

Natural Scenes Image Classification

Machine Learning 1 (Fall 2021)

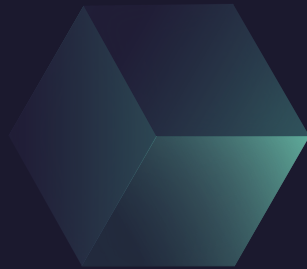
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Group 1

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Introduction

- Dataset
- Convolutional Neural Network
- Preprocessing
- Models
- Results



Dataset

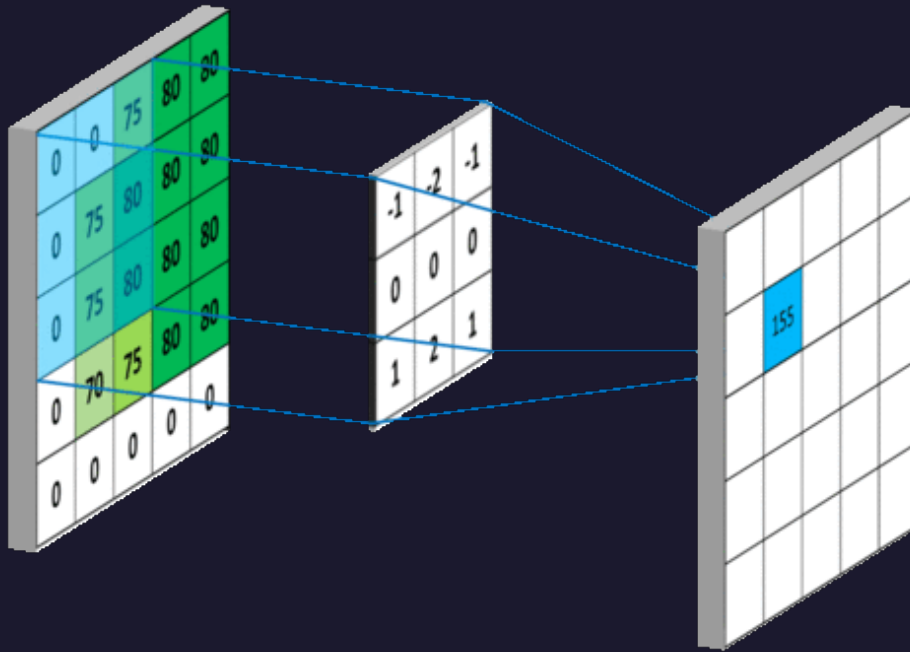
- Kaggle dataset "[Intel Image Classification](#)" of natural scenes around the world. Images are in color and contain 150x150 pixels
- The dataset separated train and test data into main directories and placed each image in a subdirectory corresponding to its class

Total Number of Images	17,034
• Training	14,034
• Test	3,000

Classes	Number
• Building	0
• Forest	1
• Glacier	2
• Mountain	3
• Sea	4
• Street	5



Convolutional Neural Network



- Feedforward Neural Network (FNN) is not scalable for image processing. Perceptron required for each pixel of image
- FNN sensitive to variations in image whereas CNN can handle variations in image
- CNN is superior model to FNN in terms of accuracy and speed because it is designed for computer vision

Data Visualization

- What do images from each class look like?

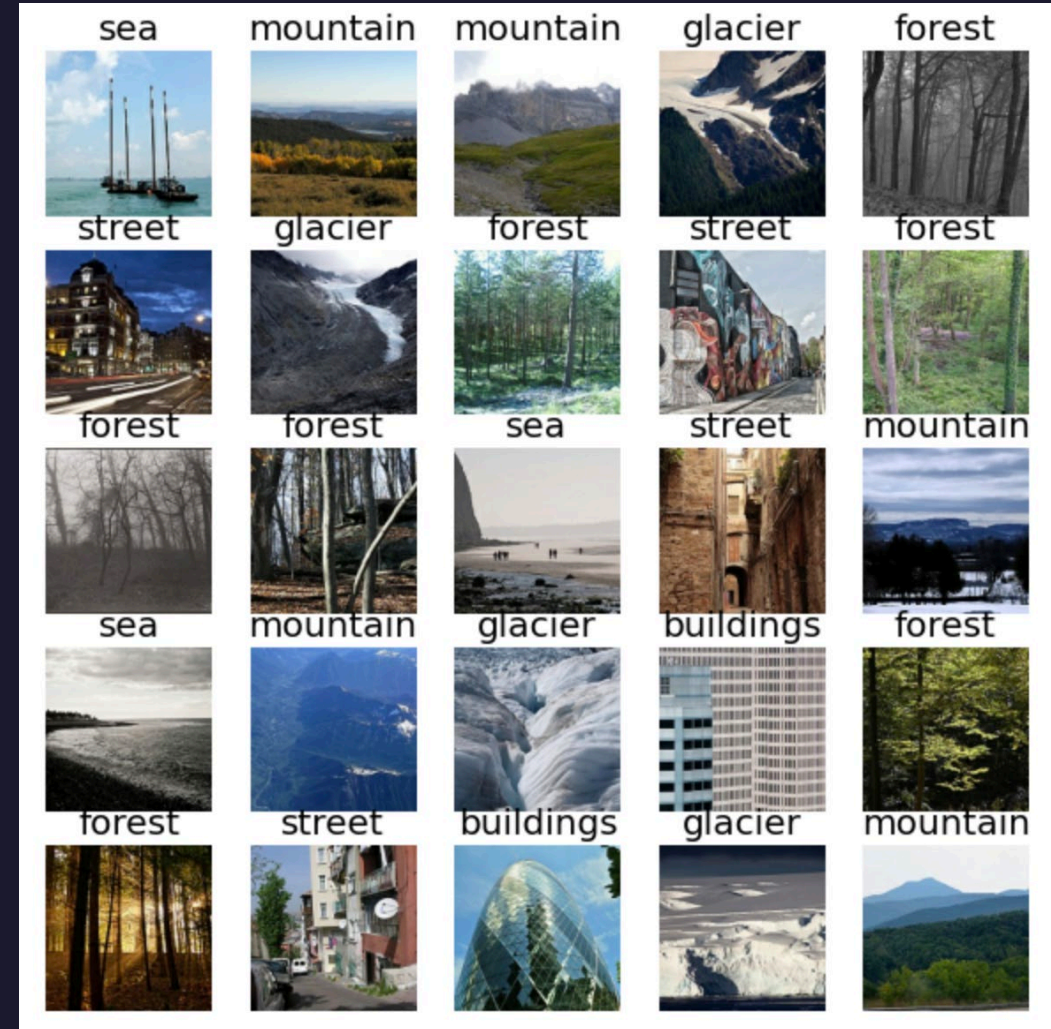


Figure: Sample Images from the Training Data

Preprocessing

- Unrelated images found in each class directory:
 - The Glacier class was the biggest culprit
 - Other classes had fewer irrelevant images
- Cleaned up bad data:
 - Problem images were removed from the training data



Figure A: images found in glacier's class directory.

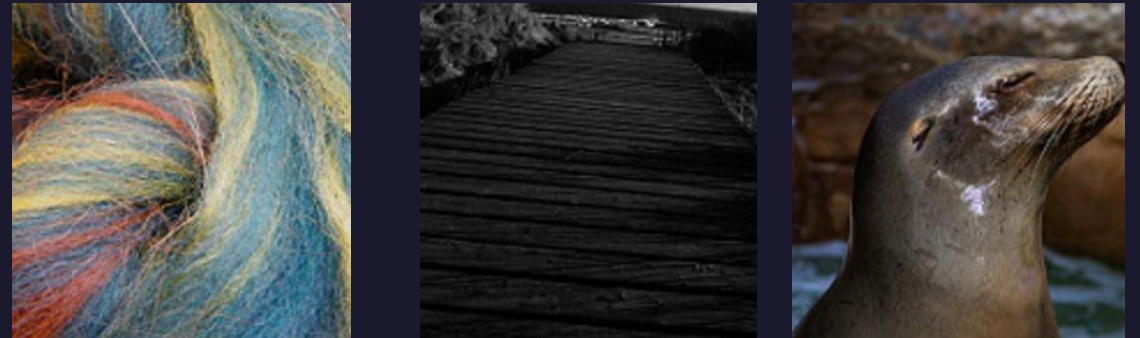
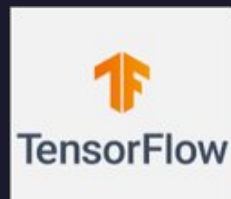


Figure B: Images found in other directories.



Train versus Test Data Points



- `tf.keras.utils.image_dataset_from_directory`
- Combined training and validation data in 80:20 split

Total Number of Images	16,942
• Training	11,154
• Validation	2,788
• Test	3,000

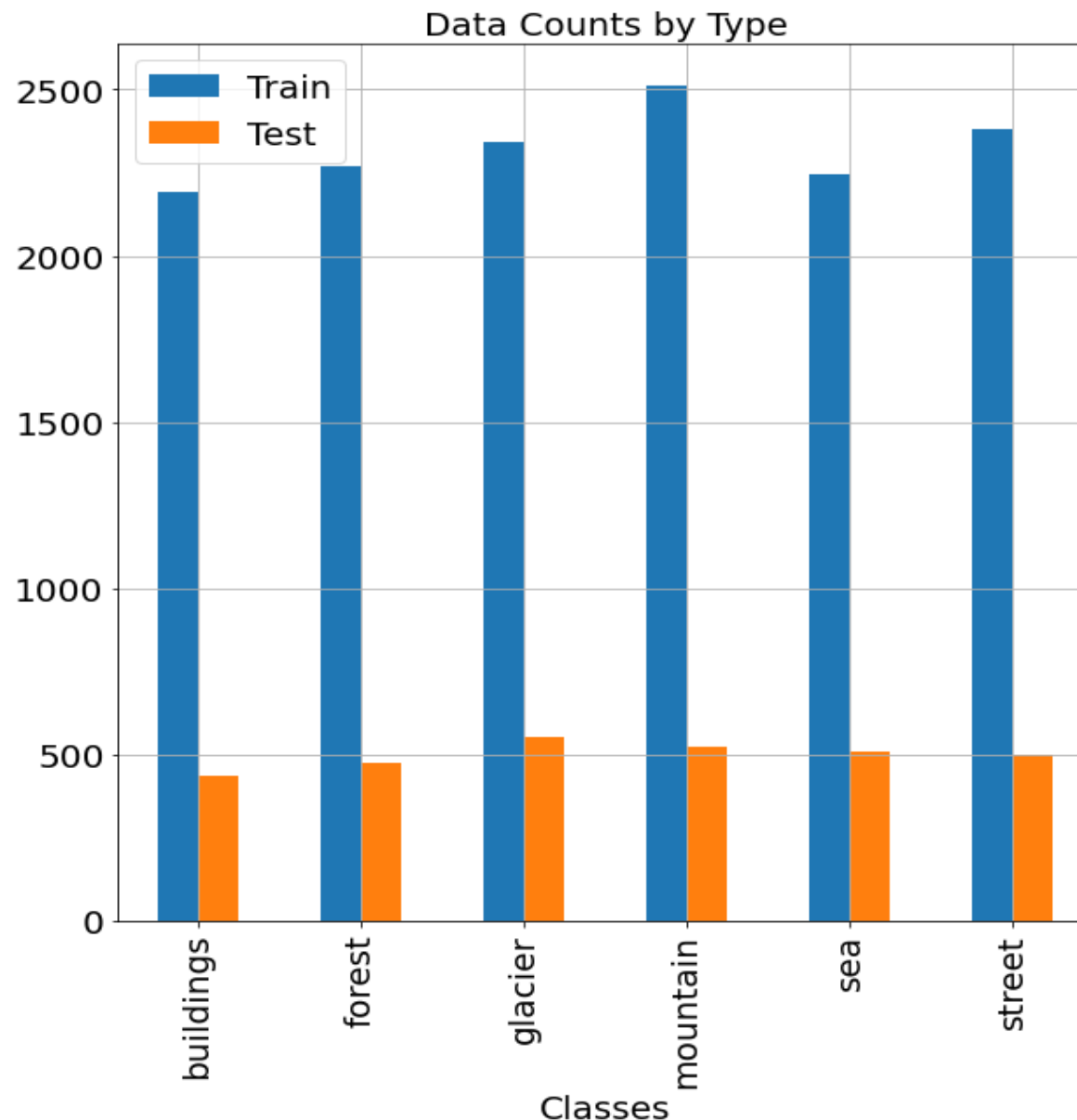


Figure: Data counts by Type

COMMON PARAMETERS

- CNN Transfer Learning using ResNet50, VGG16 and AlexNet
- Epochs: 5
- Callbacks
 - Early stopping patience of 2
 - Reduce learning by 0.1 with validation loss does not improve within 1 epoch

Model	Pretrained CNNs	Hyperparameter Tuning
CNN Case Study (Baseline)	<u>ResNet50</u>	Adam optimizer (learning rate = 0.001)
Model 1	<u>ResNet50</u>	SGD optimizer (learning rate = 0.0001)
Model 2	<u>VGG16</u>	Adam optimizer (learning rate=0.0002)
Model 3	<u>AlexNet</u>	SGD optimizer (learning rate = 0.001)

ResNet50

ResNet

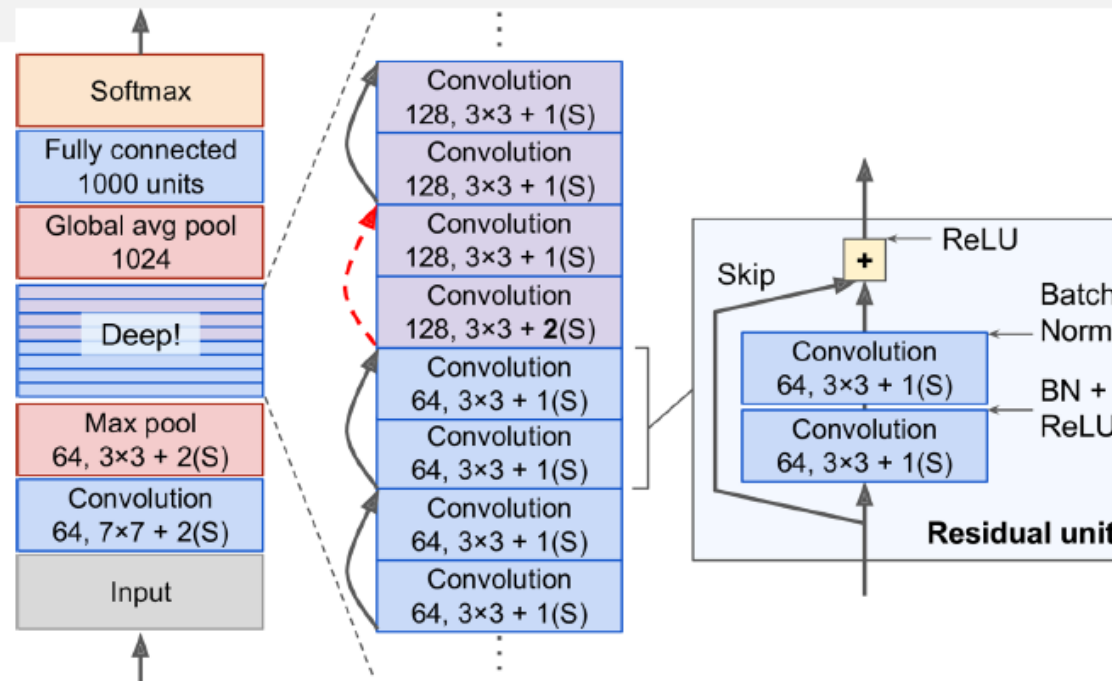
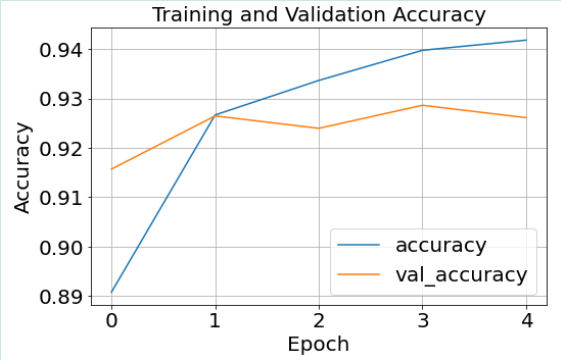
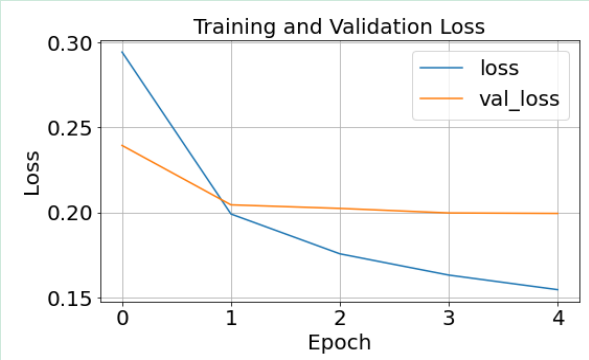
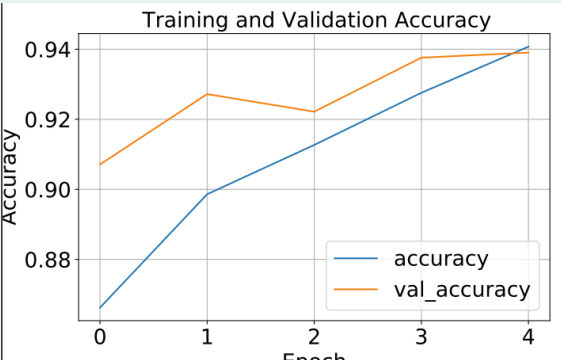
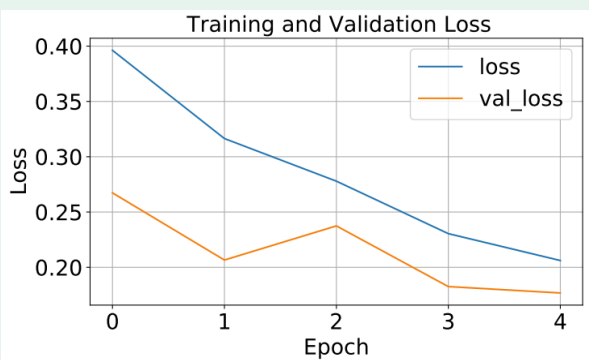
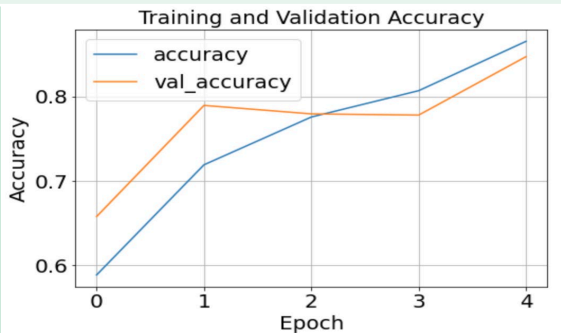
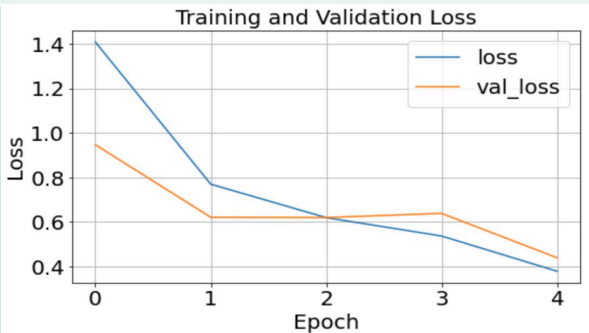


Figure 19: The architecture of ResNet. Picture courtesy of *Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow (2nd Edition)*.

Results

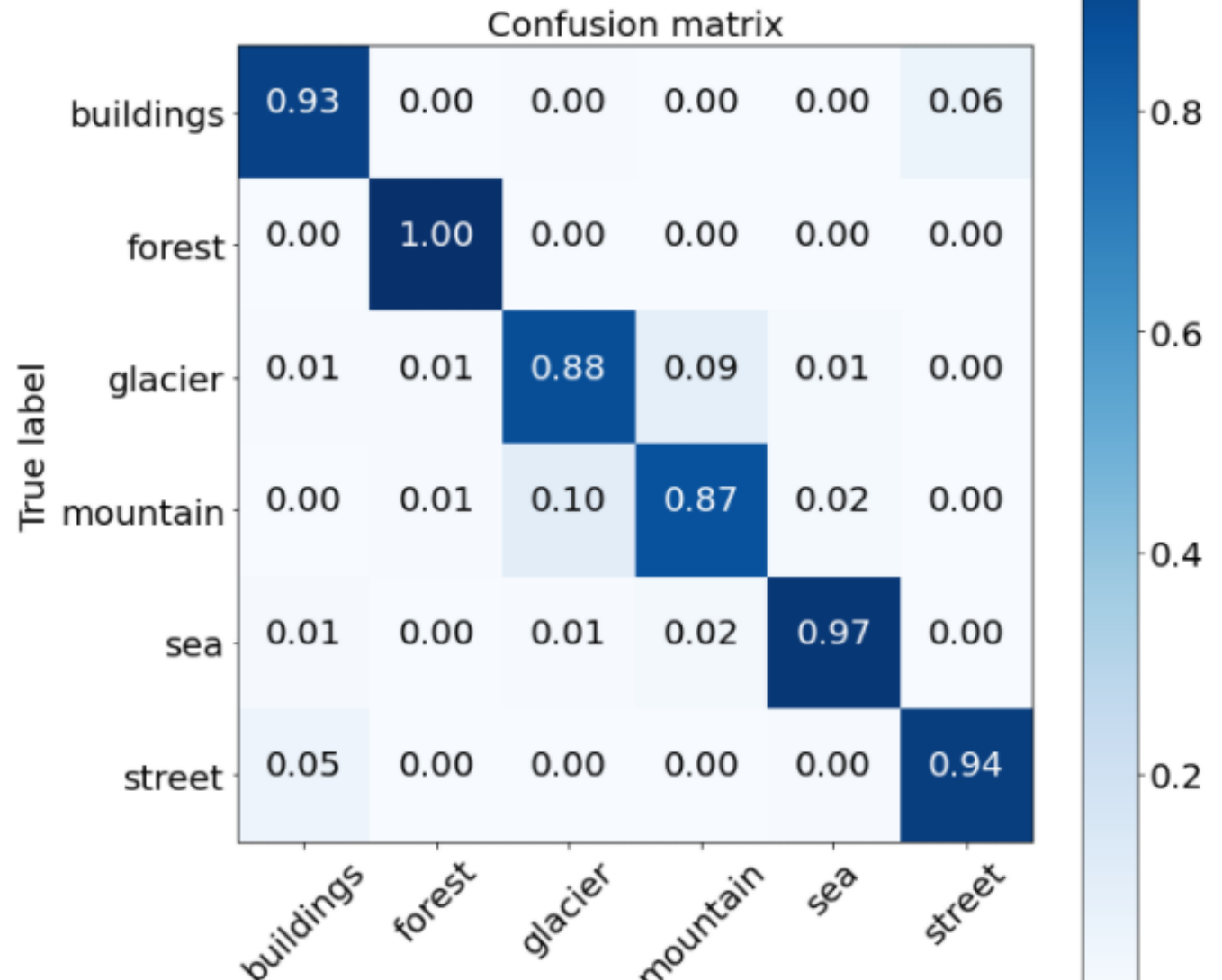
- Model 1 had the highest accuracy but only slightly higher than Model 2
- Model 2 had the lowest loss
- Collab Notebooks executed using GPU so accuracy is not reproducible

Model	Network	Optimizer	Accuracy*	Loss
CNN Case Study	ResNet50	Adam optimizer (learning rate = 0.001)	0.8887	0.3414
Model 1	ResNet50	SGD optimizer (learning rate = 0.0001)	max=0.9353 μ = 0.9301 std = 0.0052 min = 0.9290	max=0.2207 μ = 0.2132 std = 0.0064 min = 0.2207
Model 2	VGG16	Adam optimizer (learning rate = 0.0002)	max=0.9310 μ = 0.9296 std = 0.0019 min = 0.9263	max=0.2089 μ = 0.2022 std = 0.0056 min = 0.1972
Model 3	AlexNet	SGD optimizer (learning rate = 0.001)	max=0.8703 μ = 0.8595 std = 0.0111 min = 0.8453	max=0.4646 μ = 0.4311 std = 0.0243 min = 0.3974

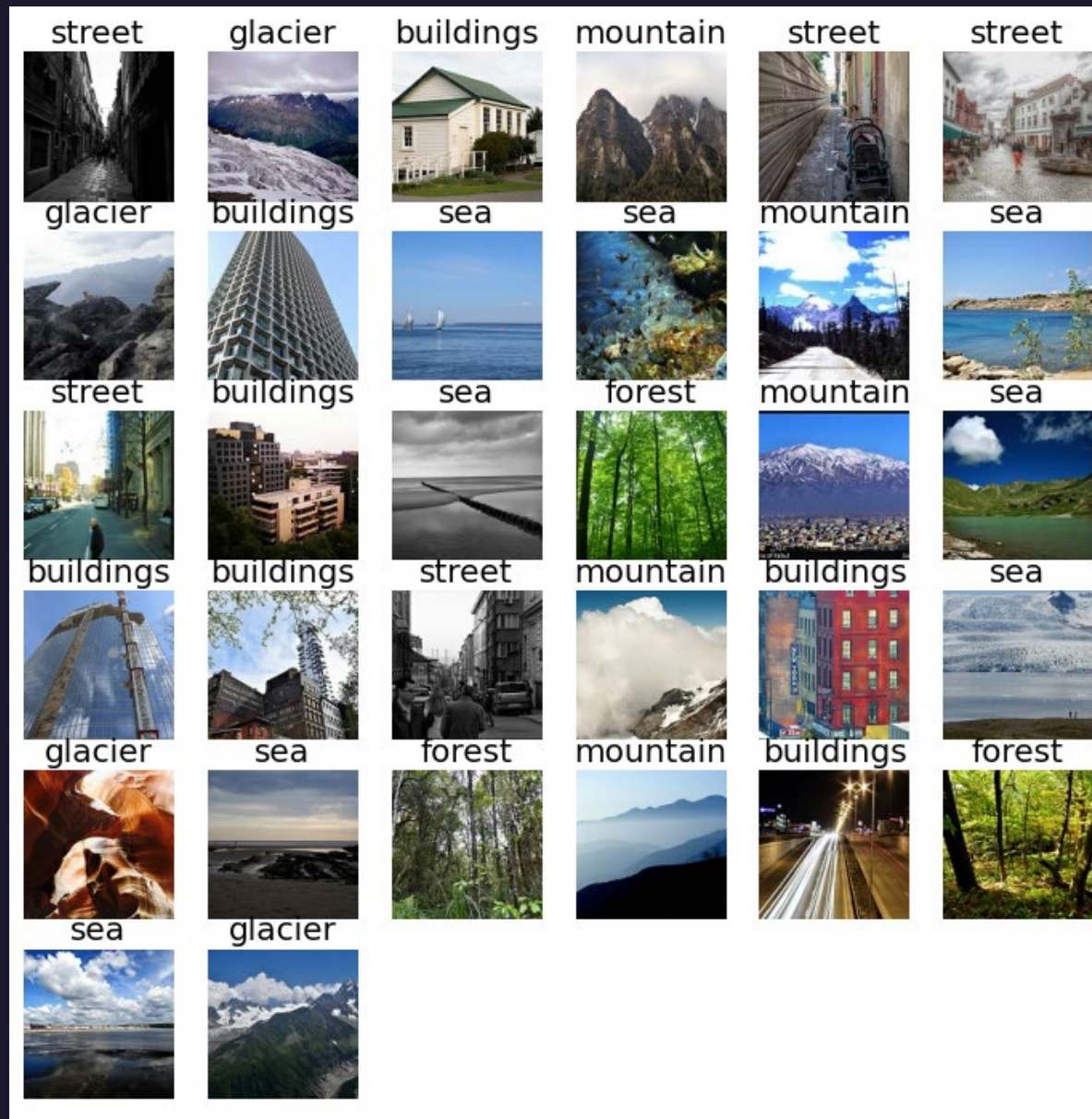
Model	Accuracy	Loss																																				
• Model 1 (ResNet50)	 <table border="1"><caption>Training and Validation Accuracy for Model 1 (ResNet50)</caption><thead><tr><th>Epoch</th><th>accuracy</th><th>val_accuracy</th></tr></thead><tbody><tr><td>0</td><td>0.89</td><td>0.915</td></tr><tr><td>1</td><td>0.925</td><td>0.925</td></tr><tr><td>2</td><td>0.935</td><td>0.925</td></tr><tr><td>3</td><td>0.94</td><td>0.928</td></tr><tr><td>4</td><td>0.942</td><td>0.925</td></tr></tbody></table>	Epoch	accuracy	val_accuracy	0	0.89	0.915	1	0.925	0.925	2	0.935	0.925	3	0.94	0.928	4	0.942	0.925	 <table border="1"><caption>Training and Validation Loss for Model 1 (ResNet50)</caption><thead><tr><th>Epoch</th><th>loss</th><th>val_loss</th></tr></thead><tbody><tr><td>0</td><td>0.29</td><td>0.24</td></tr><tr><td>1</td><td>0.20</td><td>0.205</td></tr><tr><td>2</td><td>0.18</td><td>0.202</td></tr><tr><td>3</td><td>0.165</td><td>0.20</td></tr><tr><td>4</td><td>0.155</td><td>0.20</td></tr></tbody></table>	Epoch	loss	val_loss	0	0.29	0.24	1	0.20	0.205	2	0.18	0.202	3	0.165	0.20	4	0.155	0.20
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• Model 2 (VGG16)	 <table border="1"><caption>Training and Validation Accuracy for Model 2 (VGG16)</caption><thead><tr><th>Epoch</th><th>accuracy</th><th>val_accuracy</th></tr></thead><tbody><tr><td>0</td><td>0.865</td><td>0.905</td></tr><tr><td>1</td><td>0.90</td><td>0.925</td></tr><tr><td>2</td><td>0.915</td><td>0.92</td></tr><tr><td>3</td><td>0.93</td><td>0.938</td></tr><tr><td>4</td><td>0.94</td><td>0.94</td></tr></tbody></table>	Epoch	accuracy	val_accuracy	0	0.865	0.905	1	0.90	0.925	2	0.915	0.92	3	0.93	0.938	4	0.94	0.94	 <table border="1"><caption>Training and Validation Loss for Model 2 (VGG16)</caption><thead><tr><th>Epoch</th><th>loss</th><th>val_loss</th></tr></thead><tbody><tr><td>0</td><td>0.40</td><td>0.27</td></tr><tr><td>1</td><td>0.32</td><td>0.21</td></tr><tr><td>2</td><td>0.28</td><td>0.24</td></tr><tr><td>3</td><td>0.235</td><td>0.185</td></tr><tr><td>4</td><td>0.205</td><td>0.18</td></tr></tbody></table>	Epoch	loss	val_loss	0	0.40	0.27	1	0.32	0.21	2	0.28	0.24	3	0.235	0.185	4	0.205	0.18
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• Model 3 (AlexNet)	 <table border="1"><caption>Training and Validation Accuracy for Model 3 (AlexNet)</caption><thead><tr><th>Epoch</th><th>accuracy</th><th>val_accuracy</th></tr></thead><tbody><tr><td>0</td><td>0.58</td><td>0.66</td></tr><tr><td>1</td><td>0.72</td><td>0.79</td></tr><tr><td>2</td><td>0.78</td><td>0.78</td></tr><tr><td>3</td><td>0.81</td><td>0.78</td></tr><tr><td>4</td><td>0.85</td><td>0.84</td></tr></tbody></table>	Epoch	accuracy	val_accuracy	0	0.58	0.66	1	0.72	0.79	2	0.78	0.78	3	0.81	0.78	4	0.85	0.84	 <table border="1"><caption>Training and Validation Loss for Model 3 (AlexNet)</caption><thead><tr><th>Epoch</th><th>loss</th><th>val_loss</th></tr></thead><tbody><tr><td>0</td><td>1.4</td><td>0.95</td></tr><tr><td>1</td><td>0.78</td><td>0.62</td></tr><tr><td>2</td><td>0.62</td><td>0.62</td></tr><tr><td>3</td><td>0.55</td><td>0.64</td></tr><tr><td>4</td><td>0.4</td><td>0.45</td></tr></tbody></table>	Epoch	loss	val_loss	0	1.4	0.95	1	0.78	0.62	2	0.62	0.62	3	0.55	0.64	4	0.4	0.45
Epoch	accuracy	val_accuracy																																				
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Normalized Confusion Matrix

- Model 1 (ResNet 50)
- Main Takeaways:
 - **Forest** class had all 474 images correctly predicted.
 - Glacier and Mountain had the smallest percentages of correct predictions.
 - Most of the incorrectly predicted images for the Street class were classified as Buildings, and vice versa.



Model 1 Predicted Images



Conclusion

- Benefits of our models
 - Create IoT drone device to identify objects in nature
 - Aircraft and ship navigation
- Power of transfer learning:
 - ResNet50 base model with accuracy of 93%
- Future work
 - Follow up on confusion matrix and error analysis



Reference

- The code for building, compiling and training CNNs were largely inspired by the following work:
 - Géron, A., 2019. *Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow: Concepts, Tools, and Techniques to Build Intelligent Systems*. O'Reilly Media.
- The deep utilities and pipeline (including data preprocessing, building, compiling and training DNNs) implemented in [/p3 c2 s3 convolutional neural networks/case study](#)
 - Huang, Yuxiao, 2021. "Machine Learning I". Fall 2021.
- Confusion matrix function: https://github.com/imamun93/animal-image-classifications/blob/master/I_notebook.ipynb
- Load and preprocess images: https://tensorflow.google.cn/tutorials/load_data/images
- Keras Applications: <https://keras.io/api/applications/>
- AlexNet Architecture: <https://towardsdatascience.com/implementing-alexnet-cnn-architecture-using-tensorflow-2-0-and-keras-2113e090ad98>