CS 542 Class Challenge Report
Image Classification of COVID-19 X-rays

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Contents

1 Introduction

In this class challenge, we will classify X-ray images. The data we will use has been collected by Adrian Xu, combining the Kaggle Chest X-ray dataset with the COVID-19 Chest X-ray dataset collected by Dr. Joseph Paul Cohen of the University of Montreal. There are two folders: two that will be used for a binary classification task (Task1), and all that will be used for multi-class classification (Task2). An ipython notebook template is provided for each task.

The rest of this report will be organized as follows. Section 2 discusses the data preprocessing and data augmentation methods employed in these tasks. Section 3 and 4 provide solution for task 1 and task 2, respectively. Each task firstly introduces the model architecture and then list the optimizer, loss function, regularization and parameters. Finally, a t-Distributed Stochastic Neighbor Embedding (t-SNE) is used to reduce feature dimension. In task 1, a pre-train VGG16 performs well in a binary classification problem and it achieves a high accuracy of 95%, but a random guess test accuracy. Task 2 is a classification task with 4 classes. VGG16 as a good starter still achieves a high accuracy of 75%. Then, ResNet50V2 architecture is taken as a competing model, which can only achieves 45% validation accuracy and it gets a high test accuracy of 61.11%.

2 Data Preprocessing and Data Augmentation

We could use tf.keras.preprocessing.image.ImageDataGenerator to preprocess the images and generate batches of tensor image data with real-time data augmentation.

- Rescaling the images ($rescale = 1.0/255$).
- Normalize the inputs to zero mean and divide by std of the dataset.
- Synthesize new images by rotating, shifting and flipping vertially and horizontally, zooming in and out and channel shift.
- Fraction of images reserved for validation: 0.2.

3 Task 1 [30 points]

Train a deep neural network model to classify normal vs. COVID-19 Xrays using the data in the folder two. Starting from a pre-trained model typically helps performance on a new task, e.g. starting with weights obtained by training on ImageNet. After training is complete, visualize features of training data by reducing their dimensionality to 2 using t-SNE. If your extracted features are good, data points representing a specific class should appear within a compact cluster.

3.1 Dataset

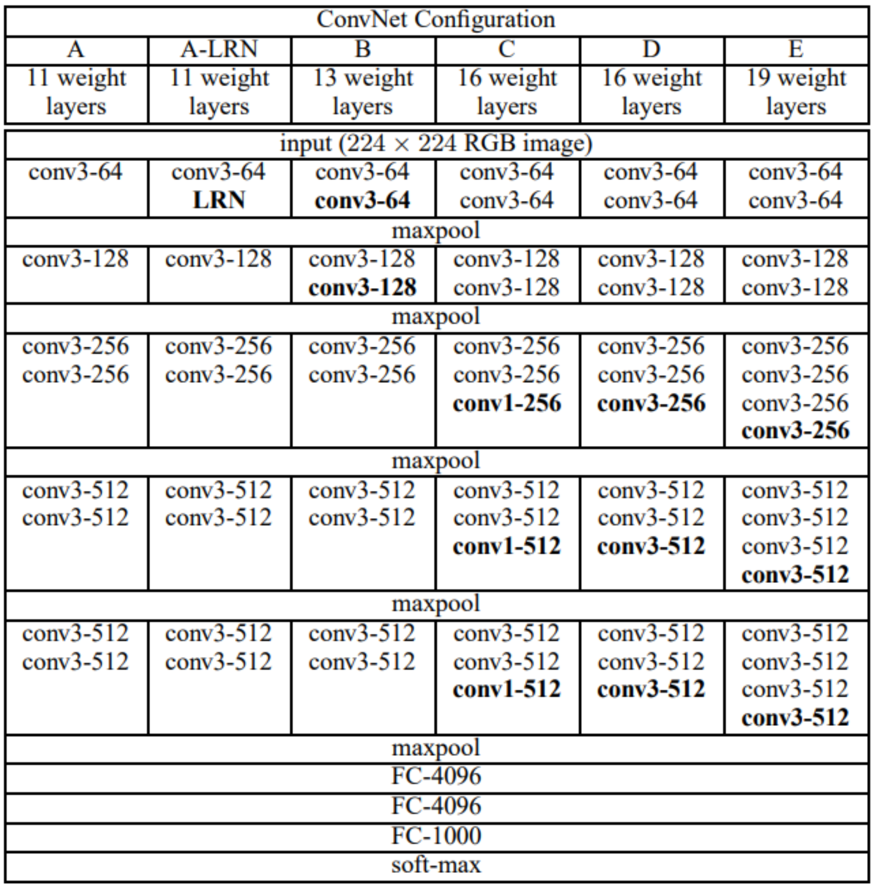
- Training set: 60 images of Covid and 70 of Normal.
- Test set: 9 images of Covid and 9 of Normal.

3.2 VGG16 Architecture for task 1

A pre-trained model VGG16 [1] has been employed in this architecture.

Architecture		
Layer (type)	Output shape	Number of parameters
Input	(None, 224, 224, 3)	0
VGG16 (Model)	(None, 7, 7, 512)	14714688
Flatten	(None, 25088)	0
Fully connected	(None, 256)	6422784
ReLu	(None, 256)	0
Fully connected	(None, 1)	257
Sigmoid	(None, 1)	0

VGG16 achieves a high accuracy on image classifcation. The 3 fully-connected layers at the top of the VGG16 network are re-defined as a flatten layer, a fully-connected layer with ReLu function and another fully-connecte layer with Sigmoid function. ReLu performs well in Convolutional Neural Network. Thus, it is chosen as the activation for the first fully-connected layer.



ConvNet Configuration					
A	A-LRN	B	C	D	E
11 weight layers	11 weight layers	13 weight layers	16 weight layers	16 weight layers	19 weight layers
input (224 × 224 RGB image)					
conv3-64	conv3-64	conv3-64	conv3-64	conv3-64	conv3-64
	LRN	**conv3-64**	conv3-64	conv3-64	conv3-64
maxpool					
conv3-128	conv3-128	conv3-128	conv3-128	conv3-128	conv3-128
		conv3-128	conv3-128	conv3-128	conv3-128
maxpool					
conv3-256	conv3-256	conv3-256	conv3-256	conv3-256	conv3-256
conv3-256	conv3-256	conv3-256	conv3-256	conv3-256	conv3-256
			conv1-256	**conv3-256**	conv3-256
					conv3-256
maxpool					
conv3-512	conv3-512	conv3-512	conv3-512	conv3-512	conv3-512
conv3-512	conv3-512	conv3-512	conv3-512	conv3-512	conv3-512
			conv1-512	**conv3-512**	conv3-512
					conv3-512
maxpool					
conv3-512	conv3-512	conv3-512	conv3-512	conv3-512	conv3-512
conv3-512	conv3-512	conv3-512	conv3-512	conv3-512	conv3-512
			conv1-512	**conv3-512**	conv3-512
					conv3-512
maxpool					
FC-4096					
FC-4096					
FC-1000					
soft-max					

Figure 1: VGG16-Architecture [1]

3.3 Training

- Optimizer: Adam.
- Loss function: tf.keras.losses.BinaryCrossentropy for binary classification problem.
- Epochs: 40.
- Batch size: 10.

3.4 Testing

The validation accuracy achieves around 95%. However, the test accuracy is only 50% over a test set with size of 18, which is a random guess in a binary classifcation problem. The reason may be that the training data is not enough in the first place, secondly, the test data may have high bias.

3.4.1 Accuracy and Loss

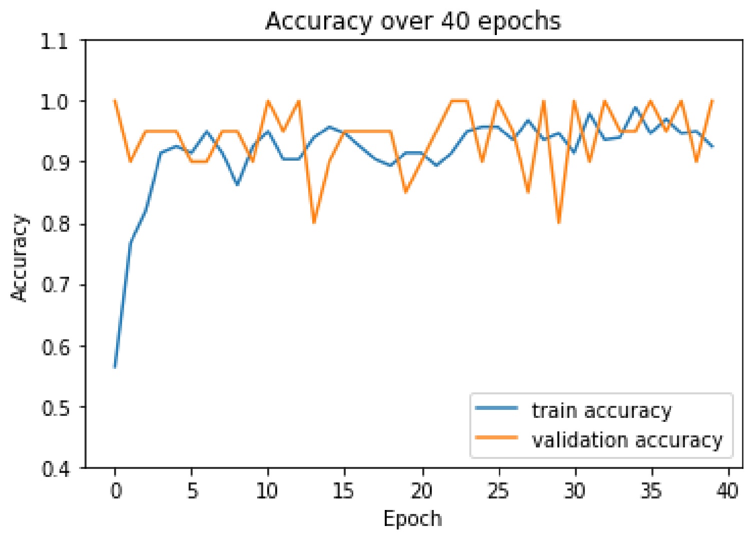


Figure 2: Accuracy on training set and validation set over 40 epochs

After 5 epochs, both train and vallidation accuracy becomes stable. Valication accuracy fluctuates around 95% more drastically than train accuracy does. The valication accuracy is approximately the same as the train accuracy, meaning that the model is not overfitting.

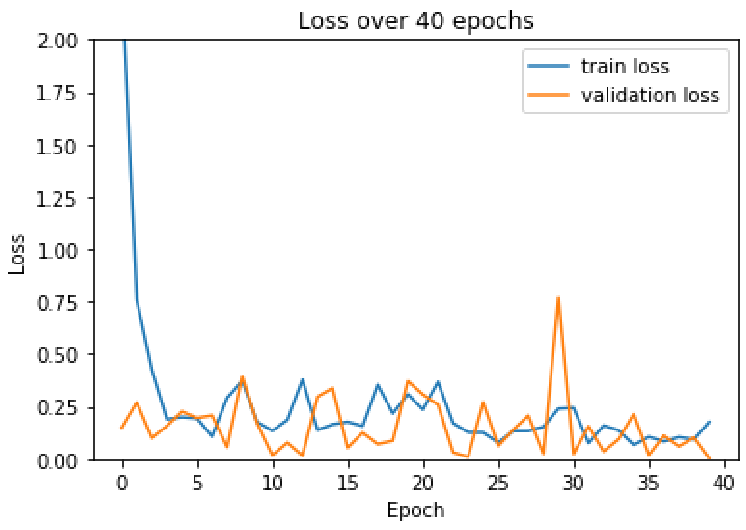


Figure 3: Loss on trainning set and validation set over 40 epochs

The train loss converges after 5 epochs, while the validation loss fluctuates and converges after 30 epochs.

3.4.2 t-SNE visualizations

We use the 130 training data to generate this feature distribution. The output of the first fully-connected layer with 256 neurons is taken as the high-dimension features. T-SEN is used to reduce 256 dimension features to 2 dimension.

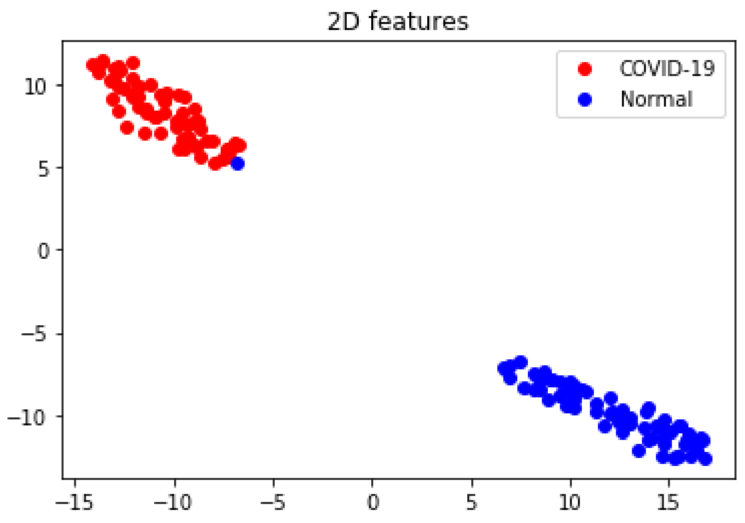


Figure 4: Two dimensional features on class COVID and Normal

The red points are COVID lung X-ray image and the blue are normal ones. The two classes is divide into two distinct clusters, meaning that a good classifier is established by the training of this VGG16 model.

4 Task 2 [30 points]

In this section you present your findings and results. Train a deep neural network model to classify an X-ray image into one of the following classes: normal, COVID-19, Pneumonia-Bacterial, and Pneumonia-Viral, using the folder all. Explore at least two different model architectures for this task, eg. AlexNet vs. VGG16. After training is complete, visualize features of training data by reducing their dimensionality to 2 using t-SNE. If your extracted features are good, data points representing a specific class should appear within a compact cluster.

4.1 Dataset

- Training set:

	COVID-19	Normal	Pneumonia-Bacterial	Pneumonia-Viral
Number of images	9	9	9	9

- Test set:

	COVID-19	Normal	Pneumonia-Bacterial	Pneumonia-Viral
Number of images	60	70	70	70

4.2 VGG16 Architecture for task 2

This is a subsection.

A pre-trained model VGG16 [1] has been employed in this architecture.

Architecture		
Layer (type)	Output shape	Number of parameters
Input	(None, 224, 224, 3)	0
VGG16 (Model)	(None, 7, 7, 512)	14714688
Flatten	(None, 25088)	0
Fully connected	(None, 256)	6422784
ReLu	(None, 256)	0
Fully connected	(None, 256)	6422784
ReLu	(None, 256)	0
Fully connected	(None, 1)	257
Softmax	(None, 4)	0

4.3 Training

- Optimizer: Adam.
- Loss function: tf.keras.losses.CategoricalCrossentropy.
- Epochs: 100.
- Regularization: dropout layers.
- Batch size: 10.

4.4 Testing

Test accuracy is 75% and test loss is 0.7699.

4.4.1 Accuracy and Loss

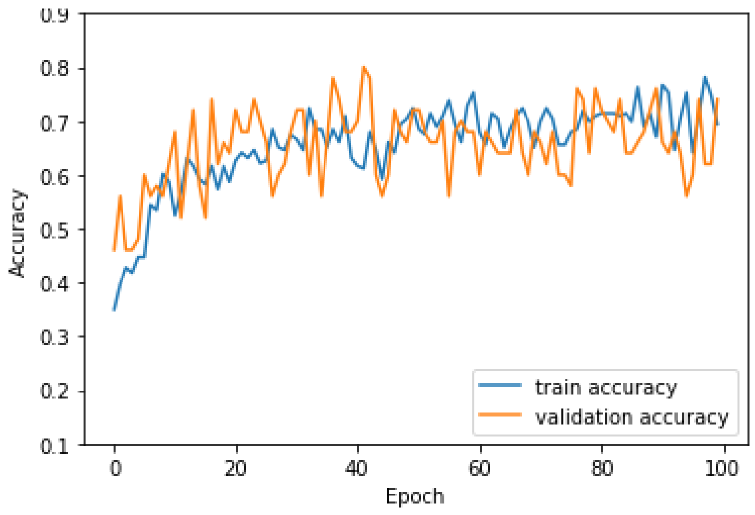


Figure 5: Accuracy on training set and validation set over 100 epochs

Train accuracy

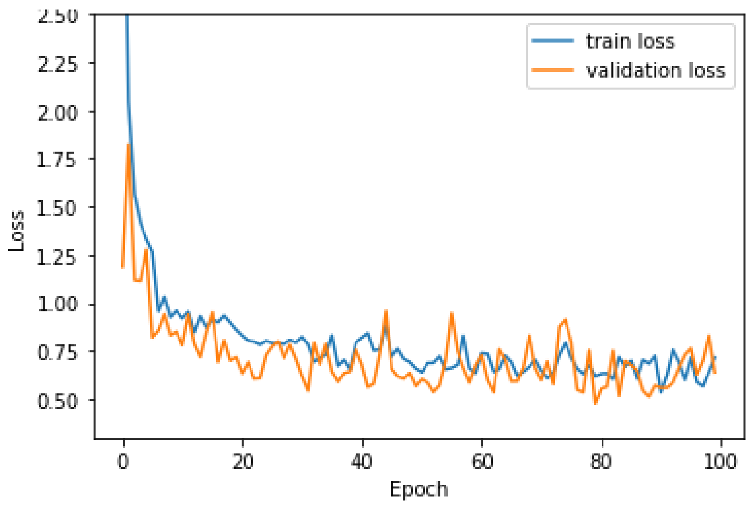


Figure 6: Loss on trainning set and validation set over 100 epochs

4.4.2 t-SNE visualizations

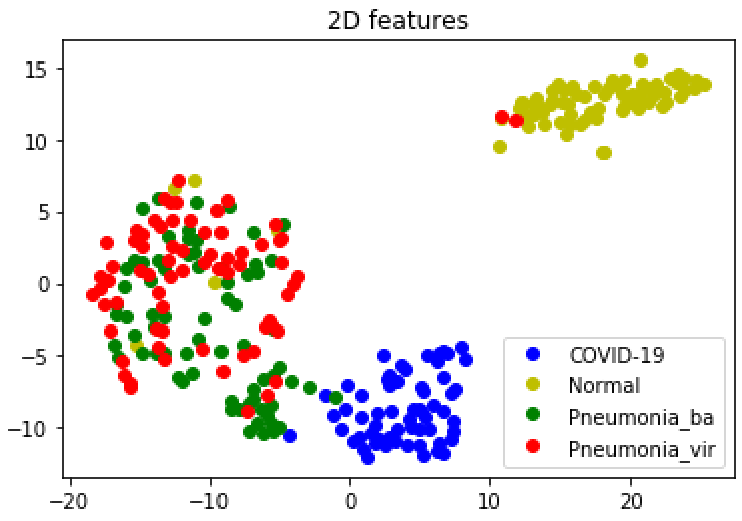


Figure 7: Two dimensional features on class COVID, Normal, Pneumonia_bacterial and Pneumonia_Viral

4.5 ResNet50V2 Architecture for task 2

4.6 Training

4.7 Testing

4.7.1 Accuraccy and Loss

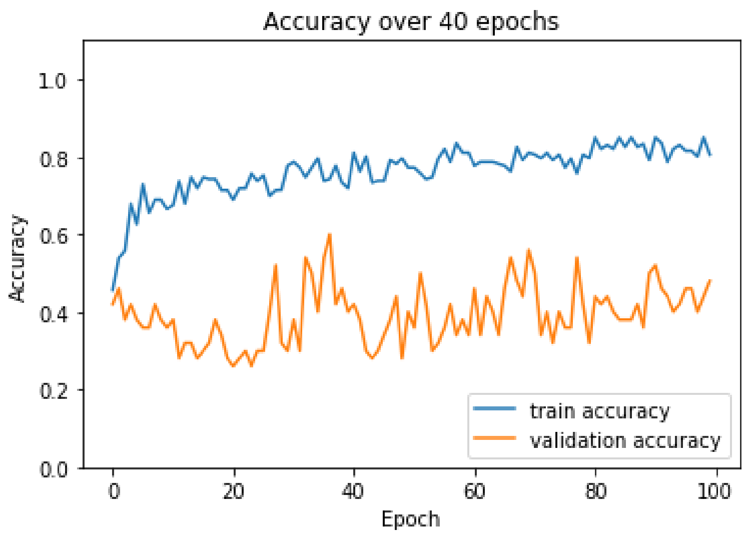


Figure 8: Accuracy on training set and validation set over 100 epochs

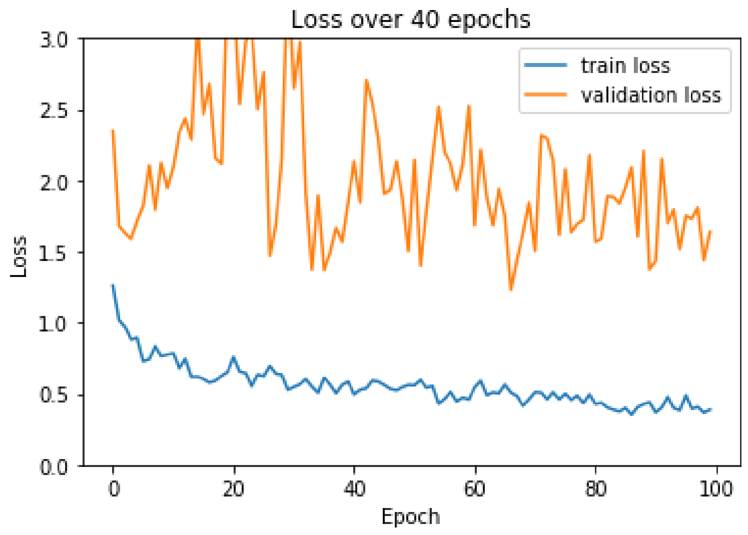


Figure 9: Loss on trainning set and validation set over 100 epochs

4.7.2 t-SNE visualization

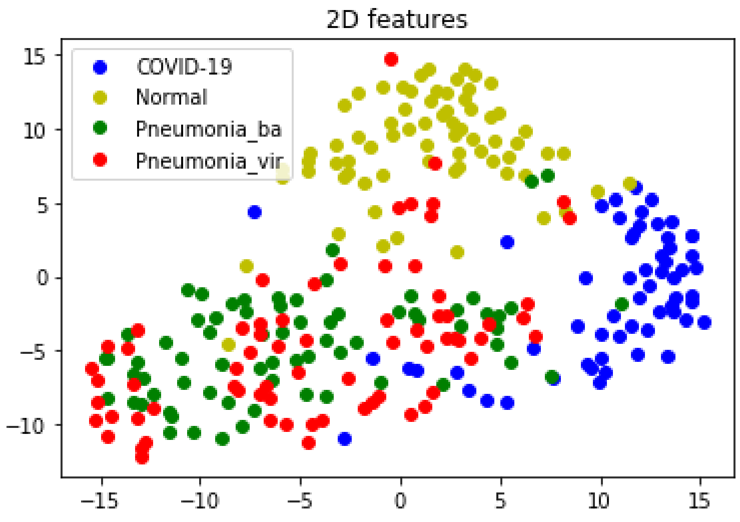


Figure 10: Two dimensional features on class COVID, Normal, Pneumonia_bacterial and Pneumonia_Viral

4.8 Comparasion between VGG16 and ResNet50V2

4.8.1 Accuraccy

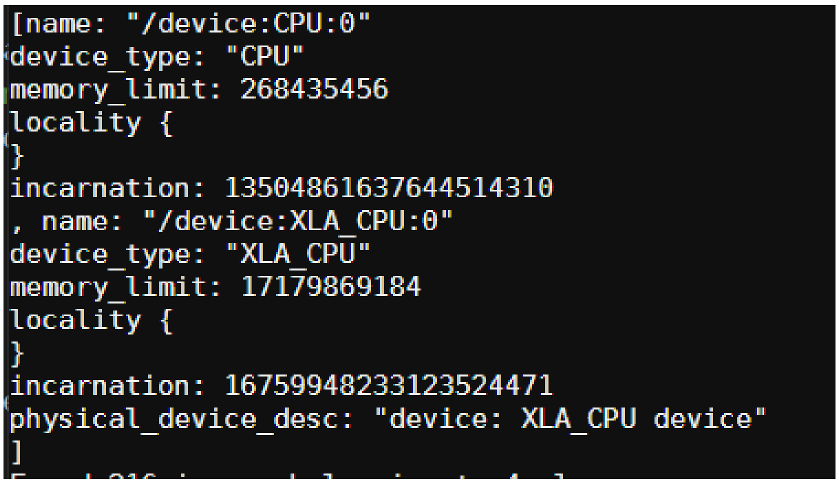
4.8.2 Layers

4.8.3 Parameters

4.8.4 Model Complexity

5 Deploy Tasks on SCC Cluster [Bonus: 10 points]

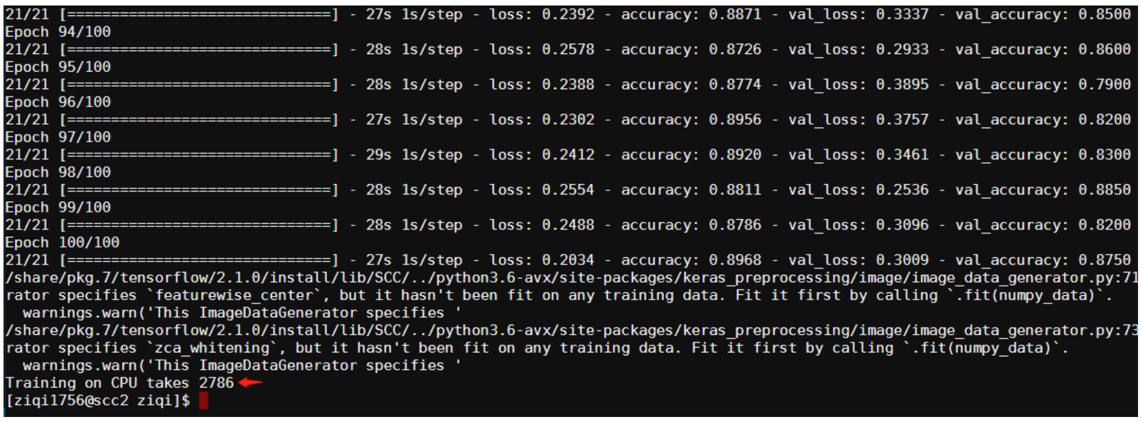
5.1 Training time on CPU



```
[name: "/device:CPU:0"
device_type: "CPU"
memory_limit: 268435456
locality {
}
incarnation: 13504861637644514310
, name: "/device:XLA_CPU:0"
device_type: "XLA_CPU"
memory_limit: 17179869184
locality {
}
incarnation: 16759948233123524471
physical_device_desc: "device: XLA_CPU device"
]
```

Figure 11: The CPU library on SCC

Print the device library. We are assigned a CPU called "device:XLA_CPU:0".

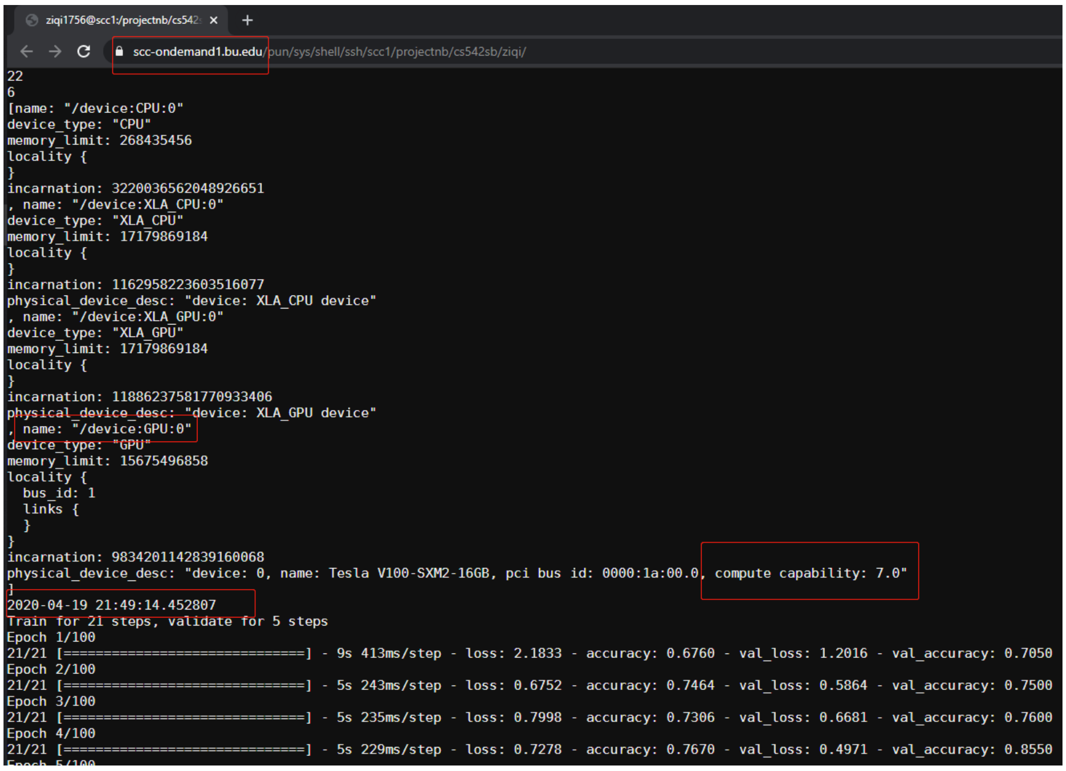


```
21/21 [==============================] - 27s 1s/step - loss: 0.2392 - accuracy: 0.8871 - val_loss: 0.3337 - val_accuracy: 0.8500
Epoch 94/100
21/21 [==============================] - 28s 1s/step - loss: 0.2578 - accuracy: 0.8726 - val_loss: 0.2933 - val_accuracy: 0.8600
Epoch 95/100
21/21 [==============================] - 28s 1s/step - loss: 0.2388 - accuracy: 0.8774 - val_loss: 0.3895 - val_accuracy: 0.7900
Epoch 96/100
21/21 [==============================] - 27s 1s/step - loss: 0.2302 - accuracy: 0.8956 - val_loss: 0.3757 - val_accuracy: 0.8200
Epoch 97/100
21/21 [==============================] - 29s 1s/step - loss: 0.2412 - accuracy: 0.8920 - val_loss: 0.3461 - val_accuracy: 0.8300
Epoch 98/100
21/21 [==============================] - 28s 1s/step - loss: 0.2554 - accuracy: 0.8811 - val_loss: 0.2536 - val_accuracy: 0.8850
Epoch 99/100
21/21 [==============================] - 28s 1s/step - loss: 0.2488 - accuracy: 0.8786 - val_loss: 0.3096 - val_accuracy: 0.8200
Epoch 100/100
21/21 [==============================] - 27s 1s/step - loss: 0.2034 - accuracy: 0.8968 - val_loss: 0.3009 - val_accuracy: 0.8750
/share/pkg.7/tensorflow/2.1.0/install/lib/SCC/../python3.6-avx/site-packages/keras_preprocessing/image/image_data_generator.py:71
rator specifies `featurewise_center`, but it hasn't been fit on any training data. Fit it first by calling `.fit(numpy_data)`.
  warnings.warn('This ImageDataGenerator specifies '
/share/pkg.7/tensorflow/2.1.0/install/lib/SCC/../python3.6-avx/site-packages/keras_preprocessing/image/image_data_generator.py:73
rator specifies `zca_whitening`, but it hasn't been fit on any training data. Fit it first by calling `.fit(numpy_data)`.
  warnings.warn('This ImageDataGenerator specifies '
Training on CPU takes 2786
[ziqi1756@scc2 ziqi]$
```

Figure 12: The time we take when training on CPU

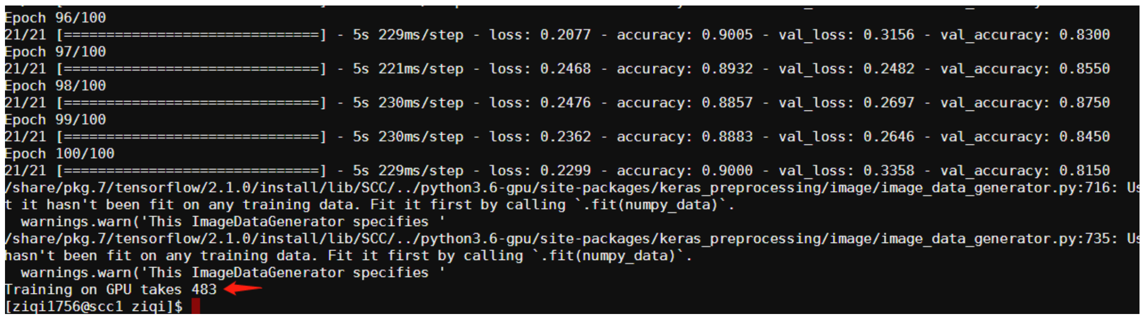
Training on CPU takes 2786 seconds as the Fig.12 shows.

5.2 Training time on GPU


ziqi1756@scc1:/projectnb/cs542
scc-ondemand1.bu.edu/pun/sys/shell/ssh/scc1/projectnb/cs542sb/ziqi/

```
22
6
[name: "/device:CPU:0"
device_type: "CPU"
memory_limit: 268435456
locality {
}
incarnation: 3220036562048926651
, name: "/device:XLA_CPU:0"
device_type: "XLA_CPU"
memory_limit: 17179869184
locality {
}
incarnation: 11629582236035160 77
physical_device_desc: "device: XLA_CPU device"
, name: "/device:XLA_GPU:0"
device_type: "XLA_GPU"
memory_limit: 17179869184
locality {
}
incarnation: 11886237581770933406
physical_device_desc: "device: XLA_GPU device"
, name: "/device:GPU:0"
device_type: "GPU"
memory_limit: 15675496858
locality {
  bus_id: 1
  links {
  }
}
incarnation: 9834201142839160068
physical_device_desc: "device: 0, name: Tesla V100-SXM2-16GB, pci bus id: 0000:1a:00.0, compute capability: 7.0"
]
2020-04-19 21:49:14.452807
Train for 21 steps, validate for 5 steps
Epoch 1/100
21/21 [==============================] - 9s 413ms/step - loss: 2.1833 - accuracy: 0.6760 - val_loss: 1.2016 - val_accuracy: 0.7050
Epoch 2/100
21/21 [==============================] - 5s 243ms/step - loss: 0.6752 - accuracy: 0.7464 - val_loss: 0.5864 - val_accuracy: 0.7500
Epoch 3/100
21/21 [==============================] - 5s 235ms/step - loss: 0.7998 - accuracy: 0.7306 - val_loss: 0.6681 - val_accuracy: 0.7600
Epoch 4/100
21/21 [==============================] - 5s 229ms/step - loss: 0.7278 - accuracy: 0.7670 - val_loss: 0.4971 - val_accuracy: 0.8550
```

Figure 13: The GPU library on SCC



```
Epoch 96/100
21/21 [==============================] - 5s 229ms/step - loss: 0.2077 - accuracy: 0.9005 - val_loss: 0.3156 - val_accuracy: 0.8300
Epoch 97/100
21/21 [==============================] - 5s 221ms/step - loss: 0.2468 - accuracy: 0.8932 - val_loss: 0.2482 - val_accuracy: 0.8550
Epoch 98/100
21/21 [==============================] - 5s 230ms/step - loss: 0.2476 - accuracy: 0.8857 - val_loss: 0.2697 - val_accuracy: 0.8750
Epoch 99/100
21/21 [==============================] - 5s 230ms/step - loss: 0.2362 - accuracy: 0.8883 - val_loss: 0.2646 - val_accuracy: 0.8450
Epoch 100/100
21/21 [==============================] - 5s 229ms/step - loss: 0.2299 - accuracy: 0.9000 - val_loss: 0.3358 - val_accuracy: 0.8150
/share/pkg.7/tensorflow/2.1.0/install/lib/SCC/../python3.6-gpu/site-packages/keras_preprocessing/image/image_data_generator.py:716: U
t it hasn't been fit on any training data. Fit it first by calling `.fit(numpy_data)`.
  warnings.warn('This ImageDataGenerator specifies '
/share/pkg.7/tensorflow/2.1.0/install/lib/SCC/../python3.6-gpu/site-packages/keras_preprocessing/image/image_data_generator.py:735: U
hasn't been fit on any training data. Fit it first by calling `.fit(numpy_data)`.
  warnings.warn('This ImageDataGenerator specifies '
Training on GPU takes 483
[ziqi1756@scc1 ziqi]$
```

Figure 14: The time we take when training on GPU

References

[1] Karen Simonyan and Andrew Zisserman, Very Deep Convolutional Networks for Large-Scale Image Recognition, arXiv 1409.1556, cs.cv, 2014

[2] ResNet50V2 Documentation, https://keras.io/examples/cifar10_resnet/