Capstone Project Report

On

Image classification Of MNIST Fashion dataset

By

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Project Overview

The capstone project is basically to understand how to use sagemaker resources together with pytorch to perform a computer vision task. This project makes use of the famous mnist fashion dataset on image classification model to create an efficient model with a convolution neural network. The benefit of computer vision is to enable computers to see the world or objects as humans do. And with the help of pretrained models, a machine learning framework such as pytorch and AWS sagemaker, this process can be a lot simplified when using a convolutional neural network algorithm. The model created during this project can serve as a useful tool to fashion brands, their customers would get a good experience when using this tool to select a particular fashion item of their choice.

The aim of this project is to master the use of creating image classification models with AWS sagemaker because it is a core part of computer vision and machine learning engineering in general

Problem statement

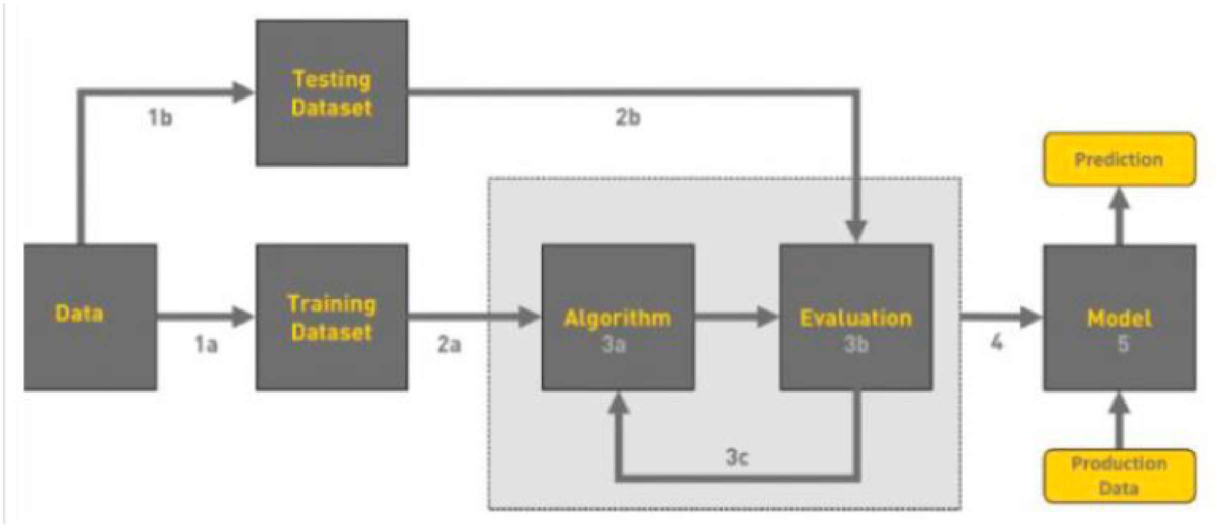
To achieve my aim, I used the following steps in solving an image classification problem with PyTorch:

1. Load the dataset from MNIST fashion website
2. Creating a validation dataset from train data, creating separate folders for train, valid and test dataset
3. Loading the datasets to s3 and performing job training on a preprocessed dataset with pytorch on AWS sagemaker
4. Performing debugging and profiling
5. Creating inference and prediction

Different pretrained models were tried with different hyperparameter tuning to achieve a good result based on accuracy.

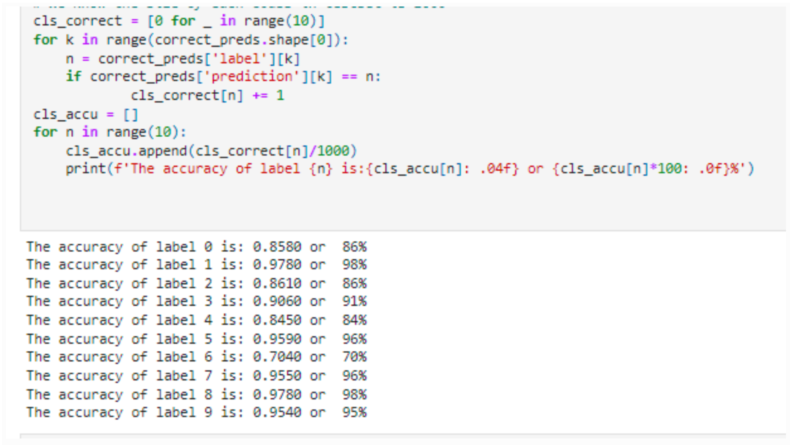
Solution statement

My idea was to create a deep learning model that is able to identify accurately the different classes of the MNIST fashion dataset (basically 10 classes) with a high percentage accuracy by using amazon sagemaker. As a result of hyperparameter tuning, data preprocessing and the use of a good pretrained model, the final architecture and hyperparameters were chosen because they performed the best among some other trials. The different steps taken to achieve this solution is as follows:



Evaluation metrics

The accuracy of the model, one of the common metrics used to judge a model, is what I made use of for this project. My aim to achieve a high accuracy after completing the project was met. Here is a screenshot of the percentage accuracy of the different classes represented in the dataset.

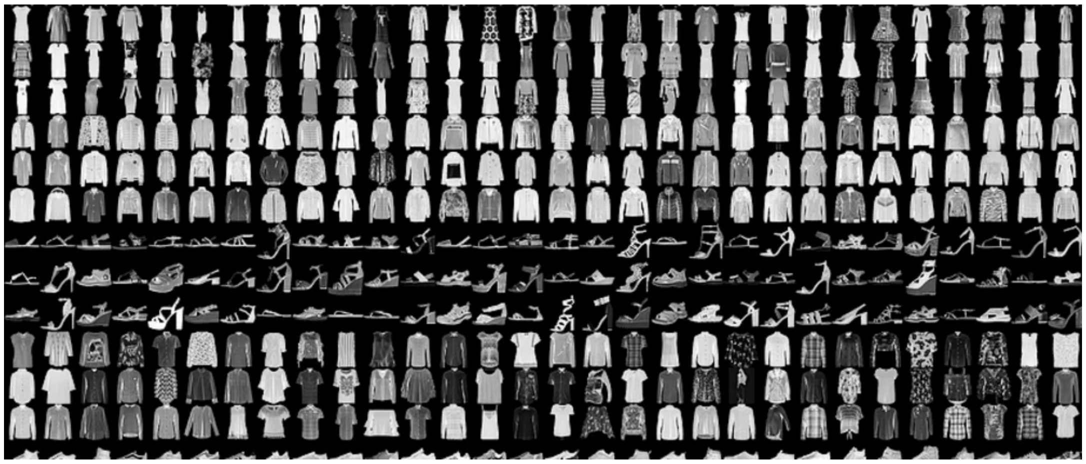


```
cls_correct = [0 for _ in range(10)]
for k in range(correct_preds.shape[0]):
    n = correct_preds['label'][k]
    if correct_preds['prediction'][k] == n:
            cls_correct[n] += 1
cls_accu = []
for n in range(10):
    cls_accu.append(cls_correct[n]/1000)
    print(f'The accuracy of label {n} is:{cls_accu[n]: .04f} or {cls_accu[n]*100: .0f}%')
```

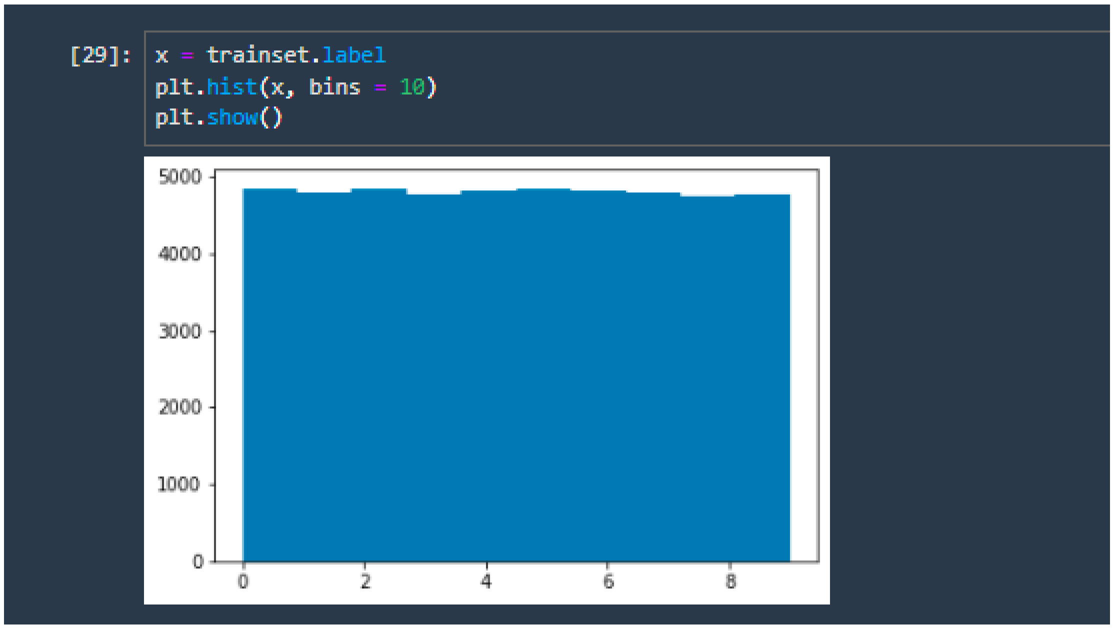
```
The accuracy of label 0 is: 0.8580 or  86%
The accuracy of label 1 is: 0.9780 or  98%
The accuracy of label 2 is: 0.8610 or  86%
The accuracy of label 3 is: 0.9060 or  91%
The accuracy of label 4 is: 0.8450 or  84%
The accuracy of label 5 is: 0.9590 or  96%
The accuracy of label 6 is: 0.7040 or  70%
The accuracy of label 7 is: 0.9550 or  96%
The accuracy of label 8 is: 0.9780 or  98%
The accuracy of label 9 is: 0.9540 or  95%
```

Datasets and inputs

The dataset used for this project is the MNIST dataset, made publicly available. It consists of about 60 images grouped in 10 classes of fashion wears. This dataset contains gray scale images of sizes 28 by 28. For easy usage and processing, I split the data into train, valid and test folders, containing subfolders subsequently. In training the model, I used the ResNet34 pretrained model to perform training and evaluation as well. After preparing the data, the data is moved to AWS S3 where training was carried out with pyTorch.



fashion MNIST dataset



```
[29]: x = trainset.label
      plt.hist(x, bins = 10)
      plt.show()
```

As seen in the screenshot from my data_images.ipynb notebook, the graph clearly shows the distribution of the 10 classes contained in the fashion MNIST. The training dataset is very balanced having a similar number of images (a little bit less than 5000) in each class. This, among other characteristics, makes the fashion MNIST dataset a standard dataset.

Benchmark of the model

The benchmark created for this project is gotten from the famous post of machine learning mastery seen by using this link:

https://machinelearningmastery.com/how-to-develop-a-cnn-from-scratch-for-fashion-mnist-clothing-classification/ According to this post, keras was used, the baseline model operated on 10 training epochs with a default batch size of 32, data transformation was also done by using normalization etc, the stochastic Gradient Descent (SGD) was used as the optimizer as well. The evaluation metric used is also accuracy and the model achieved an accuracy of 90.990%. I will say my model performed pretty well when compared to the accuracy of the benchmark model.

Comparative analysis with benchmark result

parameters	**Benchmark model**	**My model**
ML framework	Keras	Pytorch
Training epoch	10	20
Optimizer	SGD	SGD
Batch size	32	64
Learning rate	0.01	0.000988624968369079
Pretrained model	-	Resnet34
Data transformation	yes	yes
accuracy	90.990%.	89.98 %

Data Preprocessing

Not-too-intensive preprocessing needs to be done since the dataset is a standard one due to the following reasons viewed together:

- It is a large dataset (containing 60000 images)
- All images are small (28x28) and of the same size, this enables the model to focus on its class object better
- The class distribution is highly balanced with classes not being ambiguous
- It has greyscale images, colour basically has no significance in classifying fashion items(since fashion items could be any colour)in the MNIST fashion dataset.

For these reasons image transformation such as croping, resizing, double-sizing(or increasing the number of images by some amount), colour space(colour jitters) transformations and random erasing were neglected. In order to train on a neural network algorithm:

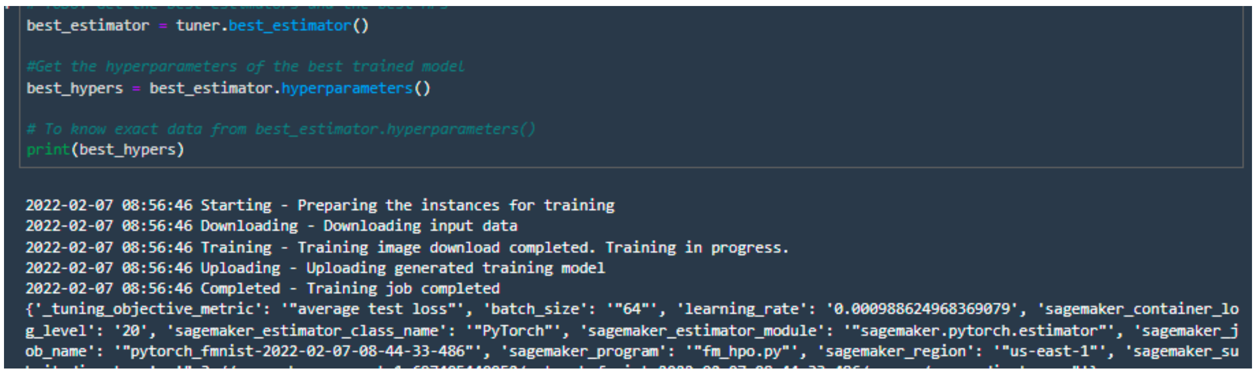
- I converted the images to a tensor which basically generalizes vectors or matrices.
- I applied random horizontal flips of 50% probability to avoid bias (as much as possible) when training the model
- I applied transforms.grayscale, which returns the images in a single channel
- I also normalized since it helps to improve the model. Normalization helps get data within a range and reduces the skewness which helps learn faster and better. It may also tackle the diminishing and exploding gradients problems that may occur during

training. It is a powerful technique in improving a model's performance, it does this to an image:

$$\text{Image} = \frac{(\text{image} - \text{mean})}{\text{Standard deviation}}$$

Algorithms and techniques

For this project, the image classifier is the convolutional neural network, a machine learning tool which is perfect for learning complex patterns on a large dataset. The hyperparameter chosen for tuning is the learning rate and batch size, these parameters greatly affects the performance of a model. After finding a very good parameter for tuning (from best estimator) with use of fm_hpo.py script as entry_point in the estimator, adequate data preprocessing was used to conduct model training(see data preprocessing section) on the MNIST fashion dataset. I Froze the convolutional layers, since resnet34 pretrained model was applied to train the model. For optimizers, which is used to specify how the neural network will learn, the stochastic Gradient Descent (SGD) was used as the optimizer to run with back propagation during model training.



```
best_estimator = tuner.best_estimator()

#Get the hyperparameters of the best trained model
best_hypers = best_estimator.hyperparameters()

# To know exact data from best_estimator.hyperparameters()
print(best_hypers)
```

```
2022-02-07 08:56:46 Starting - Preparing the instances for training
2022-02-07 08:56:46 Downloading - Downloading input data
2022-02-07 08:56:46 Training - Training image download completed. Training in progress.
2022-02-07 08:56:46 Uploading - Uploading generated training model
2022-02-07 08:56:46 Completed - Training job completed
{'_tuning_objective_metric': '"average test loss"', 'batch_size': '"64"', 'learning_rate': '0.000988624968369079', 'sagemaker_container_lo
g_level': '20', 'sagemaker_estimator_class_name': '"PyTorch"', 'sagemaker_estimator_module': '"sagemaker.pytorch.estimator"', 'sagemaker_j
ob_name': '"pytorch_fmnist-2022-02-07-08-44-33-486"', 'sagemaker_program': '"fm_hpo.py"', 'sagemaker_region': '"us-east-1"', 'sagemaker_su
```

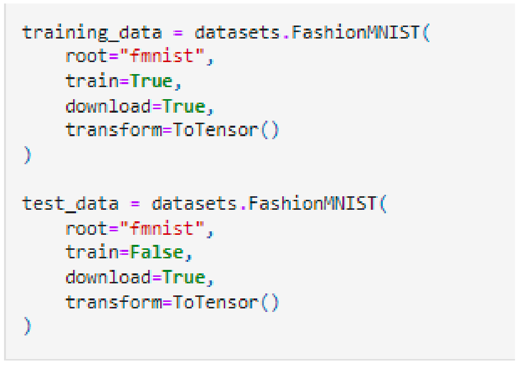
This is the result of the best parameters used for training the model in this project

Project design

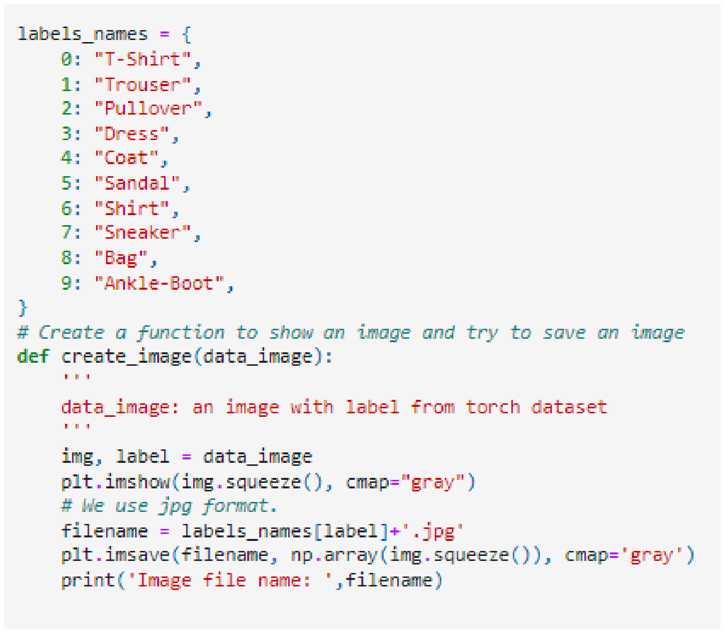
The workflow to approaching the solution is as follows:

Loading the dataset

The dataset was downloaded and saved with matplotlib's plt.imsave code as follows:

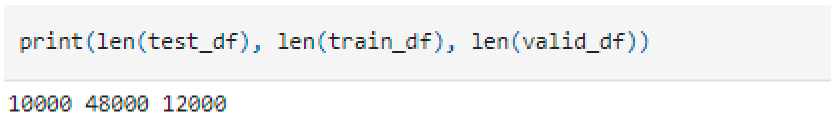


```
training_data = datasets.FashionMNIST(
    root="fmnist",
    train=True,
    download=True,
    transform=ToTensor()
)

test_data = datasets.FashionMNIST(
    root="fmnist",
    train=False,
    download=True,
    transform=ToTensor()
)
```



```
labels_names = {
    0: "T-Shirt",
    1: "Trouser",
    2: "Pullover",
    3: "Dress",
    4: "Coat",
    5: "Sandal",
    6: "Shirt",
    7: "Sneaker",
    8: "Bag",
    9: "Ankle-Boot",
}
# Create a function to show an image and try to save an image
def create_image(data_image):
    '''
    data_image: an image with label from torch dataset
    '''
    img, label = data_image
    plt.imshow(img.squeeze(), cmap="gray")
    # We use jpg format.
    filename = labels_names[label]+'.jpg'
    plt.imsave(filename, np.array(img.squeeze()), cmap='gray')
    print('Image file name: ',filename)
```

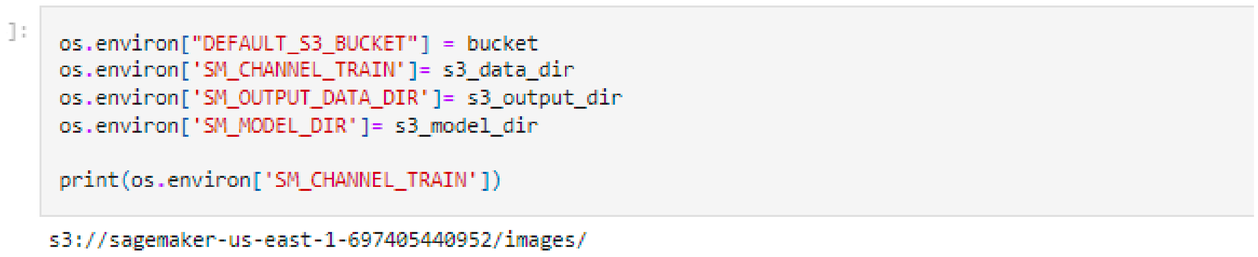
The total number of images was known to be 60000 and steps to split these among train, test and valid folders were done by creating a function that separates the files in a folder during iteration.



```
print(len(test_df), len(train_df), len(valid_df))
```

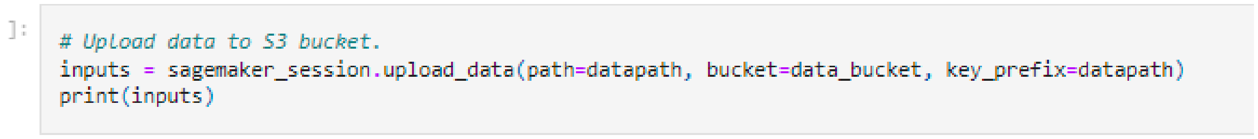
```
10000 48000 12000
```

Further steps were taken to upload the data to S3



```
]:
os.environ["DEFAULT_S3_BUCKET"] = bucket
os.environ['SM_CHANNEL_TRAIN']= s3_data_dir
os.environ['SM_OUTPUT_DATA_DIR']= s3_output_dir
os.environ['SM_MODEL_DIR']= s3_model_dir

print(os.environ['SM_CHANNEL_TRAIN'])
```

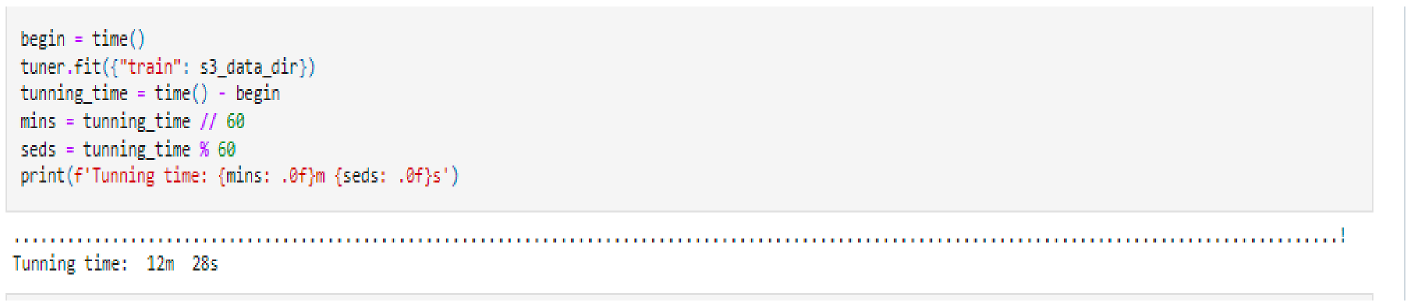
```
s3://sagemaker-us-east-1-697405440952/images/
```



```
]:
# Upload data to S3 bucket.
inputs = sagemaker_session.upload_data(path=datapath, bucket=data_bucket, key_prefix=datapath)
print(inputs)
```

Setting up parameters and estimator for job training

The learning rate and batch size as well as the estimator and tuner were set up resulting in fitting:



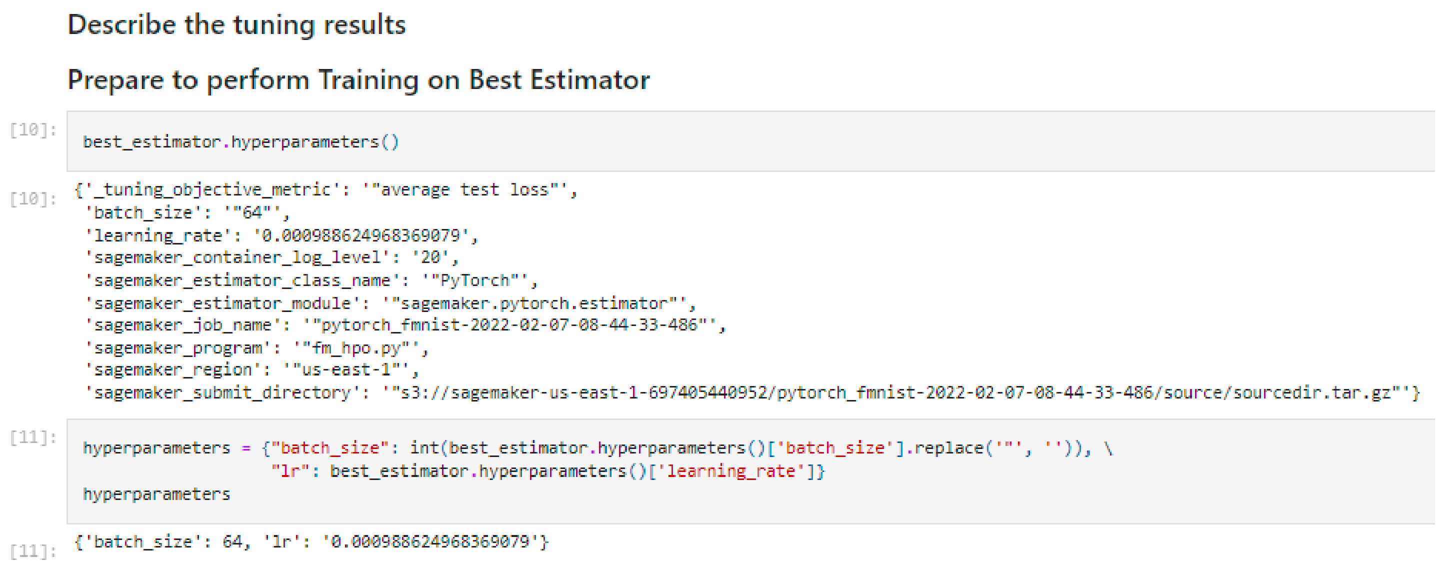
```
begin = time()
tuner.fit({"train": s3_data_dir})
tunning_time = time() - begin
mins = tunning_time // 60
seds = tunning_time % 60
print(f'Tunning time: {mins: .0f}m {seds: .0f}s')
```

```
.............................................................................................................................................!
Tunning time:  12m  28s
```

The entry_point for fitting was the fm_hpo.py script which contains code that transforms the data by flipping, normalising and transforming it to tensor during preprocessing. Resizing was not taken into consideration since image size was considerably small and good enough for training. Other function in the script was the train, test, create data loader using arguments such as an optimiser, criterion, model, scheduler, data loader etc.

Model training

The best parameters were used to perform training. With the use of fm_model.py script as entry_point, 20 epochs, resNet 34 was used on the best parameters



Describe the tuning results

Prepare to perform Training on Best Estimator

```
[10]: best_estimator.hyperparameters()
```

```
[10]: {'_tuning_objective_metric': '"average test loss"',
       'batch_size': '"64"',
       'learning_rate': '0.000988624968369079',
       'sagemaker_container_log_level': '20',
       'sagemaker_estimator_class_name': '"PyTorch"',
       'sagemaker_estimator_module': '"sagemaker.pytorch.estimator"',
       'sagemaker_job_name': '"pytorch_fmnist-2022-02-07-08-44-33-486"',
       'sagemaker_program': '"fm_hpo.py"',
       'sagemaker_region': '"us-east-1"',
       'sagemaker_submit_directory': '"s3://sagemaker-us-east-1-697405440952/pytorch_fmnist-2022-02-07-08-44-33-486/source/sourcedir.tar.gz"'}
```

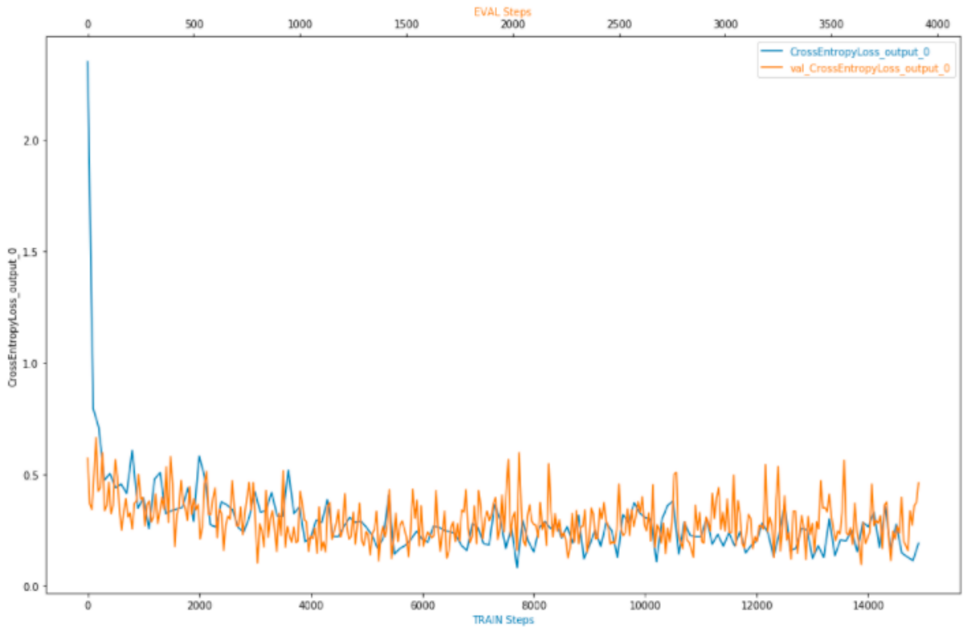
```
[11]: hyperparameters = {"batch_size": int(best_estimator.hyperparameters()['batch_size'].replace('"', '')), \
                         "lr": best_estimator.hyperparameters()['learning_rate']}
      hyperparameters
```

```
[11]: {'batch_size': 64, 'lr': '0.000988624968369079'}
```

Model evaluation, profiling and debugging.

```
In [21]:  #Plot a debugging output.
          plot_tensor(trial, tensor_name)
```

```
loaded TRAIN data
loaded EVAL data
completed TRAIN plot
completed EVAL plot
```



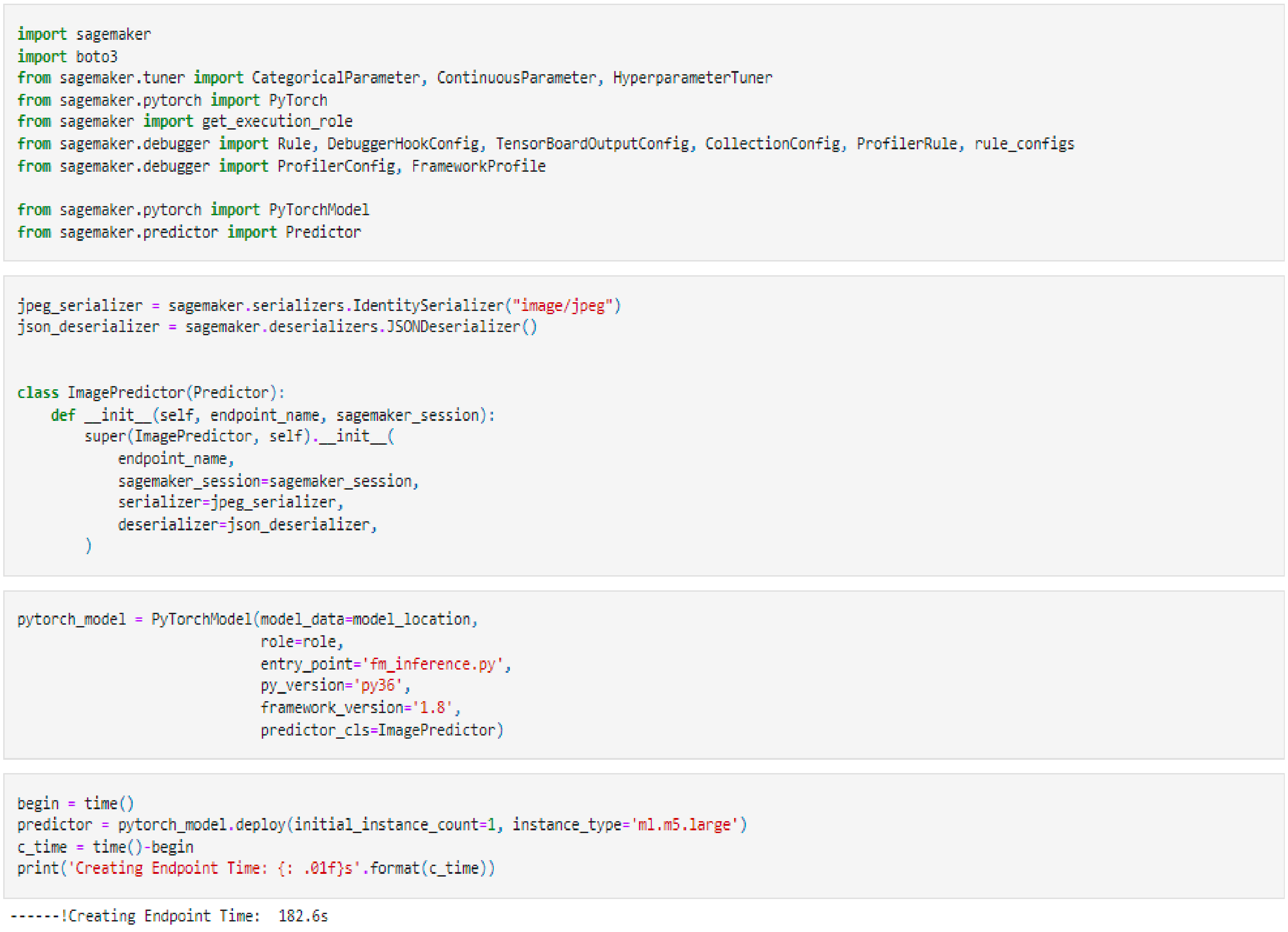
The loss function which computes a value that estimates how far away the output is from the target was calculated during this project as cross entropy loss.The graph above simply shows the reduction in cross-entropy output which is the loss function of the model. The profiling and debugging done was to show the training performance. With smdebug, the analysis of the training job was provided and the profiler report was made available with this code.

```
profiler_report_name = [
    rule["RuleConfigurationName"]
    for rule in estimator.latest_training_job.rule_job_summary()
    if "Profiler" in rule["RuleConfigurationName"]
][0]
print(profiler_report_name)
```

```
ProfilerReport
```

```
! tar czf ProfilerReport.tgz ProfilerReport/
```

After successfully conducting a training job with the best hyperparameter available, I easily called for deployment with pytorch_model.deploy(), with the use of fm_inference.py script as entry_point.



```python
import sagemaker
import boto3
from sagemaker.tuner import CategoricalParameter, ContinuousParameter, HyperparameterTuner
from sagemaker.pytorch import PyTorch
from sagemaker import get_execution_role
from sagemaker.debugger import Rule, DebuggerHookConfig, TensorBoardOutputConfig, CollectionConfig, ProfilerRule, rule_configs
from sagemaker.debugger import ProfilerConfig, FrameworkProfile

from sagemaker.pytorch import PyTorchModel
from sagemaker.predictor import Predictor
```

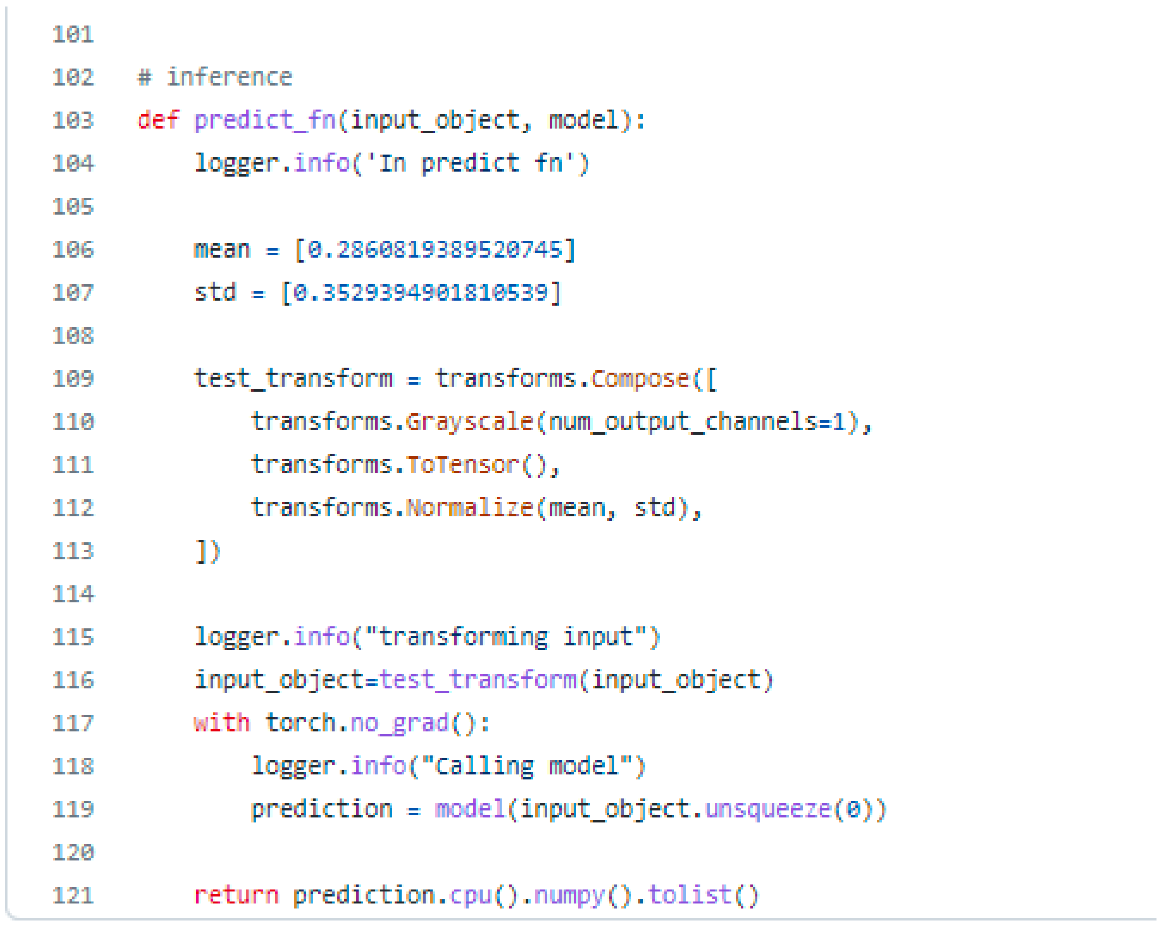
```python
jpeg_serializer = sagemaker.serializers.IdentitySerializer("image/jpeg")
json_deserializer = sagemaker.deserializers.JSONDeserializer()


class ImagePredictor(Predictor):
    def __init__(self, endpoint_name, sagemaker_session):
        super(ImagePredictor, self).__init__(
            endpoint_name,
            sagemaker_session=sagemaker_session,
            serializer=jpeg_serializer,
            deserializer=json_deserializer,
        )
```

```python
pytorch_model = PyTorchModel(model_data=model_location,
                             role=role,
                             entry_point='fm_inference.py',
                             py_version='py36',
                             framework_version='1.8',
                             predictor_cls=ImagePredictor)
```

```python
begin = time()
predictor = pytorch_model.deploy(initial_instance_count=1, instance_type='ml.m5.large')
c_time = time()-begin
print('Creating Endpoint Time: {: .01f}s'.format(c_time))
```

```
------!Creating Endpoint Time:  182.6s
```

Inference was made possible by transforming the image data, and calling the model for prediction. The code is as follows:



```python

# inference
def predict_fn(input_object, model):
    logger.info('In predict fn')

    mean = [0.2860819389520745]
    std = [0.3529394901810539]

    test_transform = transforms.Compose([
        transforms.Grayscale(num_output_channels=1),
        transforms.ToTensor(),
        transforms.Normalize(mean, std),
    ])

    logger.info("transforming input")
    input_object=test_transform(input_object)
    with torch.no_grad():
        logger.info("Calling model")
        prediction = model(input_object.unsqueeze(0))

    return prediction.cpu().numpy().tolist()
```

The model was able to predict accurately the different classes represented in the dataset, therefore the aim of this project was achieved more or less. Although it got some predictions wrong when randomly picking an image, the time in which it requires to make a prediction is also impressive, a useful asset in developing a computer vision model.

In [148…

```
output = predictor.predict(input)
output
```

Out[148…

```
[[0.5479651689529419,
  1.8651485443115234,
  -2.5988097190856934,
  5.487130641937256,
  1.931625485420227,
  -6.758813381195068,
  3.092844247817993,
  -2.8216121196746826,
  -1.2999895811080933,
  -0.9873822927474976]]
```

In [149…

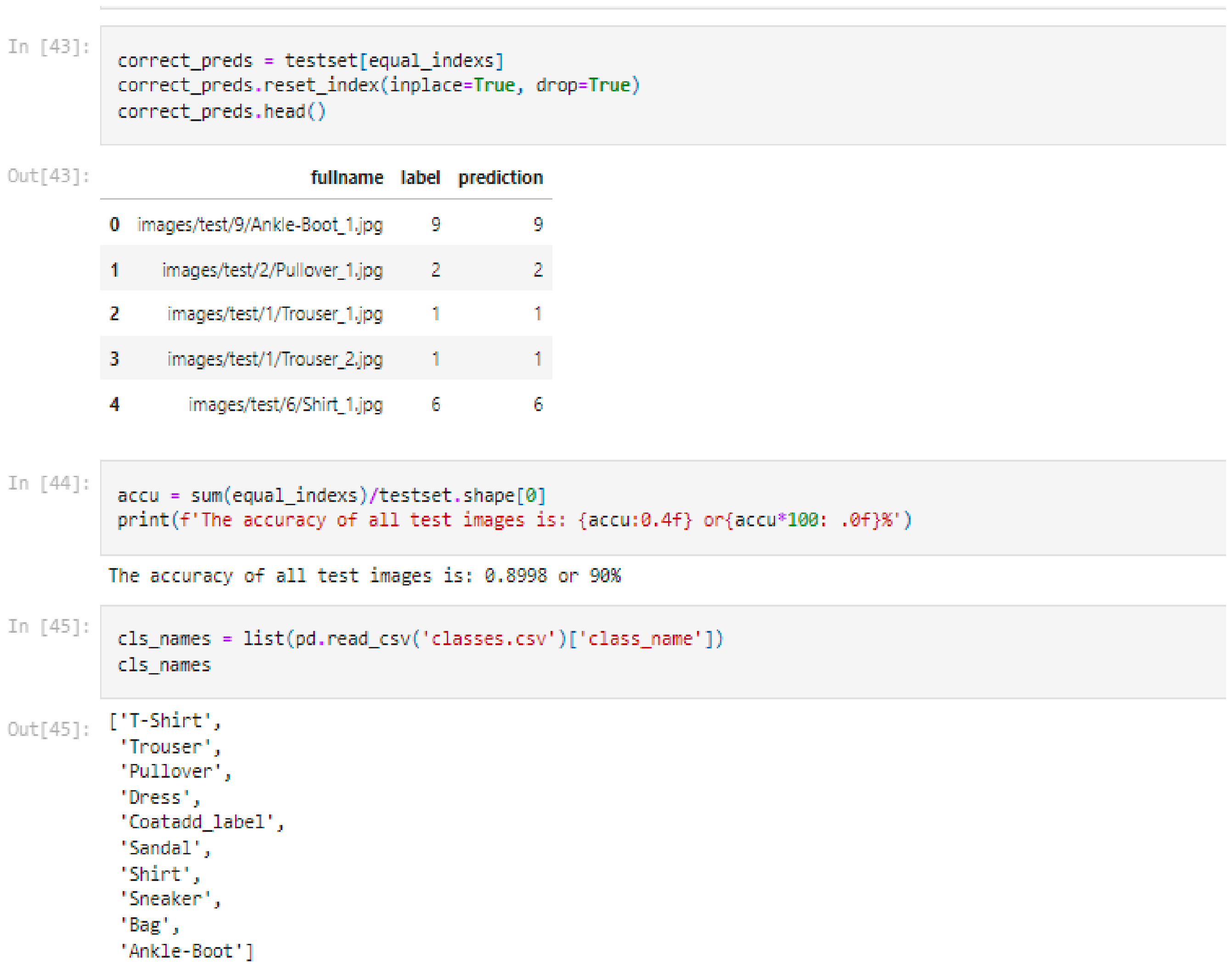
```
import numpy as np
prediction = np.argmax(output)
print('prediction:', prediction,', ', filename, 'label: ', label)
if prediction == label:
    print('Prediction is correct')
else:
    print('Prediction is not correct')
```

```
prediction: 3 ,  images/test/6/Shirt_586.jpg label:  2
Prediction is not correct
```

In [108…

```
begin = time()
preds = []
for k in range(testset.shape[0]):
    filename = testset['fullname'][k]
    with open(filename, 'rb') as f:
        input = f.read()
    output = predictor.predict(input)
    preds.append(np.argmax(output))

seconds = time() - begin
mins = seconds //60
print(f'Testing time: {seconds: 0.1f}s')
```

```
Testing time:  121.9s
```



In [43]:
```
correct_preds = testset[equal_indexs]
correct_preds.reset_index(inplace=True, drop=True)
correct_preds.head()
```

Out[43]:

	fullname	label	prediction
0	images/test/9/Ankle-Boot_1.jpg	9	9
1	images/test/2/Pullover_1.jpg	2	2
2	images/test/1/Trouser_1.jpg	1	1
3	images/test/1/Trouser_2.jpg	1	1
4	images/test/6/Shirt_1.jpg	6	6

In [44]:
```
accu = sum(equal_indexs)/testset.shape[0]
print(f'The accuracy of all test images is: {accu:0.4f} or{accu*100: .0f}%')
```

```
The accuracy of all test images is: 0.8998 or 90%
```

In [45]:
```
cls_names = list(pd.read_csv('classes.csv')['class_name'])
cls_names
```

Out[45]:
```
['T-Shirt',
 'Trouser',
 'Pullover',
 'Dress',
 'Coatadd_label',
 'Sandal',
 'Shirt',
 'Sneaker',
 'Bag',
 'Ankle-Boot']
```

PROJECT REFINEMENT AND IMPROVEMENT

There is always room for improvement on an image classification problem like this. In other words, these are possible areas that can improve on the performance of the model in general.

Data transformation: In considering largely the horizontal flip option during data transformation, improvement can be achieved with a different probability level because this type of transformation can be tricky, depending on the given dataset. Other types of transformation may also be considered.

Optimization: A different optimizer may prove to improve on the model's performance, as learning is very critical when it comes to model training

Pretrained Model: As good as the resnet pre -trained models may be, the fashion MNIST data might also train well, even better, with other pretrained models, when other parameters are also considered and put in place.

These are few steps, not all the steps, I consider that can cause some form of improvement to the model

Conclusion

I successfully completed this project with good accuracy, though there is always room for improvement. By concluding this project, I learnt how to use pytorch for image classification. With so many trials I made to choose the right parameter, I ended up using resnet34 pretrained model with 20 epochs.to conduct training and eventually making an inference

Reference

https://dev.to/sandeepbalachandran/machine-learning-dense-layer-k2i

https://towardsdatascience.com/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way-3bd2b1164a53
https://docs.microsoft.com/en-us/windows/ai/windows-ml/tutorials/pytorch-train-model

https://towardsdatascience.com/how-to-train-an-image-classifier-in-pytorch-and-use-it-to-perform-basic-inference-on-single-images-99465a1e9bf5

https://neptune.ai/blog/data-augmentation-in-python