on the images with snow coverage more than 50% is superior to the former model without data augmentation, which is only 83% accuracy. Thereby, the newly trained model is capable of estimating the snow rate of images with relatively small error.

5. Conclusion:

A novel method is proposed in this article to estimate the snow coverage ratio of parking lot road images. The experiment results demonstrate that the method is able to compute the ratio within a small error. However, there are also some drawbacks, needing to further improve. For example, the snow rate of newly generated images employs original annotation, which will cause some errors and influence on the model training. If these newly generated images are manually relabeled, the performance of the model would be further improved. Furthermore, considering generating new images by means of the Generative Adversarial Networks (GAN) to solve imbalanced data problems. Besides, preprocessing image is a feasible way to improve model prediction accuracy. When checking the wrong prediction cases, it found that the light environment and shadow of images have an effect on model prediction. Specifically, if the image without any snow cover is taken in the bright light environment due to the flash, the model would easily estimate the wrong answer. To sum up, make some efforts on these aspects will further enhance the performance of the model.