

Implementation of

- a) MLP for Classification
- b) CNN backbone model using pytorch
- c) Combining the MLP & CNN

Submitted by Group 7:

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Contributions

Name	Contribution
Sandeep Kumar Singh (Roll No. 33562487)	Question 1 & 3 – CNN backbone
Sandeep Kumar Yadav (Roll No. 233562488)	Question 1 & 3 – CNN backbone
Satendra Kumar (Roll No. 233562490)	Question 1 & 2 - MLP for classification
Sharad Raj (Roll No. 233562494)	Question 1 & 2 - MLP for classification
Sayantan Chakraborty (Roll No. 233562492)	Question 4 - Report

MLP for Classification	CNN Backbone Model
Architecture : Dense Layer Feedforward Backpropagation	Architecture: Convolutional Model Fully Connected Layers
Hyperparameters: No. of layers & nodes Batch Size Learning Rate Epochs Activation Functions	Hyperparameters: Batch Size Learning Rate Epochs Number of Filters & Filter Size
Evaluation Metrics Accuracy, Precision, F1 score, Confusion Matrix	Evaluation Metrics Accuracy, Precision, F1 score, Confusion Matrix
Performance (Experiments) of the model Batch Size Learning Rate Epochs	Performance (Experiments) of the model No. of Filters and Filter Size Learning Rate Epochs Filter weight initialization

Architecture – MLP

Data Preparation:

- Download TRAINING (60000 samples) and TEST (10000) data from FashionMNIST
- Split TRAINING data into Training (48000) and Validation (12000) datasets
- Data Normalization & Flattening (input to MLP)

Dense Layer:

This class represents a single dense layer in the MLP. It takes input dimensions, output dimensions, activation function, and regularization parameters during initialization.

Methods:

Forward pass - forward

Back propagation : backward

activation functions and their derivatives: relu, relu_prime; sigmoid, sigmoid_prime; softmax, softmax_prime.

MLP:

This class represents the entire MLP model. It maintains a list of DenseLayer objects and a training history dictionary.

Methods:

Adding layers: add_layer

Forward and backward passes: forward, backward

Prediction: predict

Calculating Loss: cross_entropy_loss and training the model: train.

Training & Testing - MLP

Hyperparameters:

Epochs = 10

input_size = 28 * 28

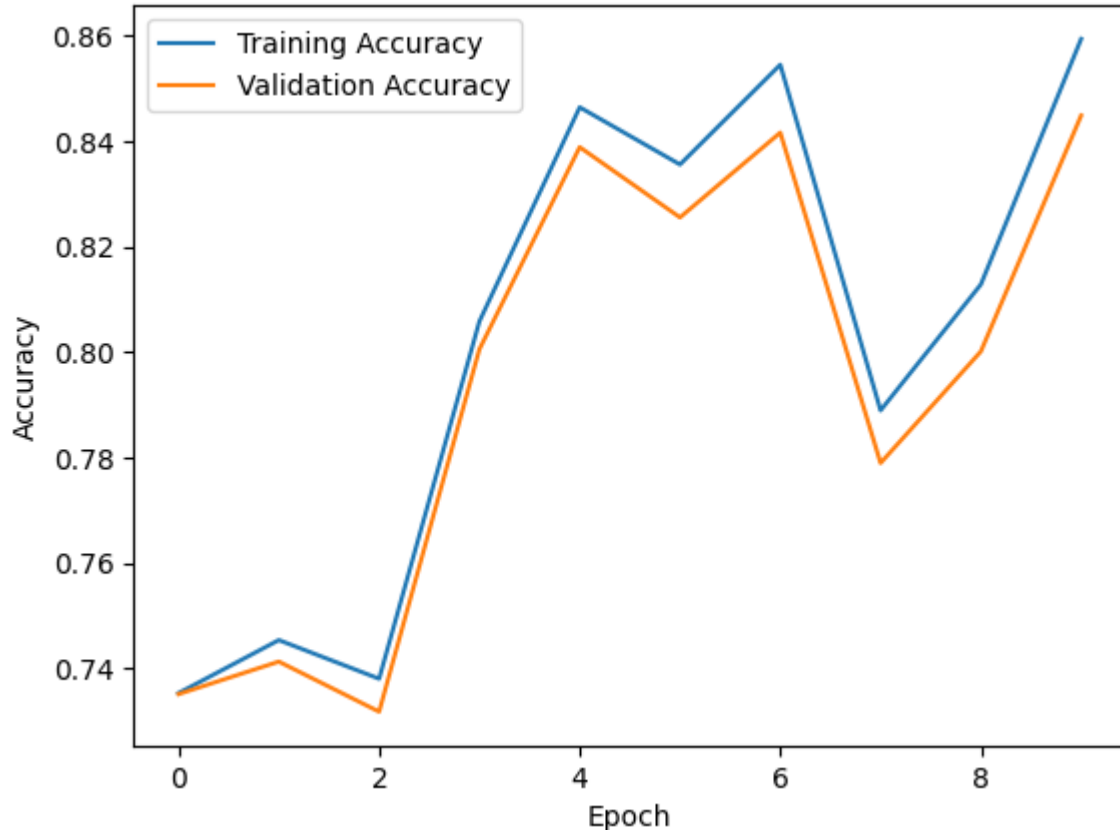
Batch Size = 64

hidden_size = 128

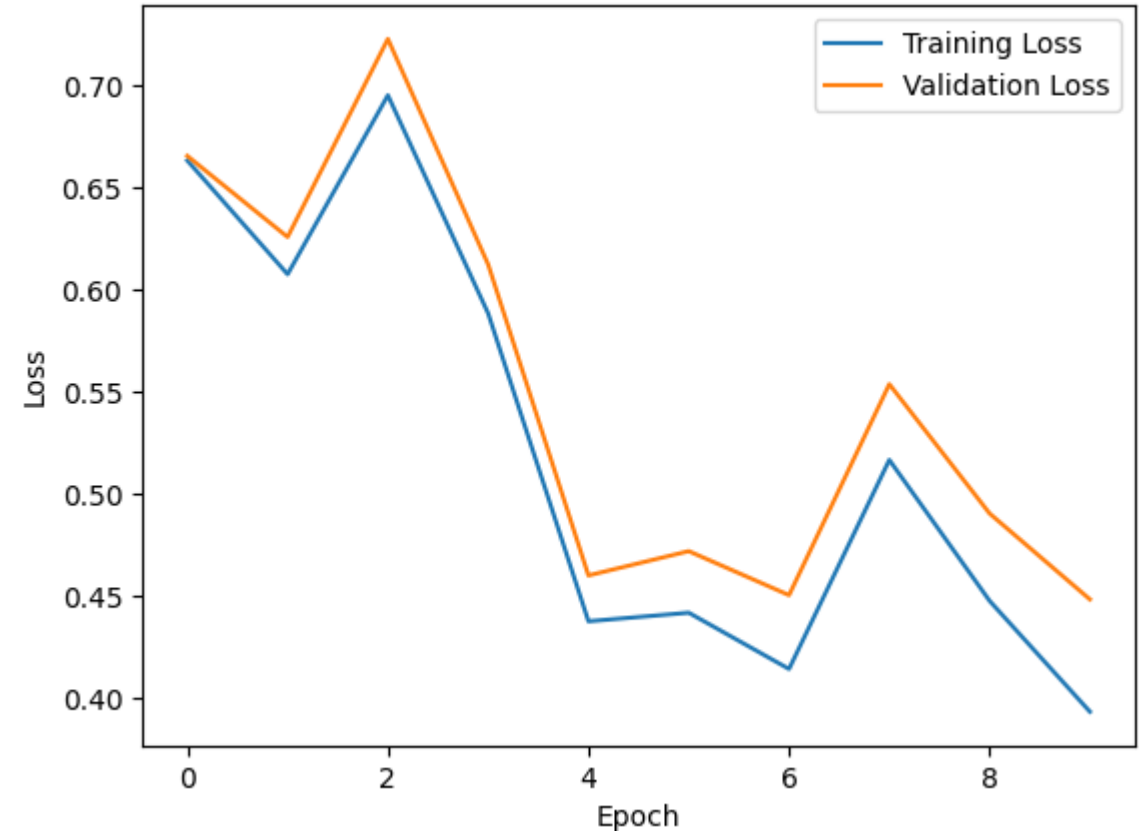
Learning Rate = 0.01

output_size = 10

Epoch vs Training/Validation Accuracy



Epoch vs Training/Validation Loss



Training & Testing - MLP

Evaluation Metrics:

Training Accuracy: 0.8594

Training Recall : 0.8594

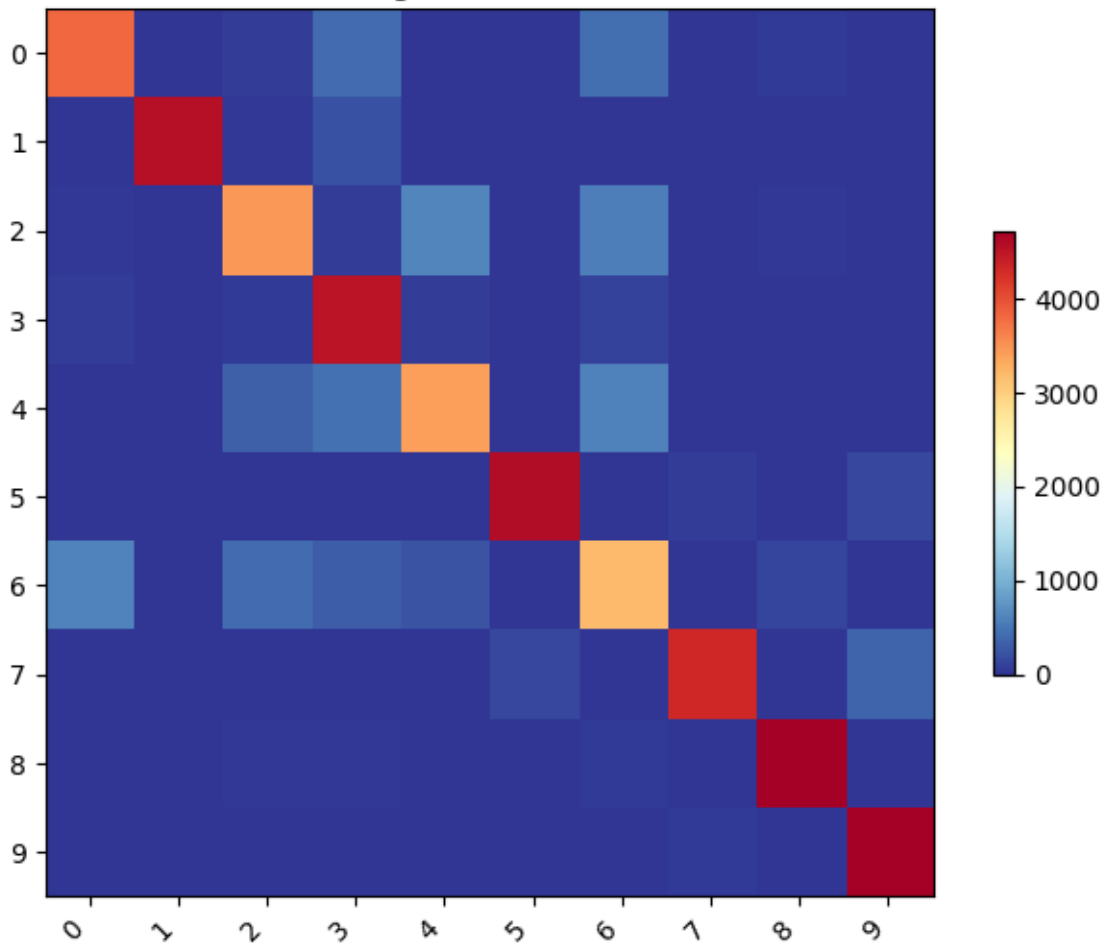
Training F1 Score: 0.8588

Validation Accuracy: 0.8448

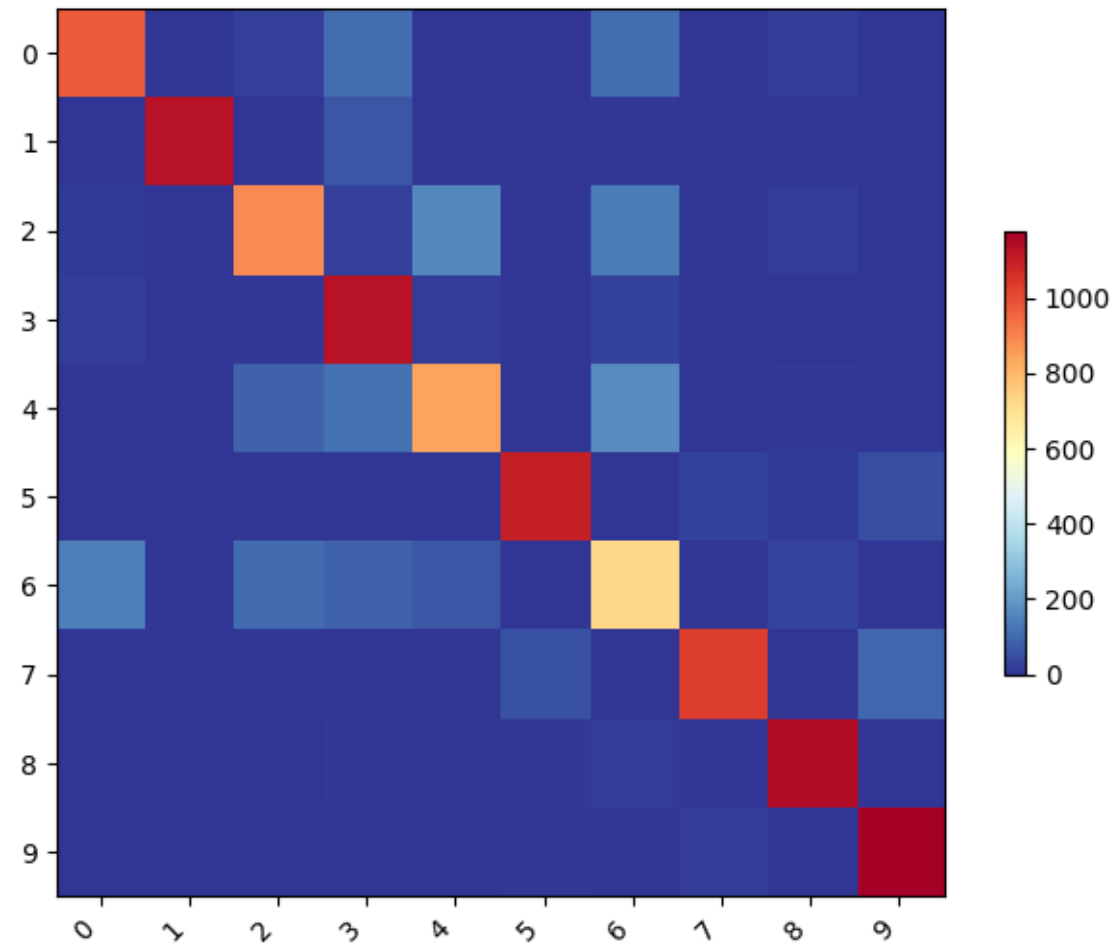
Validation Recall : 0.8448

Validation F1 Score: 0.8443

Training Confusion Matrix



Validation Confusion Matrix



Training & Testing - MLP

Evaluation Metrics:

Training Accuracy: 0.8594

Training Recall : 0.8594

Training F1 Score: 0.8588

Confusion Matrices:

Training:

		Predicted										
Actual		0	1	2	3	4	5	6	7	8	9	
0	[3804	4	63	406		8		0	426	0	53	0]
1	[3 4543		24	208		5		0	8	0	3	0]
2	[25	6	3462	73	609		0	565	0	28	0]	
3	[73	8	37 4513		56		0	98	0	11	0]	
4	[3	6	329 449 3409		0	579		0	10	0]		
5	[1	3	0	6	0 4579		0	61	15	141]		
6	[604	4	409 299 227		0 3191		0	117	0]			
7	[0	0	0	0	0	134		0 4322	9	355]		
8	[7	2	19 21	10	5	48		3 4704		1]		
9	[0	2	0	2	0	15		0 48	7	4722]		

Validation:

		Predicted										
Actual		0	1	2	3	4	5	6	7	8	9	
0	[975	0	23	109		4		0	107	0	18	0]
1	[2	1129		4	64		0		0	5	0	2 0]
2	[12	0	884	20	160		0	138	0	18	0]	
3	[16		1	9	1130		17		0	27	0	3 1]
4	[0	4	85	113	839		0	168	0	6	0]	
5	[3		1	0	1		0	1104		1	26	10 48]
6	[142	1	103	84	63		1	724	0	31	0]	
7	[0	0	0	0	0		0	54		0	1033	0 93]
8	[4	0		1	5		5	6		15	2	1142 0]
9	[0	1	0	0	0		0	7		0	17	1 1178]

Validation Accuracy: 0.8448

Validation Recall : 0.8448

Validation F1 Score: 0.8443

Experiments with – MLP (Decay Rate)

Hyperparameters:

input_size = 28 * 28

output_size = 10

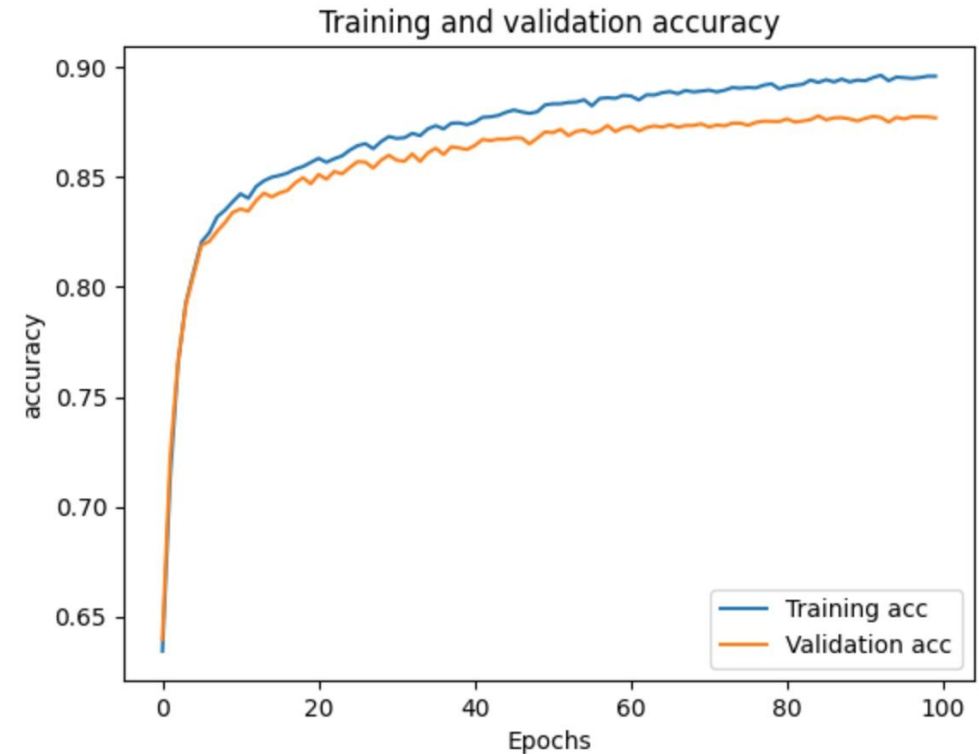
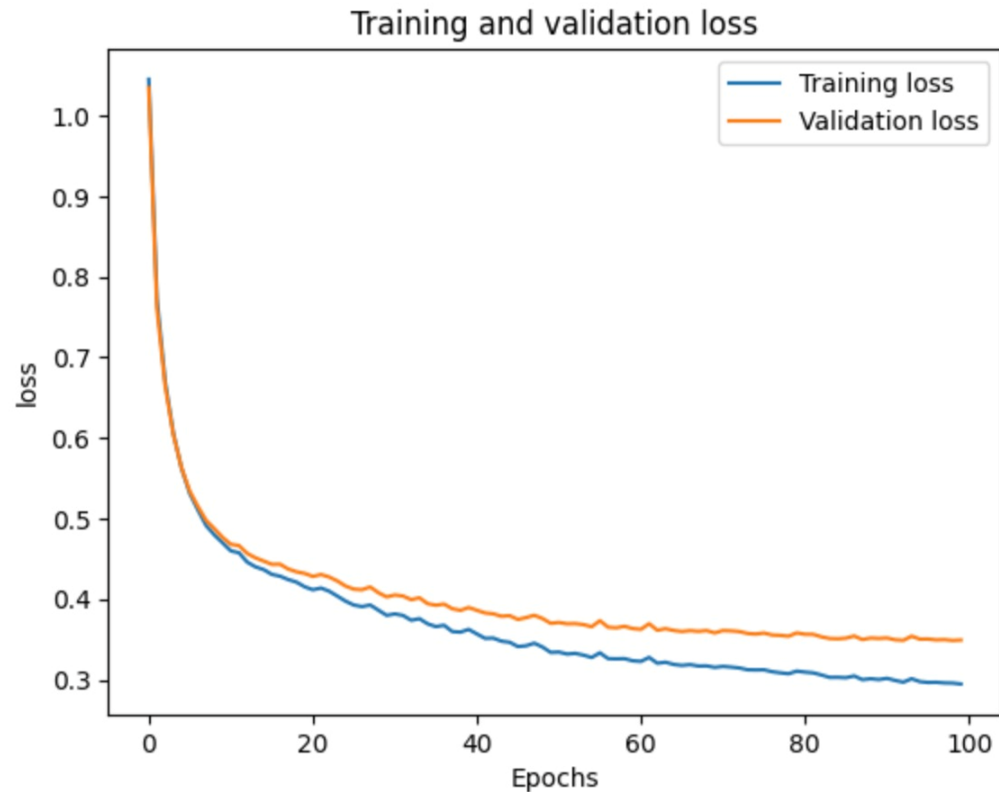
learning_rate = 0.01

Decay_rate= 0.02

hidden_size = 128

epochs = 100

dropout_rate=none



Experiments with – MLP (Dropout Rate)

Hyperparameters:

input_size = 28 * 28

output_size = 10

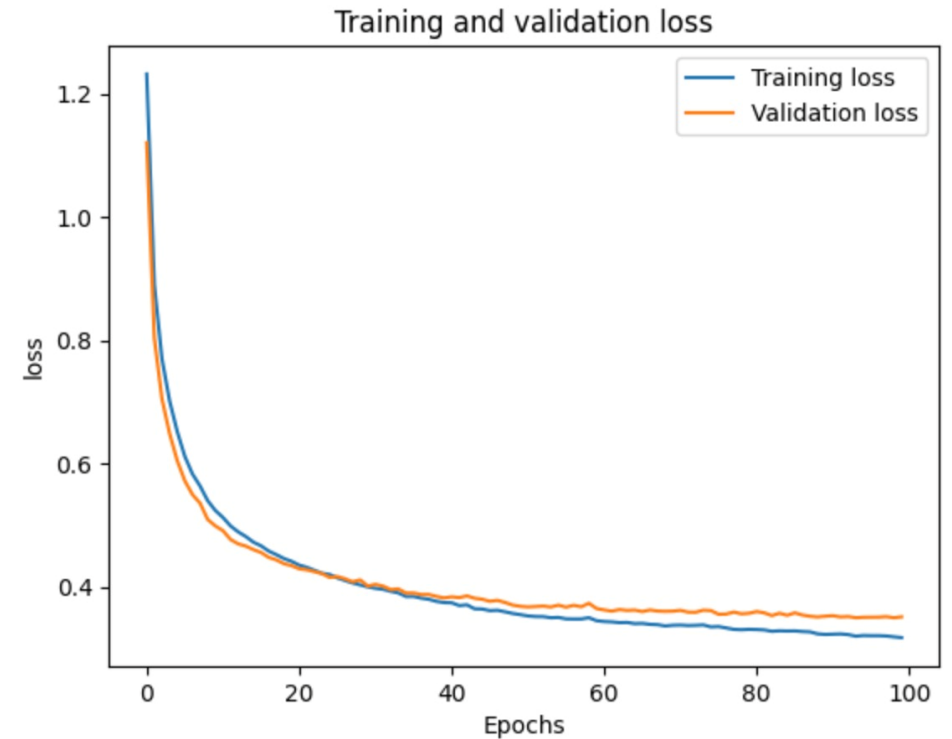
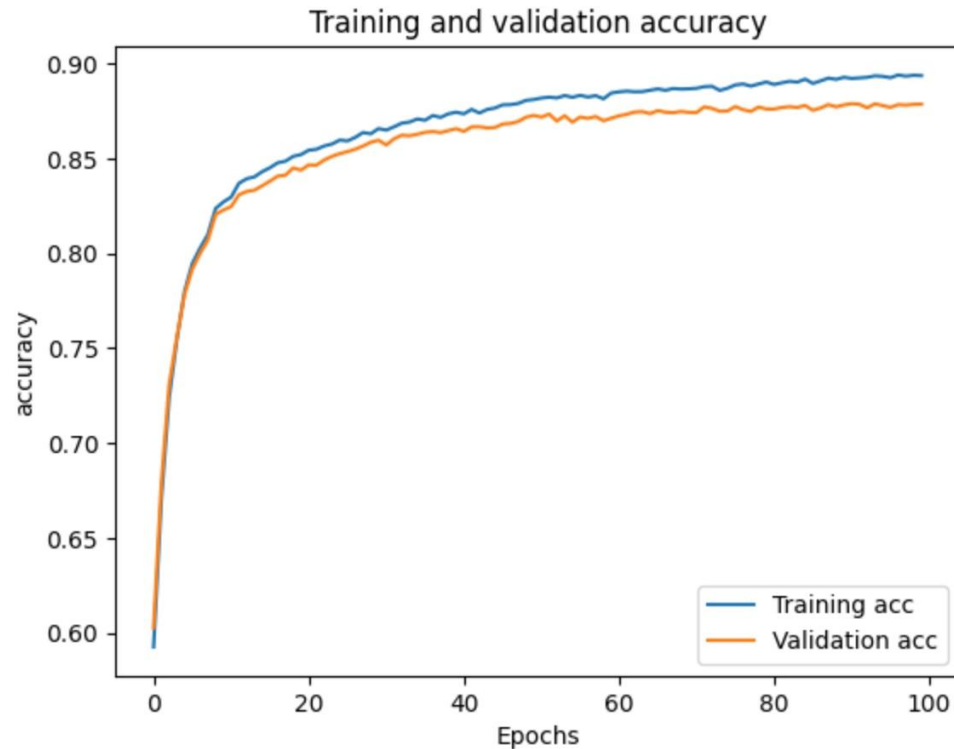
learning_rate = 0.01

Decay_rate= 0.02

hidden_size = 128

epochs = 100

dropout_rate= 0.2



Experiments with – MLP (L2 Regularization)

Hyperparameters:

input_size = 28 * 28

output_size = 10

learning_rate = 0.01

Decay_rate= 0.02

hidden_size = 128

epochs = 100

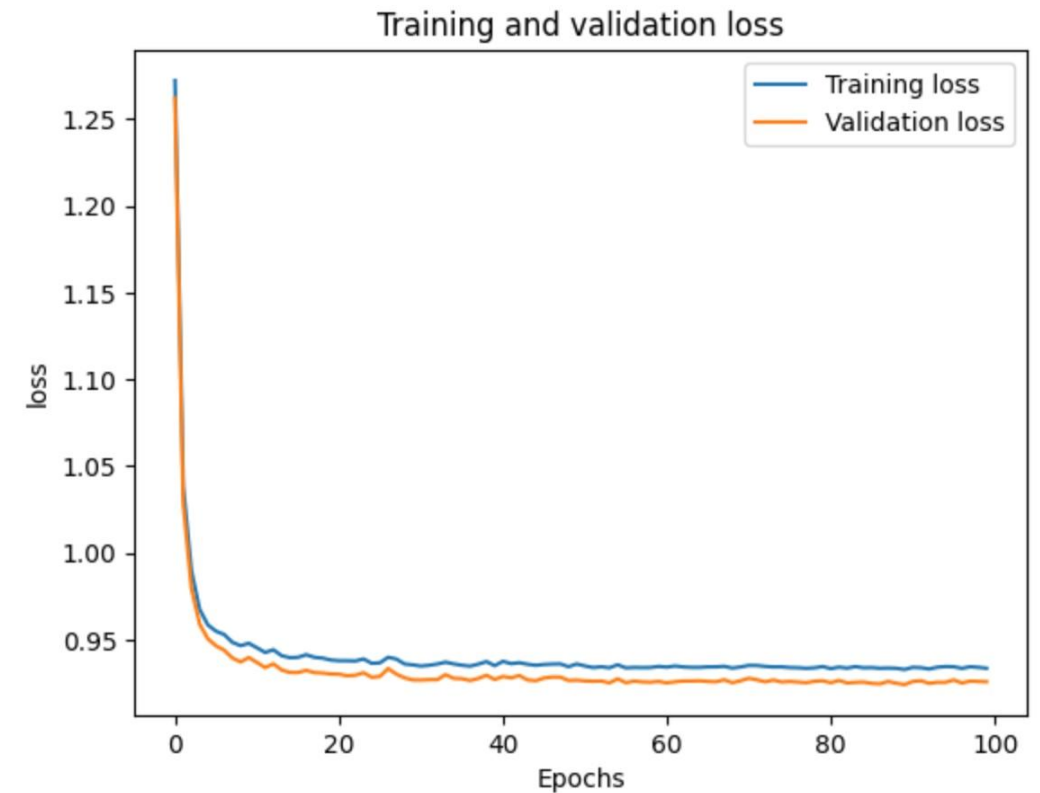
dropout_rate=None

regularization=L2

```
plt.show()
```



```
plt.show()
```



Architecture – CNN

Data Preparation:

- Download TRAINING (60000 samples) and TEST (10000) data from FashionMNIST
- Split TRAINING data into Training (48000) and Validation (12000) datasets
- Data Normalization & Flattening after convolutional layers

Convolution and Pooling Layers:

First Convolutional Block:

`nn.Conv2d(1, 49, (3, 3), stride=(1, 1), padding=(1, 1))`, # input = (1,28,28), output = (49, 28, 28)

A convolutional layer with 1 input channel (grayscale image), 49 output channels, a 3x3 kernel size, stride of 1, and padding of 1.

`nn.ReLU()`, # A ReLU activation function applied element-wise.

`nn.MaxPool2d((2, 2))`, # input = (49, 28, 28), output = (49, 14, 14)

A max-pooling layer with a 2x2 window, reducing the spatial dimensions by a factor of 2.

Architecture – CNN

Convolution and Pooling Layers:

Second Convolutional Block:

```
nn.Conv2d(49, 98, (2, 2), stride=(1, 1), padding=(1,1)), # input = (49, 14, 14), output = (98, 15, 15)
nn.ReLU(),
nn.MaxPool2d((2, 2)), # input = (98, 15, 15), output = (98, 7, 7)
```

Third Convolutional Block:

```
nn.Conv2d(98, 196, (2, 2), stride=(1, 1), padding=(1,1)), # input = (98, 7, 7), output = (196, 8, 8)
nn.ReLU(),
nn.MaxPool2d((2, 2)), # input = (196, 8, 8), output = (196, 4, 4)
```

Fourth Convolutional Block:

```
nn.Conv2d(196, 392, (2, 2), stride=(1, 1), padding=(1, 1)), # input = (196, 4, 4), output = (392, 5, 5)
nn.ReLU(),
nn.MaxPool2d((2, 2)), # input = (392, 5, 5), output = (392, 2, 2)
```

Fifth Convolutional Block:

```
nn.Conv2d(392, 784, (2, 2), stride=(1, 1), padding=(1, 1)), # input = (392, 2, 2), output = (784, 3, 3)
nn.ReLU(),
nn.MaxPool2d((2, 2)) # input = (784, 3, 3), output = (784,1,1)
```

Architecture – CNN

Flatten Layer: input = (784,1,1), output = (784)

Fully Connected Layers (Only in standalone CNN) :

Hidden Layer: input = 784, output = 128, ReLU activation

Output Layer: input = 128, output = 10

Training & Testing – CNN (Standalone)

Hyperparameters:

Epochs = 10

No. of Convolution/Maxpool Layer = 5/5

No. of Dense Layer = 2

Batch Size = 64

Input Size = (1,28,28)

Input=(784,1,1)

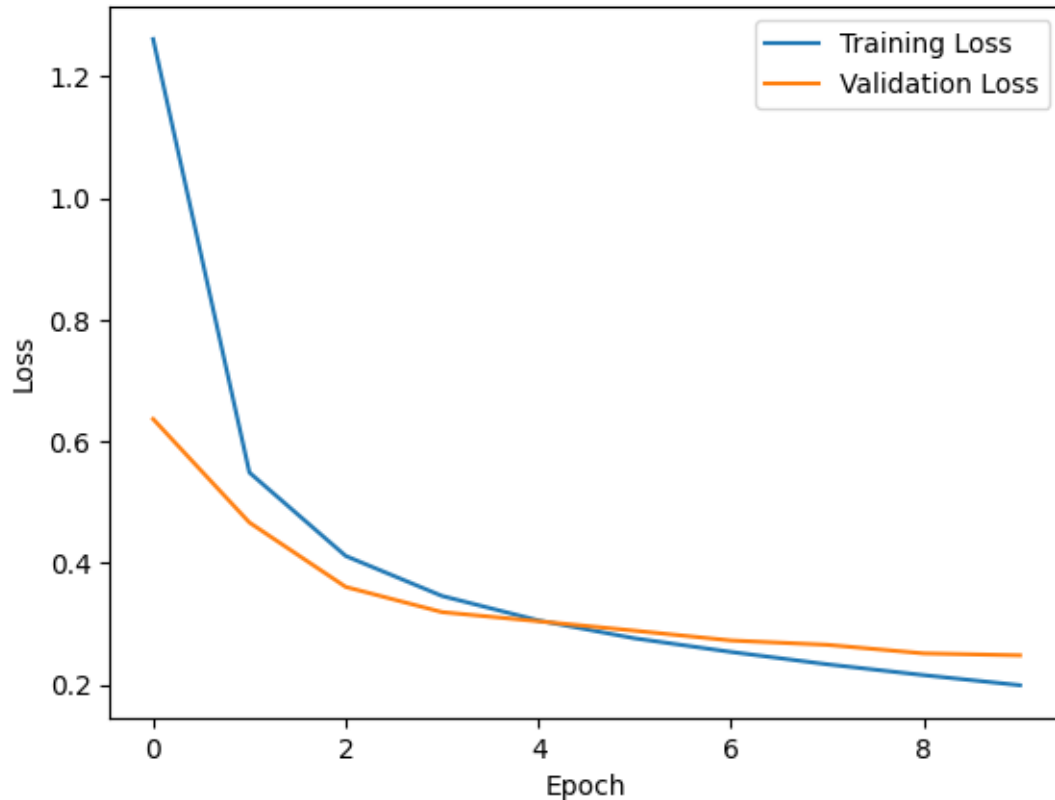
Learning Rate = 0.01

Output Size = (784,1,1)

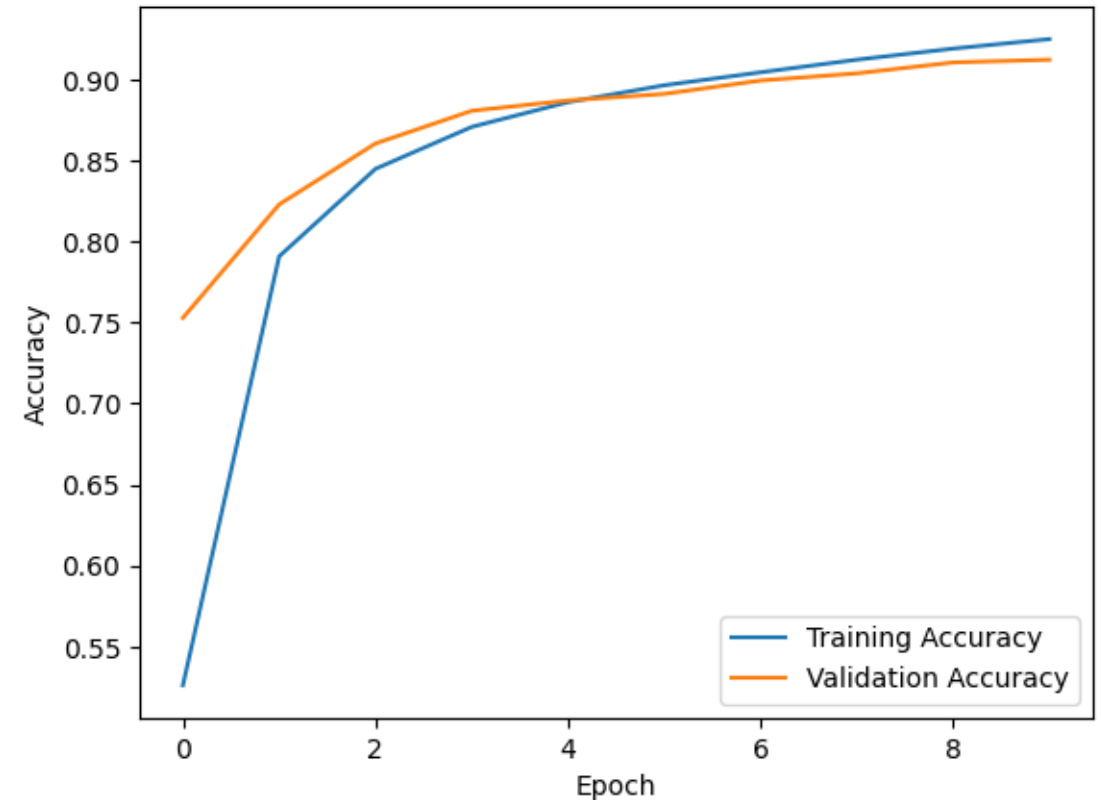
Output Size = 10

Observation: Test Phase: Accuracy: 88.5%, Avg loss: 0.322936

Epoch vs Training/Validation Loss



Epoch vs Training/Validation Accuracy



Performance – Experiments (Standalone)

Hyperparameters:

Epochs = 10

Batch Size = 64

Learning Rate = 0.1

No. of Filters:

a) Same across all layers : Accuracy: 90.1% ; Avg loss: 0.299253

b) Double across successive layers: Accuracy: 89.4% ; Avg loss: 0.290769

Size of Convolution Layer Filters:

a) (3,3) in first layer, (2,2) in next four layers : Accuracy: 89.2% ; Avg loss: 0.293090

b) (3,3) in first three layers, (2,2) in next two layers : Accuracy: 90.4%; Avg loss: 0.274256

Note: In order to maintain dimension of input features to standalone MLP i.e. (28 *28) was matched with the output of the backbone CNN which is 784.

Stride:

a) (2,2) in first layer

b) (1,1) in first layer

Observation: Larger stride resulted in poor accuracy

Evaluation Metrics (Combined)

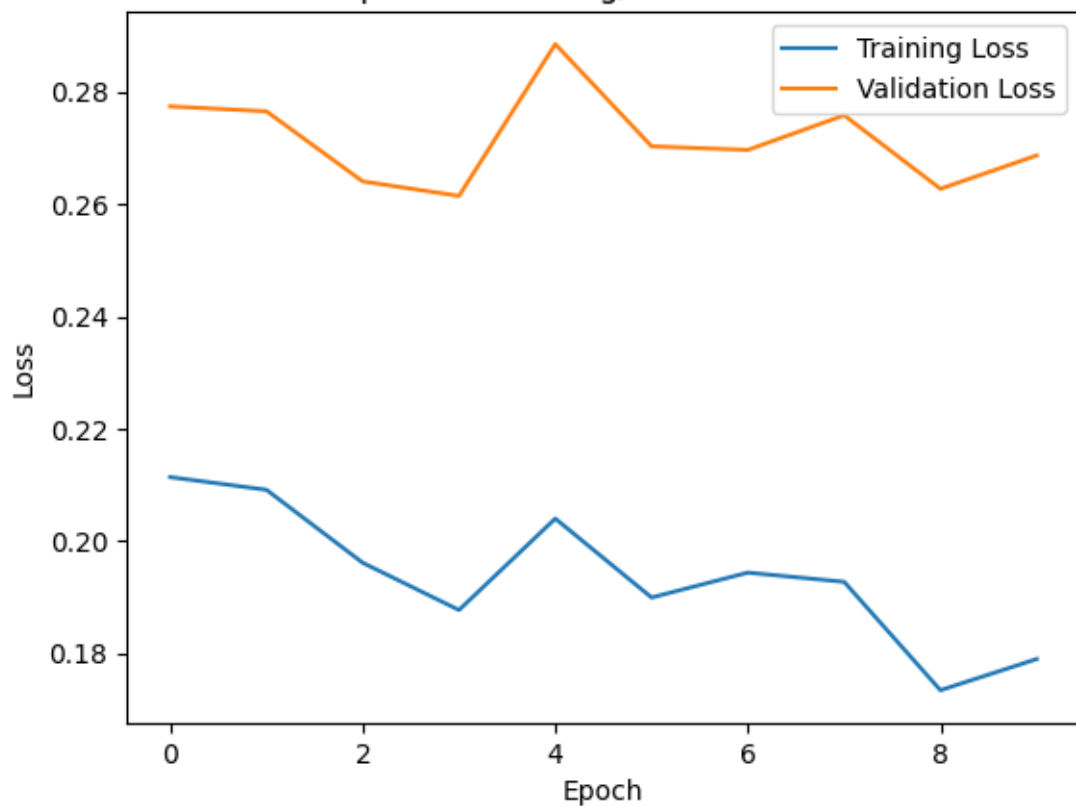
Hyperparameters:

Epochs = 10

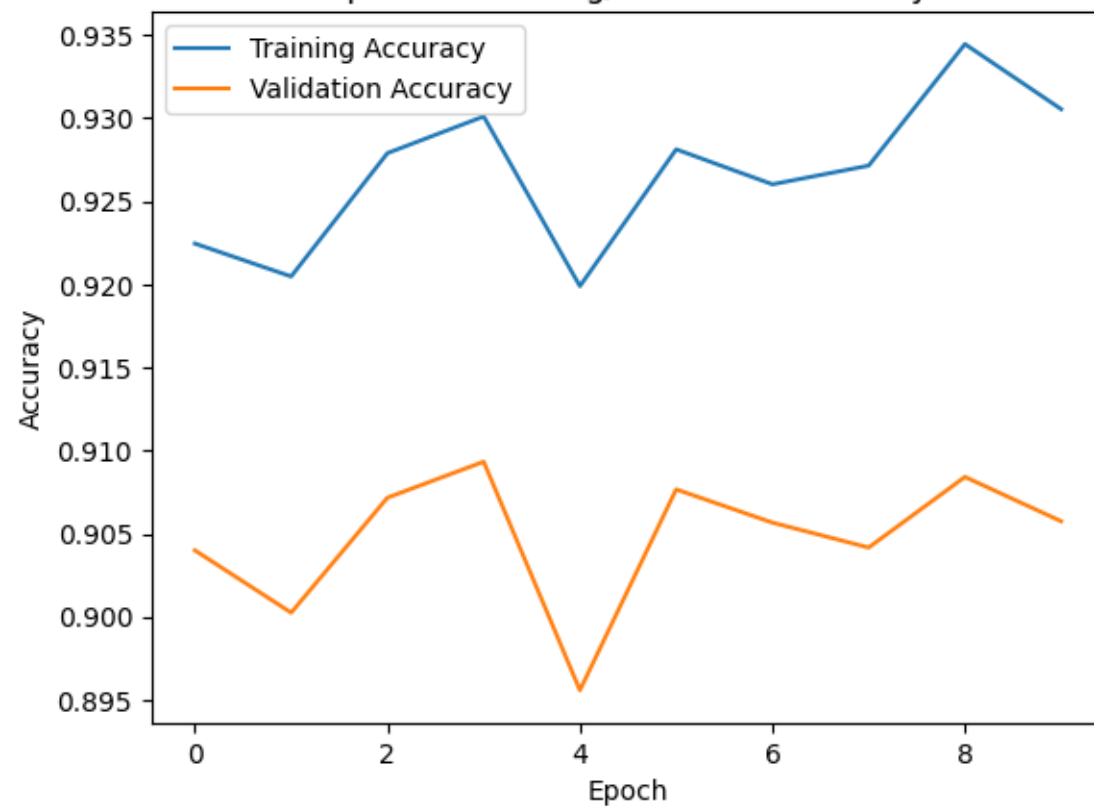
Batch Size = 64

Learning Rate = 0.1

Epoch vs Training/Validation Loss

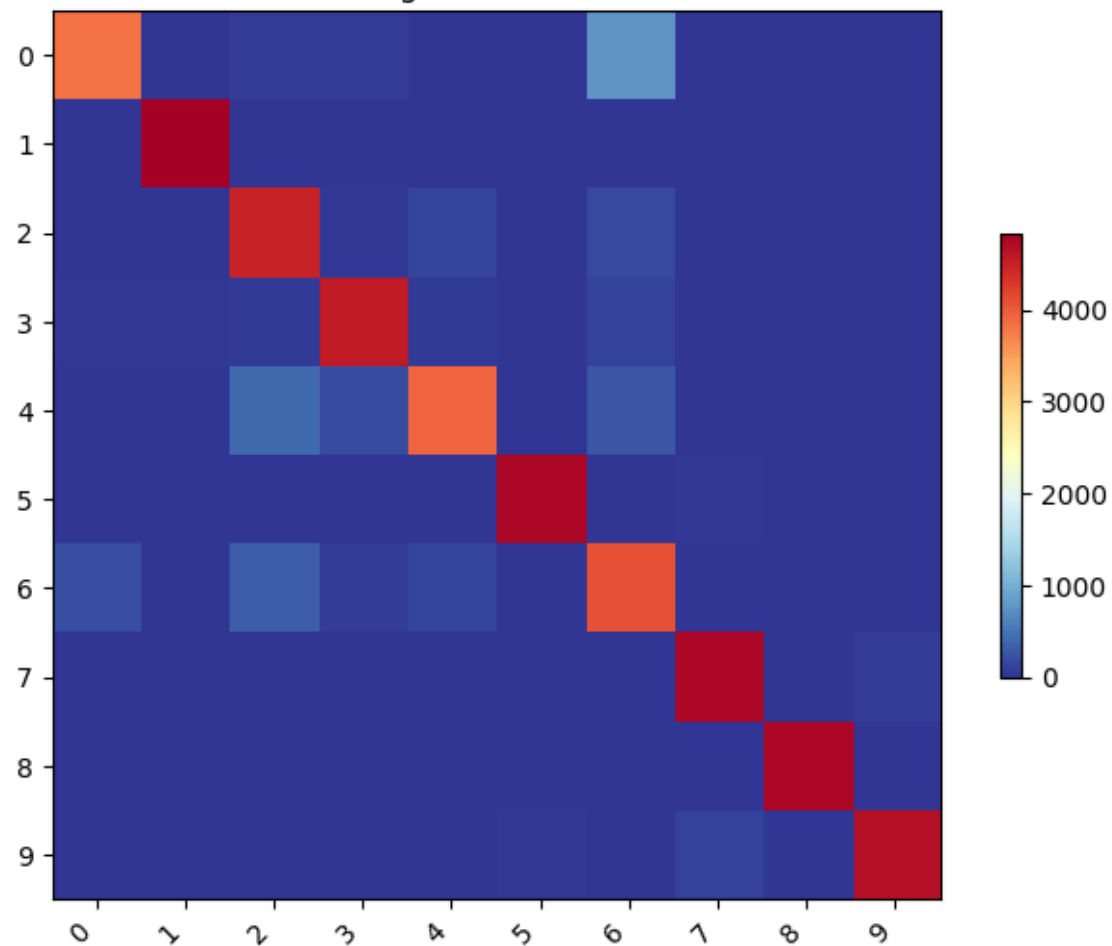


Epoch vs Training/Validation Accuracy

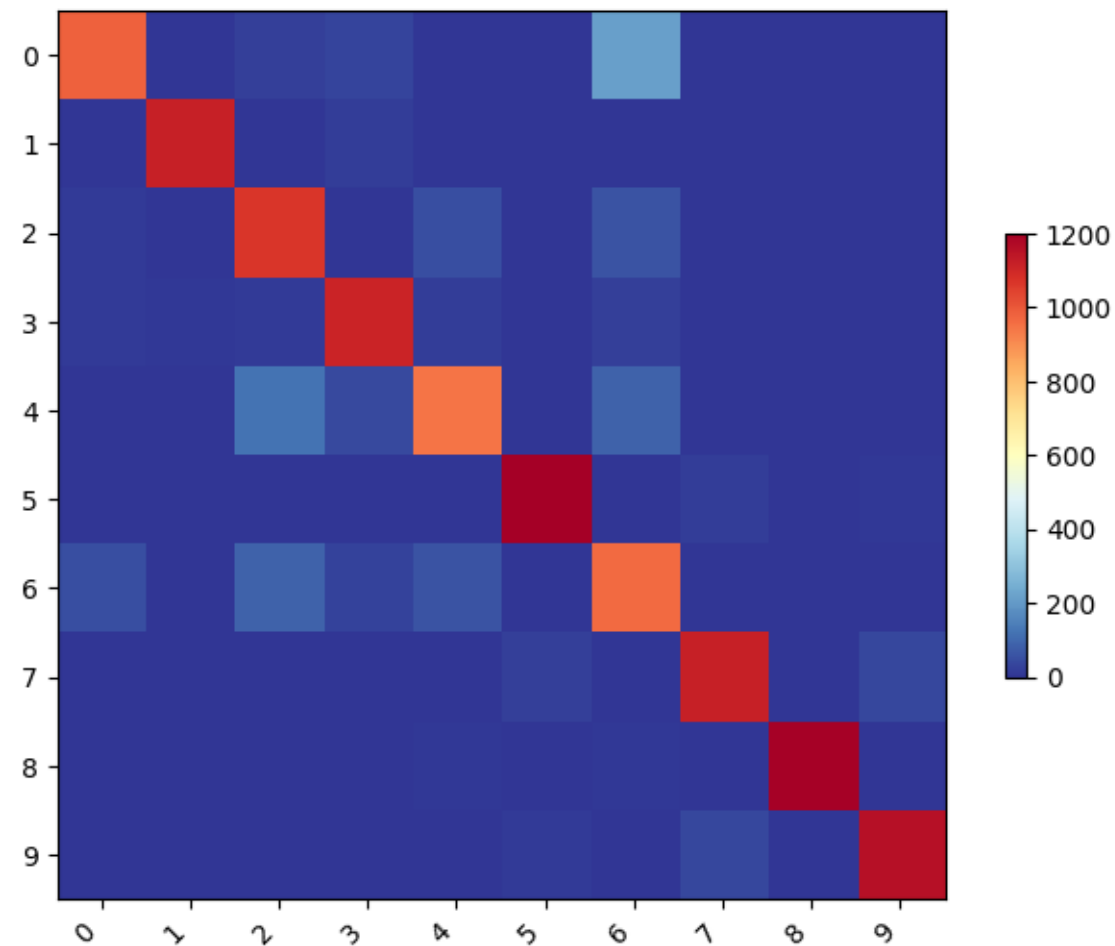


Evaluation Metrics (Combined)

Training Confusion Matrix



Validation Confusion Matrix



Evaluation Metrics (Combined)

Evaluation Metrics:

Training Accuracy: 0.9782

Training Recall : 0.9782

Training F1 Score: 0.9782

Validation Accuracy: 0.9047

Validation Recall : 0.9047

Validation F1 Score: 0.9051

Confusion Matrices:

Training:

		Predicted									
Actual		0	1	2	3	4	5	6	7	8	9
0	[3837	2	66	63	3	0	759	0	14	0]
1	[0	4839	0	15	0	0	3	0	0	0]
2	[13	1	4485	22	126	0	155	0	3	0]
3	[25	21	52	4559	45	1	101	0	7	0]
4	[1	1	410	186	3940	0	247	0	11	0]
5	[0	0	0	0	0	4748	0	27	0	2]
6	[199	1	308	67	126	0	4091	0	13	0]
7	[0	0	0	0	0	14	0	4746	0	67]
8	[0	0	6	1	2	1	10	0	4761	0]
9	[0	0	0	0	0	23	0	112	2	4660]

Validation:

		Predicted									
Actual		0	1	2	3	4	5	6	7	8	9
0	[982	0	23	31	4	1	212	0	3	0]
1	[1	1119	0	18	1	0	3	0	1	0]
2	[12	2	1069	3	50	0	58	0	1	0]
3	[13	9	13	1111	18	0	22	0	3	0]
4	[3	2	122	41	948	0	85	0	3	0]
5	[0	0	0	0	0	1202	0	15	1	5]
6	[50	3	89	27	57	0	966	0	3	0]
7	[0	0	0	0	0	19	0	1120	1	33]
8	[4	0	4	4	5	1	5	1	1195	0]
9	[0	1	0	0	0	10	0	35	0	1157]

Reference:

- *Pytorch:* https://pytorch.org/tutorials/beginner/basics/quickstart_tutorial.html
- *Derivative of Softmax:*
<https://towardsdatascience.com/derivative-of-the-softmax-function-and-the-categorical-cross-entropy-loss-ffceefc081d1>
- *CNN backbone model:* <https://www.baeldung.com/cs/neural-network-backbone>
- *Weight initialization -* <https://machinelearningmastery.com/weight-initialization-for-deep-learning-neural-networks/>



Question