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Department of Computer Science and Engineering

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1. Dataset Creation

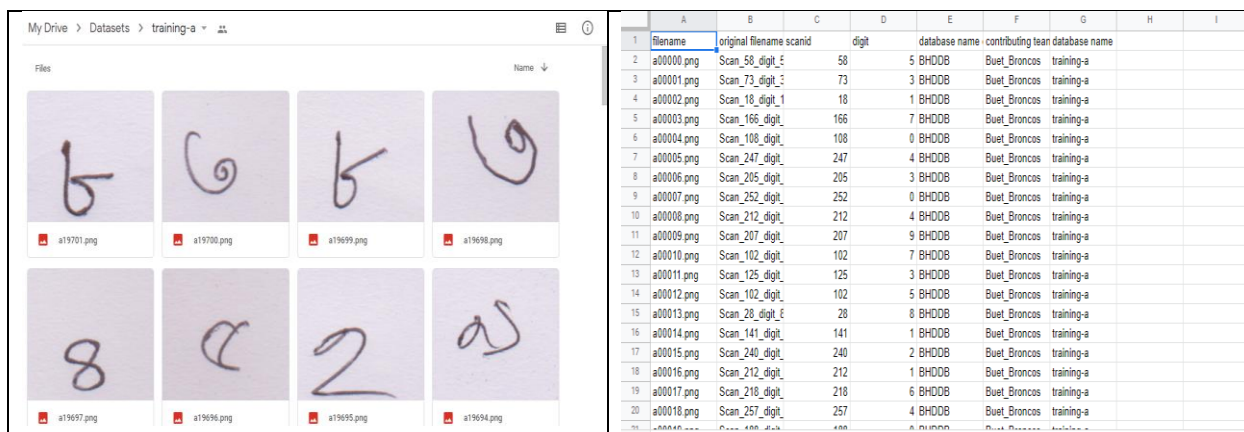
In this section, we know about the creation process of the dataset.

For the data creation process, we divide it into two different sub-processes.

1. Data Download
2. Creating Dataset Proper Format

1.1. Data Downloading:

In the data downloading process, first, we need to download the files based on the ID. My is 170104028. So, it is even ID. That's why I need to download the [Dataset A](#). In dataset we saw that this is Bangla Hand Written digit. After extracting the dataset, we can saw that there are two files. One is train training-a folder training-a.csv. In folder we see all the image. **training-a.csv** file have the information of the image. The two files content is-



1	A	B	C	D	E	F	G	H	I
	Filename	original filename	scanid	digit	database name	contributing team	database name		
2	a00000.png	Scan_50_digit_5	58	5	BHDOB	Buet_Broncos	training-a		
3	a00001.png	Scan_73_digit_3	73	3	BHDOB	Buet_Broncos	training-a		
4	a00002.png	Scan_18_digit_1	18	1	BHDOB	Buet_Broncos	training-a		
5	a00003.png	Scan_166_digit_166	166	7	BHDOB	Buet_Broncos	training-a		
6	a00004.png	Scan_108_digit_108	108	0	BHDOB	Buet_Broncos	training-a		
7	a00005.png	Scan_247_digit_247	247	4	BHDOB	Buet_Broncos	training-a		
8	a00006.png	Scan_205_digit_205	205	3	BHDOB	Buet_Broncos	training-a		
9	a00007.png	Scan_252_digit_252	252	0	BHDOB	Buet_Broncos	training-a		
10	a00008.png	Scan_212_digit_212	212	4	BHDOB	Buet_Broncos	training-a		
11	a00009.png	Scan_207_digit_207	207	9	BHDOB	Buet_Broncos	training-a		
12	a00010.png	Scan_102_digit_102	102	7	BHDOB	Buet_Broncos	training-a		
13	a00011.png	Scan_125_digit_125	125	3	BHDOB	Buet_Broncos	training-a		
14	a00012.png	Scan_102_digit_102	102	5	BHDOB	Buet_Broncos	training-a		
15	a00013.png	Scan_28_digit_28	28	8	BHDOB	Buet_Broncos	training-a		
16	a00014.png	Scan_141_digit_141	141	1	BHDOB	Buet_Broncos	training-a		
17	a00015.png	Scan_240_digit_240	240	2	BHDOB	Buet_Broncos	training-a		
18	a00016.png	Scan_212_digit_212	212	1	BHDOB	Buet_Broncos	training-a		
19	a00017.png	Scan_218_digit_218	218	6	BHDOB	Buet_Broncos	training-a		
20	a00018.png	Scan_257_digit_257	257	4	BHDOB	Buet_Broncos	training-a		

Figure 1: Raw Dataset

Form this, dataset we saw that this is not properly formatted. That's why we need to format the dataset.

For download the dataset I used gdown package. Because this is google drive link. For downloading I used given code-

```
!gdown --id 1txyKhs1Zt5AKswGgK9VI_jE0JNHuQT85
```

```
Downloading...
```

```
From: https://drive.google.com/uc?id=1txyKhs1Zt5AKswGgK9VI_jE0JNHuQT85
```

```
To: /content/Dataset A.zip
```

```
815MB [00:08, 98.7MB/s]
```

Figure 2: Data Download Code

1.2. Creating Dataset Proper Format

After Collecting the raw data. We need to generate our dataset. In to a good format. Because, next time when we train, we don't need to change anything our dataset. Also, future, we can train our dataset easily. After formatted dataset the dataset looks like-

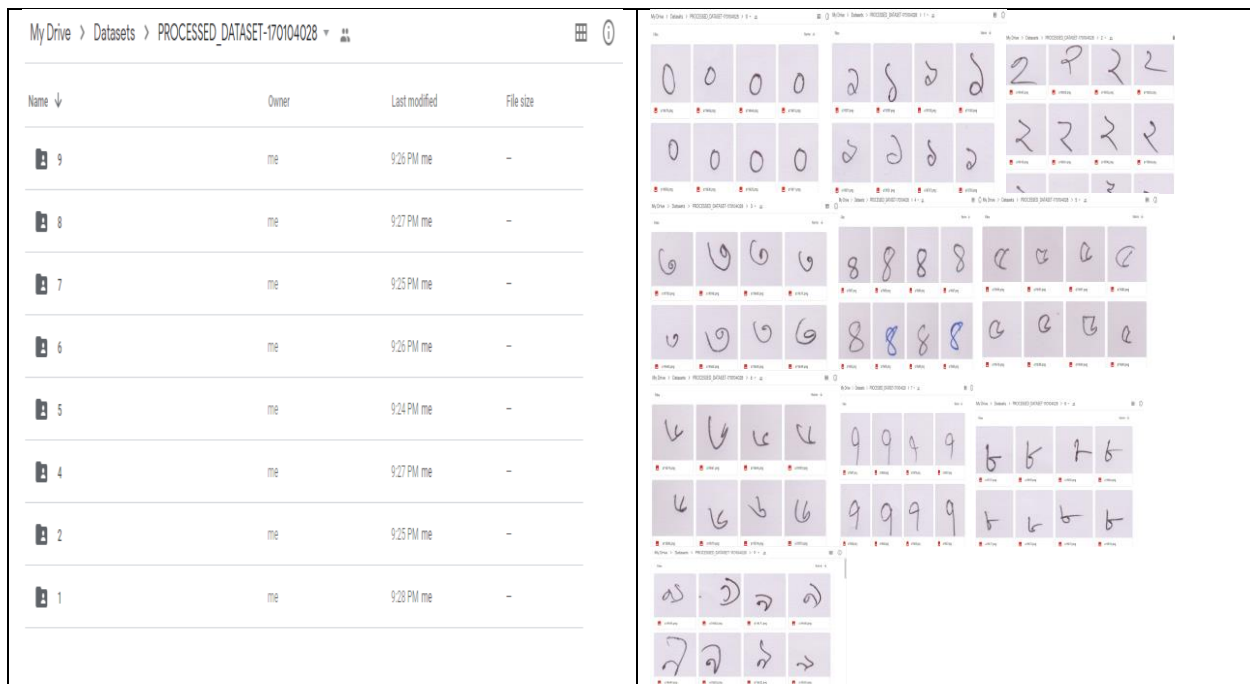


Figure 3: After format data

To format the dataset, we used the given code -

```
[ ] traning_csv = '/content/training-a.csv'
read_df = pd.read_csv(traning_csv)

number_of_digit_class = read_df['digit'].nunique()

DATASET_ROOT_DIR = './PROCESSED_DATASET_170104028/' ← Saved Path
path = Path(DATASET_ROOT_DIR)
path.mkdir(parents=True, exist_ok=True)
DATASET_ROOT_DIR = os.path.abspath(path)

for i in range(0, number_of_digit_class):
    select_digit = read_df[read_df['digit'] == i]
    for index, val in select_digit.iterrows():
        file_relative_path_from = f"./{val['database name']}/{val['filename']}"
        file_relative_dir_to = f"{DATASET_ROOT_DIR}/{val['digit']}"
        Path(file_relative_dir_to).mkdir(parents=True, exist_ok=True)
        shutil.copy(file_relative_path_from, file_relative_dir_to) ← Folder creation based on the digit
        print(file_relative_path_from, file_relative_dir_to, "OK") ← Copy file

img_path: "/content/PROCESSED_DATASET-170104028"
Show code

ZIP_FILE_NAME = 'PROCESSED_DATASET-170104028.zip'
!zip -r $ZIP_FILE_NAME 'PROCESSED_DATASET-170104028/' ← Zip Create
```

Figure 4: Data format code

2. Training Process

For training process, we need to follow two parts. First one is Experiment 1 and second one is Experiment 2.

2.1. Experiment 1

For experiment 1, must follow some rules. The rules are, we must use 6 hidden layer, 200 nodes, 0.01 learning rate etc. For model creation I use this code -

```
class LIN_MODEL(torch.nn.Module):
    def __init__(self, outDim):
        super(LIN_MODEL, self).__init__()

        self.fc_1 = torch.nn.Linear(784, 90)
        self.fc_2 = torch.nn.Linear(90, 50)
        self.fc_3 = torch.nn.Linear(50, 30)
        self.fc_4 = torch.nn.Linear(30, 18)
        self.fc_5 = torch.nn.Linear(18, 12)
        self.fc_6 = torch.nn.Linear(12, outDim)

        self.linear = torch.nn.Linear(784, outDim)

    def forward(self, x):
        x = x.view(-1, 28 * 28)
        x = torch.nn.functional.relu(self.fc_1(x))
        x = torch.nn.functional.softmax(self.fc_2(x), dim=1)
        x = torch.nn.functional.relu(self.fc_3(x))
        x = torch.nn.functional.softmax(self.fc_4(x), dim=1)
        x = torch.nn.functional.relu(self.fc_5(x))
        x = self.fc_6(x)
        # x = torch.nn.functional.softmax(self.linear(x), dim=1)
        return x

model_1 = LIN_MODEL(OUTPUT_DIM).to(device)

summary(model_1, input_size=(1, 28, 28))
# select CPU or GPU as a device
print(model_1)
```

model forward pass

Layer (type)	Output Shape	Param #
Linear-1	[-1, 90]	70,650
Linear-2	[-1, 50]	4,550
Linear-3	[-1, 30]	1,530
Linear-4	[-1, 18]	558
Linear-5	[-1, 12]	228
Linear-6	[-1, 10]	130

Total params: 77,646
Trainable params: 77,646
Non-trainable params: 0

Input size (MB): 0.00
Forward/backward pass size (MB): 0.00
Params size (MB): 0.30
Estimated Total Size (MB): 0.30

Figure 5: Experiment 1, Model 1

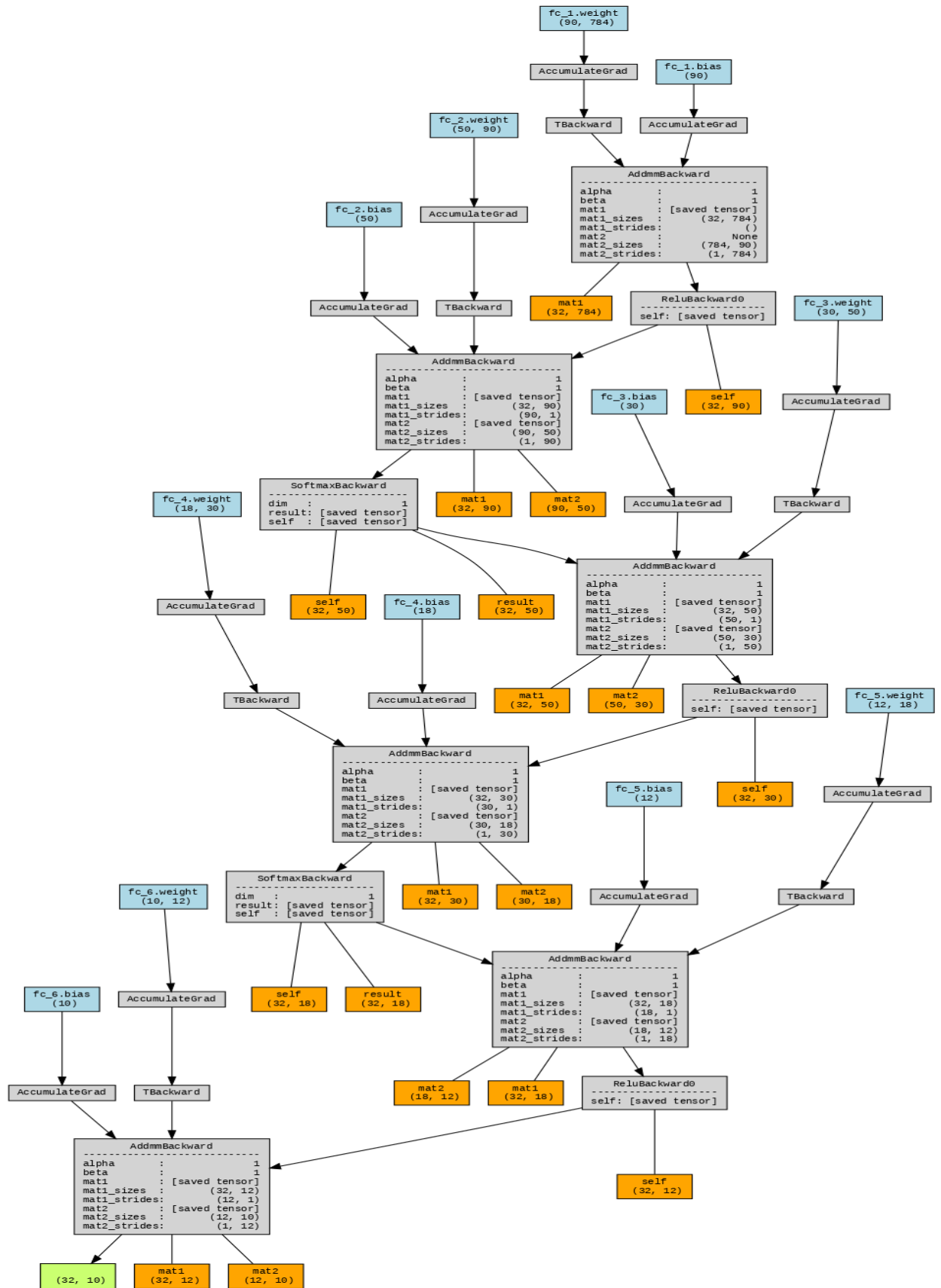


Figure 6: Model 1 summary

2.2. Experiment 2

For experiment 2, must follow the 85% accuracy of dataset.

2.2.1. Model-1 V2

```
class LIN_MODEL_2(torch.nn.Module):
    def __init__(self,outDim):
        super(LIN_MODEL_2, self).__init__()

        self.fc_1 = torch.nn.Linear(784, 742)
        self.fc_2 = torch.nn.Linear(742, 621)
        self.fc_3 = torch.nn.Linear(621, 510)
        self.fc_6 = torch.nn.Linear(510, outDim)

    def forward(self, x):

        x = x.view(-1, 28 * 28)
        x = torch.nn.functional.relu(self.fc_1(x))
        x = torch.nn.functional.relu(self.fc_2(x))
        x = torch.nn.functional.relu(self.fc_3(x))
        x = torch.nn.functional.relu(self.fc_6(x))

        return x

model_1_2 = LIN_MODEL_2(OUTPUT_DIM).to(device)

summary(model_1_2, input_size=(1, 28, 28))
# select CPU or GPU as a device
print(model_1_2)
```

```
-----
Layer (type)          Output Shape          Param #
-----
Linear-1              [-1, 742]             582,470
Linear-2              [-1, 621]             461,403
Linear-3              [-1, 510]             317,220
Linear-4              [-1, 10]              5,110
=====
Total params: 1,366,203
Trainable params: 1,366,203
Non-trainable params: 0
-----
Input size (MB): 0.00
Forward/backward pass size (MB): 0.01
Params size (MB): 5.21
Estimated Total Size (MB): 5.23
-----
```

Figure 7: Experiment 2, Model 1 V2, This is based on linear layer

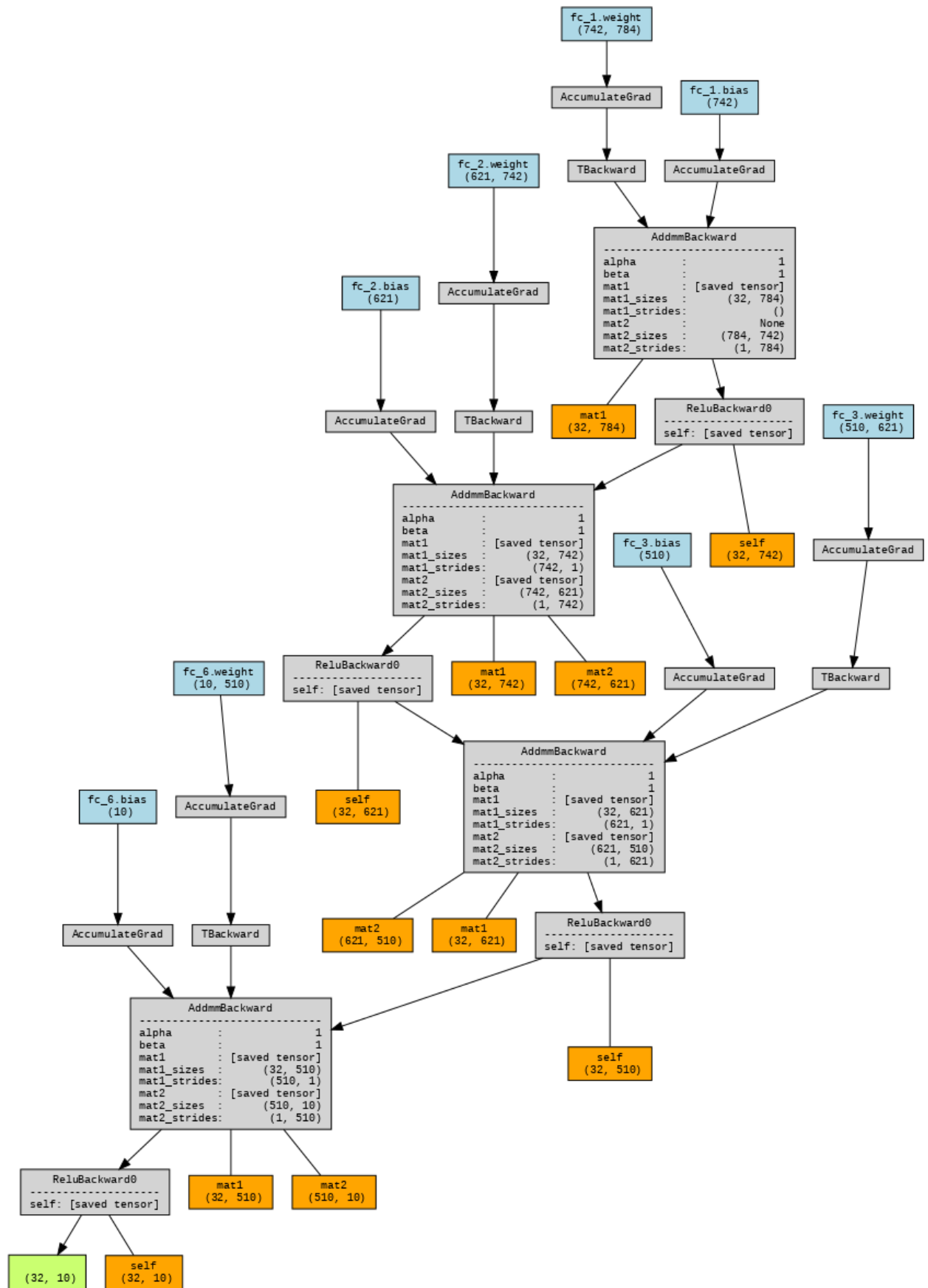


Figure 8: Model V2 flow

2.2.1. Model-1 V3

```
class LIN_MODEL_3(torch.nn.Module):
    def __init__(self,outDim):
        super(LIN_MODEL_3, self).__init__()

        self.fc_1 = torch.nn.Linear(784, 512)
        self.fc_2 = torch.nn.Linear(512, 256)
        self.fc_6 = torch.nn.Linear(256, outDim)

    def forward(self, x):

        x = x.view(-1, 28 * 28)
        x = torch.nn.functional.relu(self.fc_1(x))
        x = torch.nn.functional.relu(self.fc_2(x))
        x = torch.nn.functional.relu(self.fc_6(x))

        return x

model_1_3 = LIN_MODEL_3(OUTPUT_DIM).to(device)

summary( model_1_3, input_size=(1, 28, 28))
print(model_1_3)
```

```
-----
              Layer (type)              Output Shape          Param #
=====
              Linear-1                  [-1, 512]              401,920
              Linear-2                  [-1, 256]              131,328
              Linear-3                  [-1, 10]                2,570
=====
Total params: 535,818
Trainable params: 535,818
Non-trainable params: 0
-----
Input size (MB): 0.00
Forward/backward pass size (MB): 0.01
Params size (MB): 2.04
Estimated Total Size (MB): 2.05
-----
```

Figure 9:Model 1 V3.



2.2.2. Model-2-CNN

```
class CNN(torch.nn.Module):
    def __init__(self, outDim):
        super(CNN, self).__init__()

        #initializing convolution layer
        self.conv1 = torch.nn.Conv2d(in_channels=3, out_channels=16, kernel_size=3)
        self.conv2 = torch.nn.Conv2d(in_channels=16, out_channels=32, kernel_size=3)

        #initializing dropout
        self.dropout = torch.nn.Dropout(0.2)

        #initializing dropout
        self.pool= torch.nn.MaxPool2d(2,2)

        #initializing linear
        self.fc1 = torch.nn.Linear(32* 30* 30, 512)
        self.fc2 = torch.nn.Linear(512,64)
        self.fc3 = torch.nn.Linear(64,10)

    def forward(self, x):
        x = self.pool(torch.nn.functional.relu(self.conv1(x)))
        x = self.dropout(x)
        x = self.pool(torch.nn.functional.relu(self.conv2(x)))
        x = self.dropout(x)
        x = x.view(-1, 32* 30* 30)
        # print(x.shape)
        x = torch.nn.functional.relu(self.fc1(x))
        x = torch.nn.functional.relu(self.fc2(x))
        x = self.fc3(x)
        return x

model_2 = CNN(OUTPUT_DIM).to(device)

summary( model_2, input_size=(3, 128, 128))
# select CPU or GPU as a device
print(model_2)
```

```
-----
Layer (type)          Output Shape          Param #
-----
Conv2d-1              [-1, 16, 126, 126]    448
MaxPool2d-2           [-1, 16, 63, 63]      0
Dropout-3             [-1, 16, 63, 63]      0
Conv2d-4              [-1, 32, 61, 61]      4,640
MaxPool2d-5           [-1, 32, 30, 30]      0
Dropout-6             [-1, 32, 30, 30]      0
Linear-7              [-1, 512]             14,746,112
Linear-8              [-1, 64]              32,832
Linear-9              [-1, 10]              650
=====
Total params: 14,784,682
Trainable params: 14,784,682
Non-trainable params: 0
-----
Input size (MB): 0.19
Forward/backward pass size (MB): 4.26
Params size (MB): 56.40
Estimated Total Size (MB): 60.85
-----
```

Figure 11: Model 3, Based on the CNN

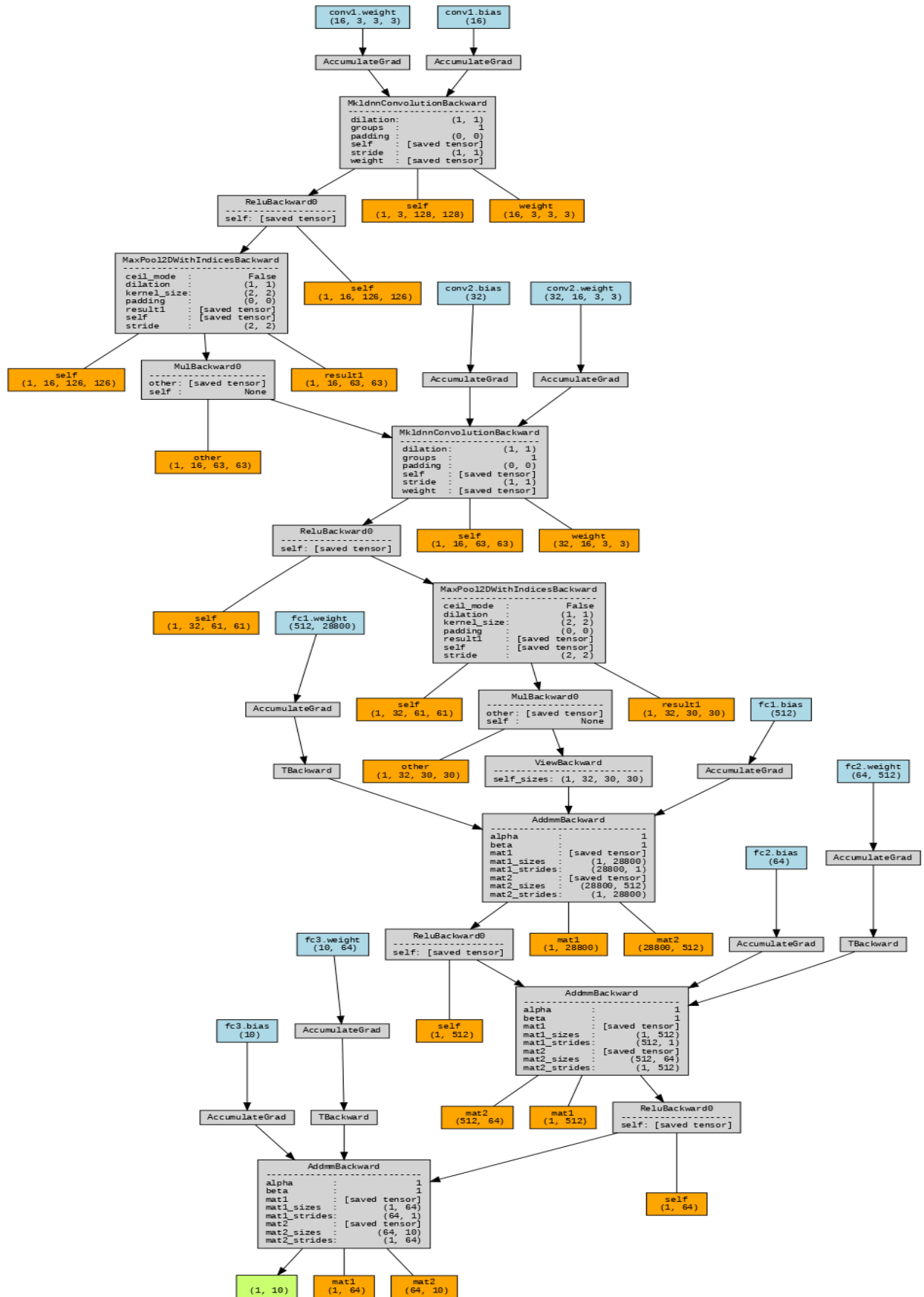


Figure 12: Model 2 flow summary

2.2.3. Model-3-RSNET152

```
def set_parameter_requires_grad(model, feature_extracting):
    if feature_extracting:
        for param in model.parameters():
            param.requires_grad = False

num_classes = OUTPUT_DIM

model_3 = models.resnet152(pretrained=True)
set_parameter_requires_grad(model_3, True)
num_fts = model_3.fc.in_features
model_3.fc = torch.nn.Linear(num_fts, num_classes)

model_3 = model_3.to(device)
```

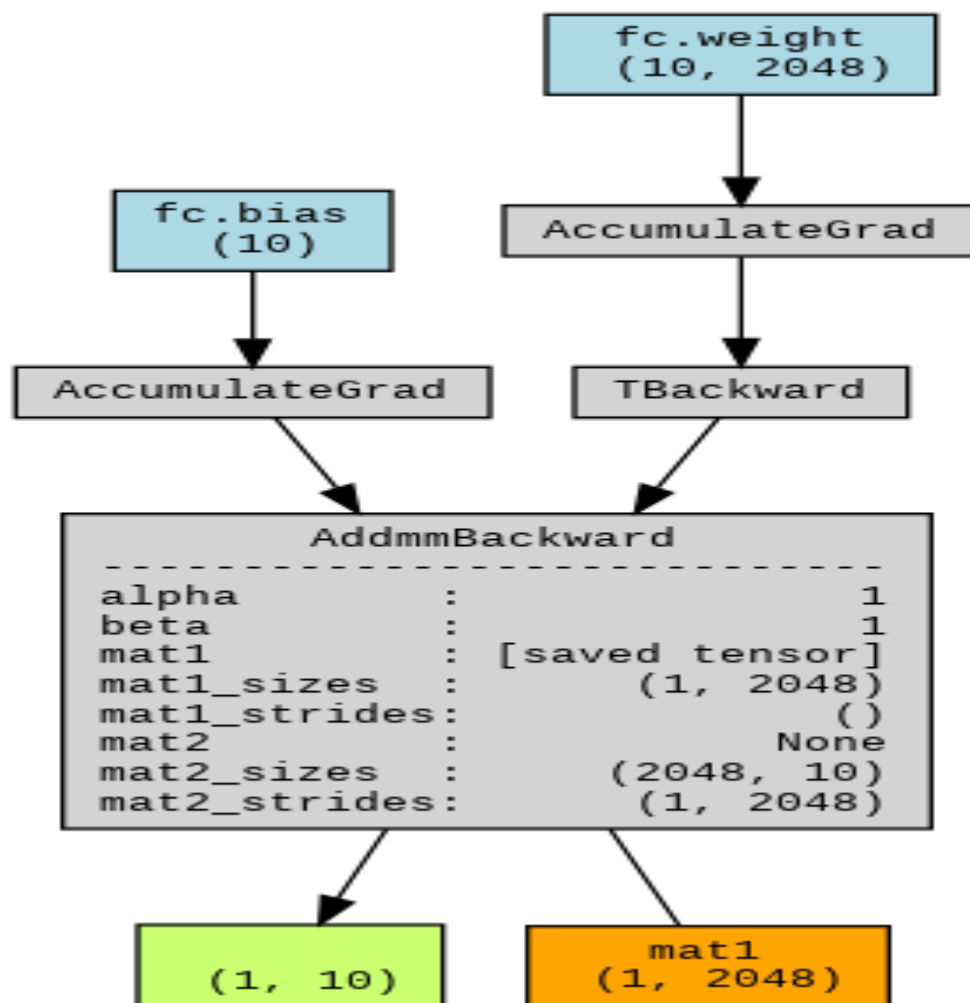


Figure 13: Model 3, Based on the pretrained and flow of summary

2.3. Training Flow

For training the model, I use 4 basic flows.

1. Hyper parameter and variables
2. Load dataset
3. Model Creation
4. Model train and save the model

2.3.1. Hyper parameter

For model hyper parameter and variables, I used this code.

```
base_dir = '/content/PROCESSED_DATASET-170104028'
BATCH_SIZE = 32

# 28(model-1), 128(model-2), 224(model-3),
IMAGE_SIZE = 128
LEARNING_RATE = 0.01
TEST_SIZE = 0.2
OUTPUT_DIM=10
```

```
from pathlib import Path

START=0
model_save_path = './EXP-2-GRAY-OWN/' # must give `/' for the folder directory

model_used= 'EXPERIMENT_MODEL_2_GRAY'
# model_ft = model_1
# model_ft = model_1_2
# model_ft = model_1_3
model_ft = model_2
# model_ft = model_3
optimizer_ft = optimizer
all_training_loss = []
all_validation_loss = []
all_training_accuracy = []
all_validation_accuracy = []

load_saved_model='/content/EXP-1-2-OWN/EXPERIMENT_MODEL_1_2-checkpoint-epoch-187.pt'
p = Path(load_saved_model)
if len(load_saved_model) > 1 and p.exists():
    loadedModel = torch.load(load_saved_model, map_location=device)
    model_used = loadedModel['MODEL_USED']
    model_ft = loadedModel['model_full']
    model_ft.load_state_dict(loadedModel['model_state'])
    optimizer_ft = loadedModel['optimizer_full']
    optimizer_ft.load_state_dict(loadedModel['optimizer_state'])
    START = loadedModel['epoch'] + 1
    all_training_loss = loadedModel['training_loss']
    all_validation_loss = loadedModel['validation_loss']
    all_training_accuracy = loadedModel['training_acc']
    all_validation_accuracy = loadedModel['validation_acc']

END=100
trainloader= trainloader
testloader = validationloader
```

Figure 14: Training Parameter's

2.3.2. Load Dataset

For loading the dataset. I use ImageFolder pytorch function. And I use transforms of the dataset based on the model parameters. Mainly I used three shape of image there are 1*28*28, 1*128*128, 3*128*128, 3*224*224, 1*224*224. The main code is-

```
transform = transforms.Compose([
    # transforms.ToPILImage(),

    ## this is only for when model is 1
    # transforms.Grayscale(),

    # transforms.RandomRotation(20,expand=True), ## adding random rotation 20deg
    # torchvision.transforms.ColorJitter(hue=.05, saturation=.05), ## adding color filter
    # transforms.RandomVerticalFlip(), ## adding vertical flip
    # transforms.RandomHorizontalFlip(), ## adding horizontal flip
    transforms.Resize(IMAGE_SIZE), ## image resize
    transforms.CenterCrop(IMAGE_SIZE), ## image center crop
    transforms.ToTensor(), ## array converted into torch tensor and then divided by 255 (1.0/255)
    # transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))
])

#load training dataset
dataset = torchvision.datasets.ImageFolder(base_dir, transform=transform)
n = len(dataset)
n_test = int(TEST_SIZE * n) # 10% validation
trainDataset, validDataset = torch.utils.data.random_split(dataset,[n - n_test,n_test]) #random split dataset
trainloader = torch.utils.data.DataLoader(trainDataset, batch_size=BATCH_SIZE, shuffle=True, pin_memory=True,)
validationloader = torch.utils.data.DataLoader(validDataset, batch_size=BATCH_SIZE, shuffle=True, pin_memory=True,)
print("Length of the trainloader:", len(trainloader) * BATCH_SIZE)
print("Length of the validationloader:", len(validationloader) * BATCH_SIZE)

Length of the trainloader: 15776
Length of the validationloader: 3968
```

Figure 15: Dataset Transform

The basic visualization of dataset-

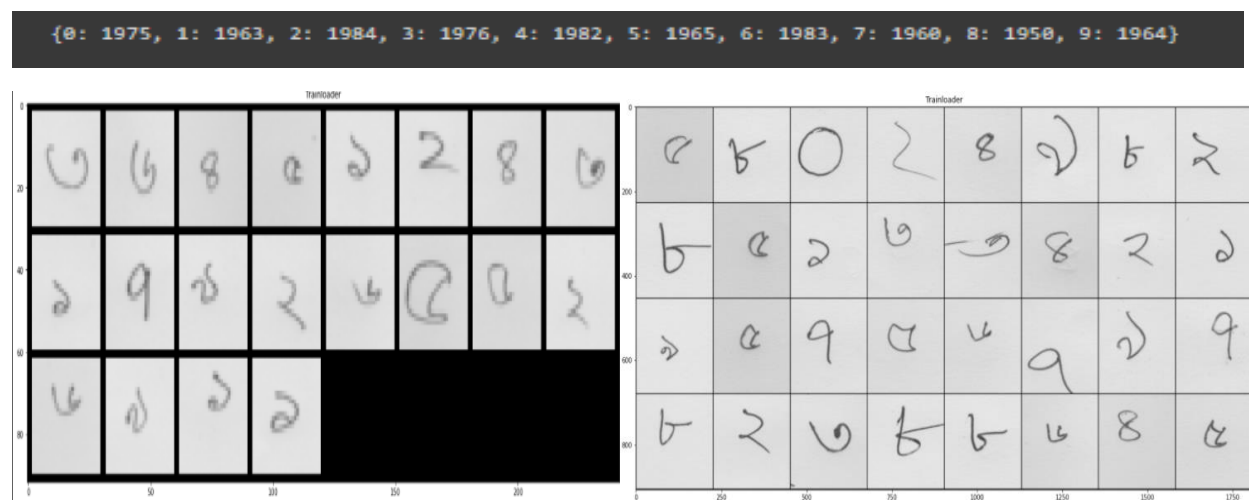


Figure 16: Basic Visualization

2.3.3. Model Creation

In model creation I divide into 2 parts first one is the model class creation and other one optimizer & criterion. In Section 2.1 and Section 2.2 we saw all the model information. And the optimizer & criterion is given below-

```
criterion = torch.nn.CrossEntropyLoss()
optimizer = torch.optim.SGD(model_2.parameters(),lr=LEARNING_RATE, )
```

2.3.4. Model train and save the model

For training the model I use two functions first one is Model save and second one is model training function. For model saving the I use this function-

```
def save_model(
    MODEL_USED,
    SAVEPATH,
    epoch,
    batch_size,
    model,
    optimizer,
    image_size,
    training_loss=[],
    training_acc=[],
    validation_loss=[],
    validation_acc=[],
    learning_rate=0.001,
    meta_data=None):
    SAVEPATH += f'({MODEL_USED})-checkpoint-epoch-{epoch}.pt'
    save_obj = {
        "MODEL_USED": MODEL_USED,
        "batch_size": batch_size,
        "epoch": epoch,
        "model_full": model,
        "optimizer_full": optimizer,
        "model_state": model.state_dict(),
        "optimizer_state": optimizer.state_dict(),
        "image_size": image_size,
        "training_loss": training_loss,
        "training_acc": training_acc,
        "validation_loss": validation_loss,
        "validation_acc": validation_acc,
        "learning_rate": learning_rate,
        "meta_data": meta_data
    }
    torch.save(save_obj, SAVEPATH)
```

Figure 17: Model saved code

And the model train function is –

```
def train_model(START, END, model_used, model_save_path, model_ft, criterion, optimizer_ft, trainloader, testloader,
                all_training_loss,
                all_validation_loss,
                all_training_accuracy,
                all_validation_accuracy):
    # Training loop
    for epoch in range(START, END):
        # Training phase
        trainloader.reset()
        for batch_idx, (data, target) in enumerate(trainloader):
            # Forward pass
            data = data.to(device)
            target = target.to(device)
            optimizer_ft.zero_grad()
            model_ft.train()
            output = model_ft(data)
            loss = criterion(output, target)
            loss.backward()
            optimizer_ft.step()

            # Accumulate training loss and accuracy
            all_training_loss.append(loss.item())
            _, predicted = output.max(1, keepdim=True)
            all_training_accuracy.append(predicted.eq(target).sum().item())

        # Validation phase
        testloader.reset()
        model_ft.eval()
        validation_loss = 0
        validation_accuracy = 0
        for batch_idx, (data, target) in enumerate(testloader):
            data = data.to(device)
            target = target.to(device)
            output = model_ft(data)
            loss = criterion(output, target)
            validation_loss += loss.item()

            _, predicted = output.max(1, keepdim=True)
            validation_accuracy += predicted.eq(target).sum().item()

        # Save the model
        model_save_path += f'({model_used})-checkpoint-epoch-{epoch}.pt'
        torch.save(model_ft.state_dict(), model_save_path)

    # Return the final results
    return all_training_loss, all_validation_loss, all_training_accuracy, all_validation_accuracy
```

```
train_model(START, END, model_used, model_save_path, model_ft, criterion, optimizer_ft, trainloader, testloader,
            all_training_loss,
            all_validation_loss,
            all_training_accuracy,
            all_validation_accuracy)
```

Figure 18: Model Train Function

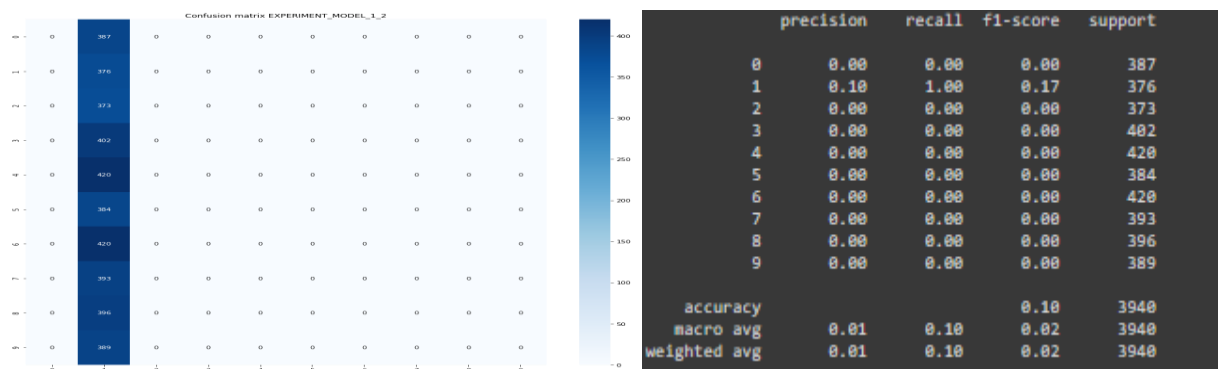
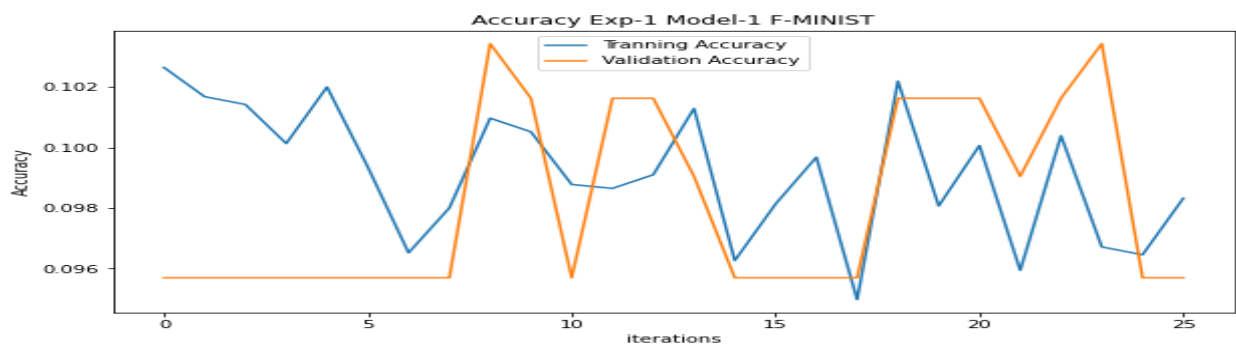
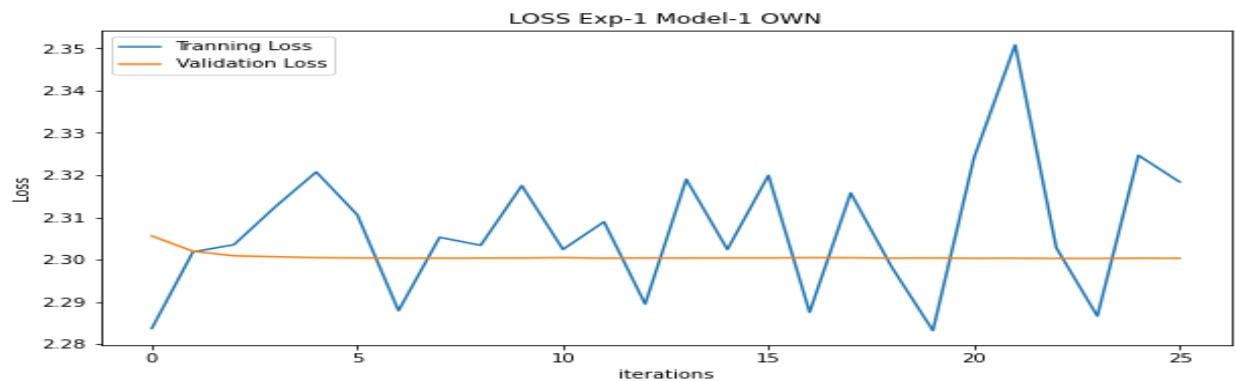
3. Training Results

Here we can see all the training results of the model. Also, you can see the parameters of the model training process.

3.1. Experiment 1

3.1.1. Own(training-a)

Name	Values
Total dataset	19702
Learning rate	0.01
Batch Size	20
Iteration	20490
Training and Testing Split	80% and 20%
Image Shape	1 * 28 * 28
Optimizer	SGD



3.1.2. Fashion-MNIST

Name	Values
Total dataset	60000
Learning rate	0.01
Batch Size	20
Iteration	65000
Image Shape	1 * 28 * 28
Optimizer	SGD

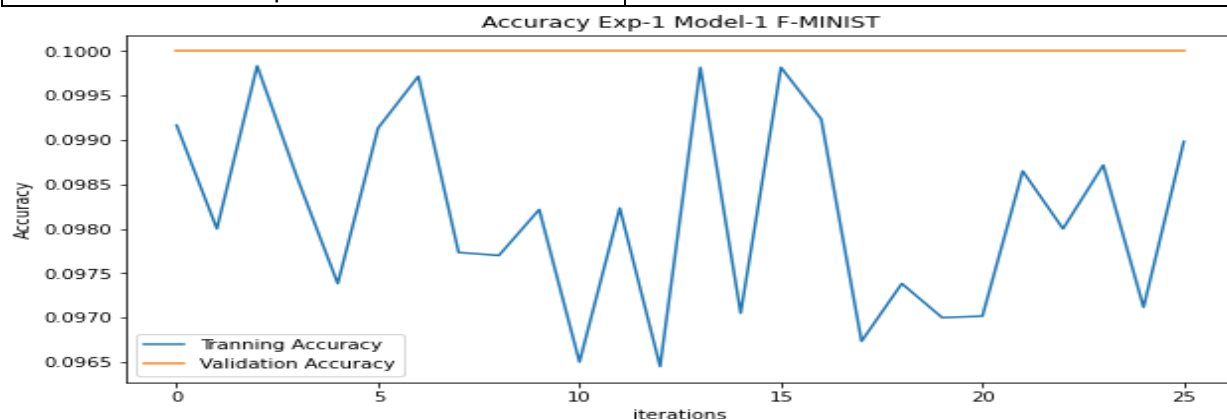


Figure 19: Accuracy Graph Exp-1

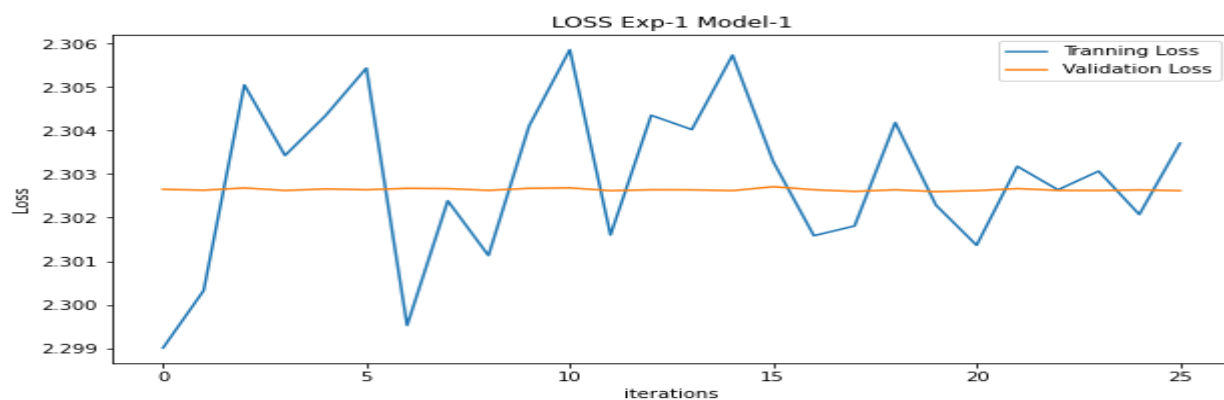


Figure 20: Loss Graph Exp-1

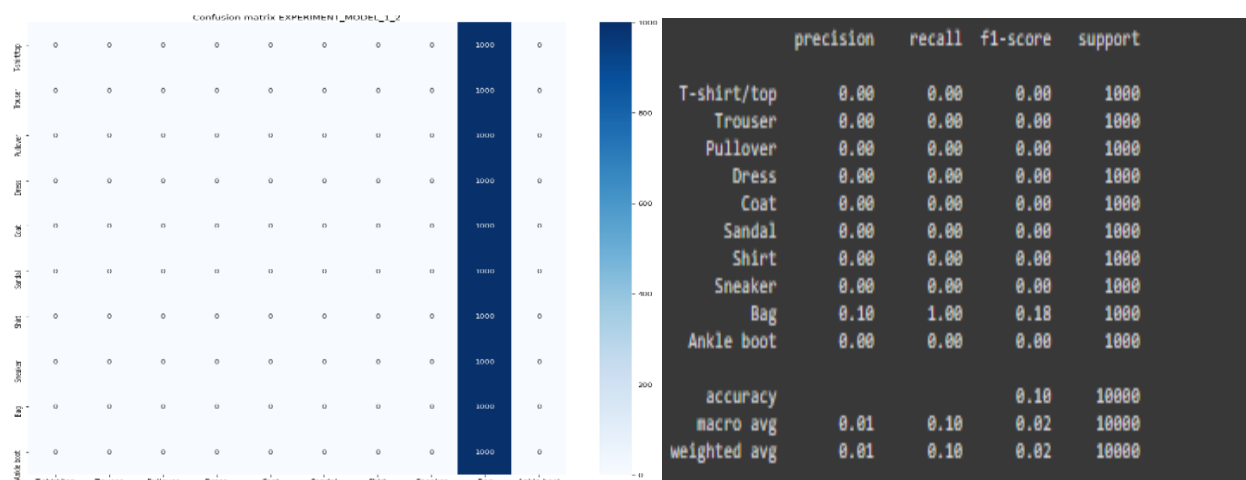


Figure 21: Performance Matrice of exp-1

3.2. Experiment 2 – Model 1-V2

3.2.1. Own(training-a)

Name	Values
Total dataset	19702
Learning rate	0.01
Batch Size	32
Iteration	125715
Training and Testing Split	80% and 20%
Image Shape	1 * 28 * 28
Epochs	255
Optimizer	SGD

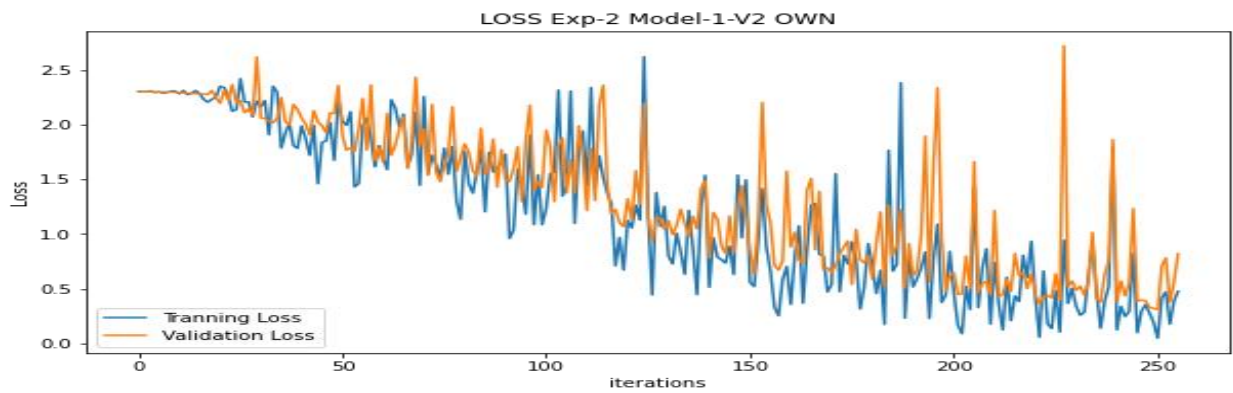


Figure 22: Loss graph exp-2

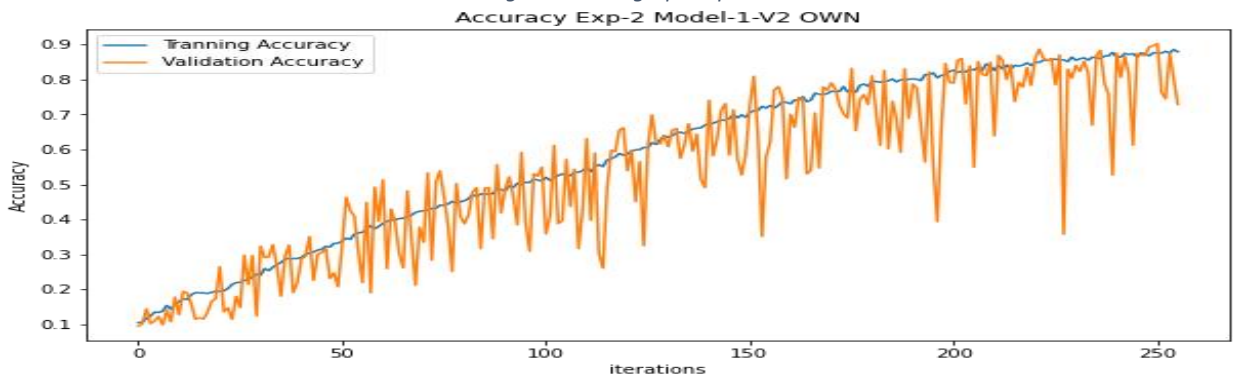


Figure 23: Accuracy graph exp-2

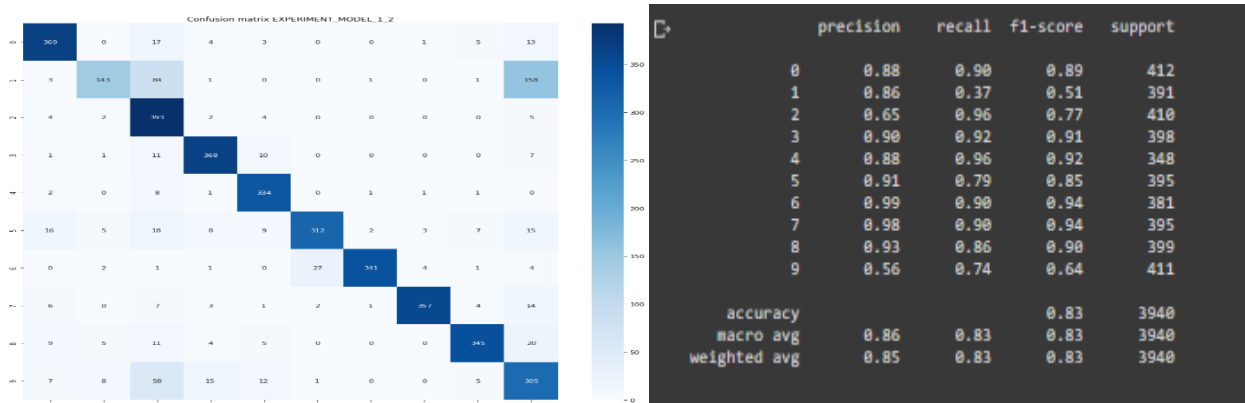


Figure 24: Performance matrices of exp-2 model v2

3.2.2. Fashion-MNIST

Name	Values
Total dataset	60000
Learning rate	0.01
Batch Size	32
Iteration	478125
Training and Testing Split	80% and 20%
Image Shape	1 * 28 * 28
Epochs	255
Optimizer	SGD

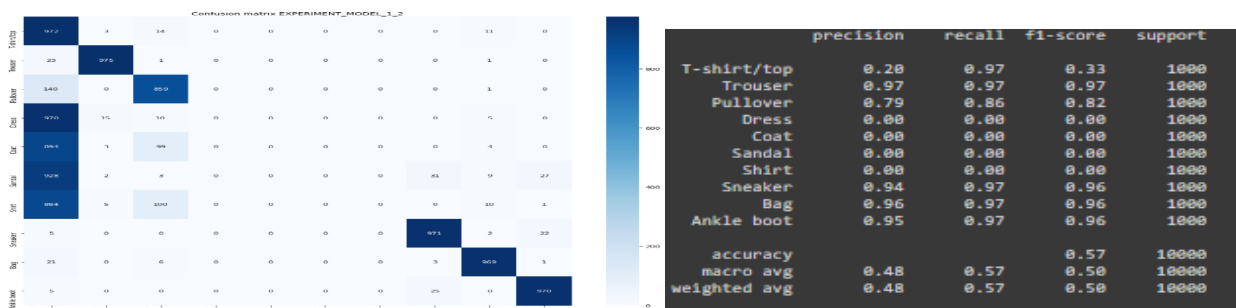
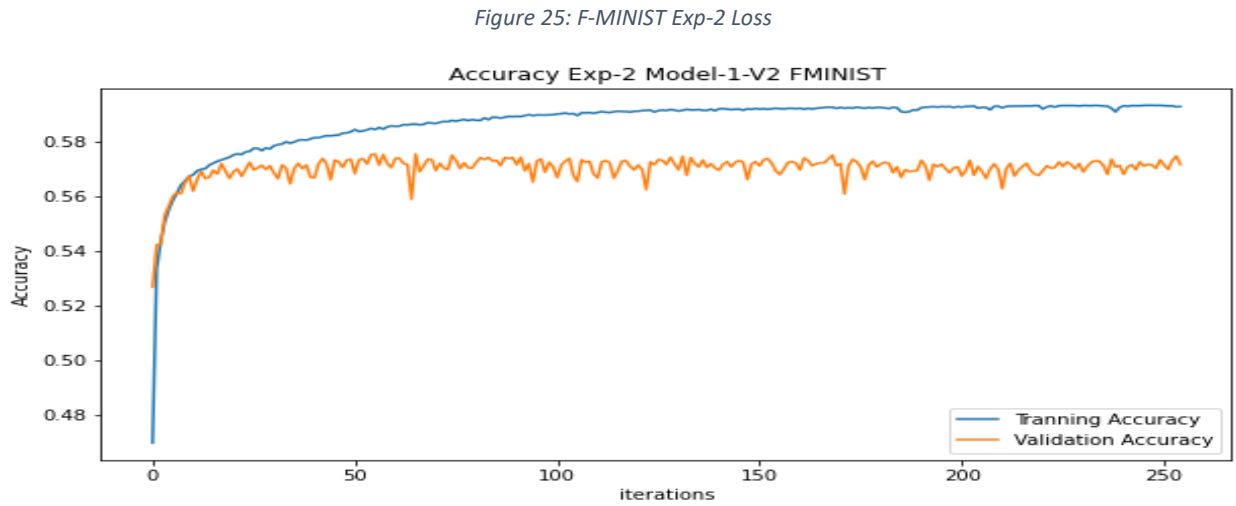
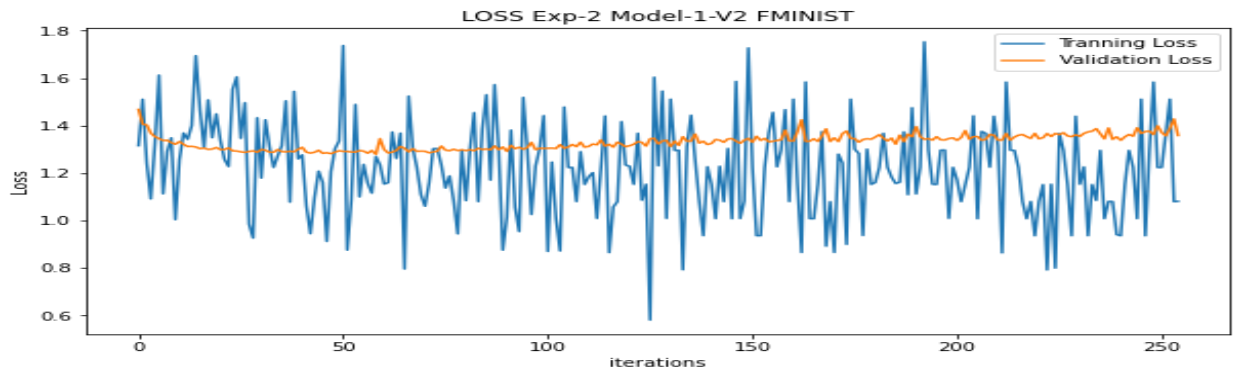


Figure 27: Performance matrices F- MINIST

3.3. Experiment 2 – Model 1-V3

3.3.1. Own(training-a)

Name	Values
Total dataset	19702
Learning rate	0.01
Batch Size	32
Iteration	125715
Training and Testing Split	80% and 20%
Epochs	299
Image Shape	1 * 28 * 28
Optimizer	SGD

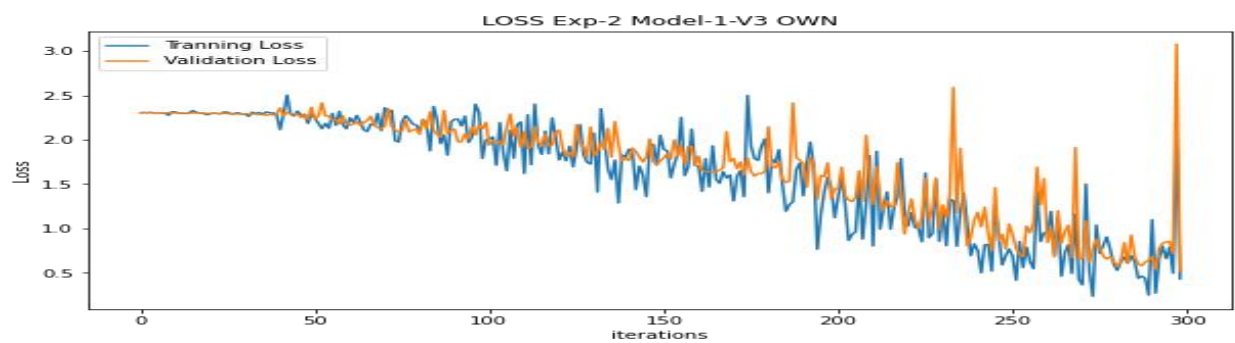


Figure 28: Loss graph exp-2

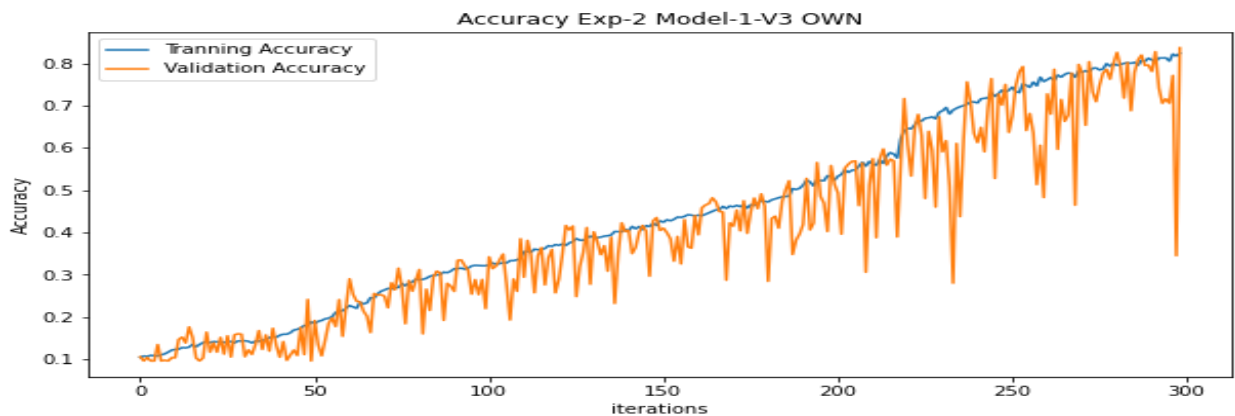


Figure 29: Accuracy graph exp-2

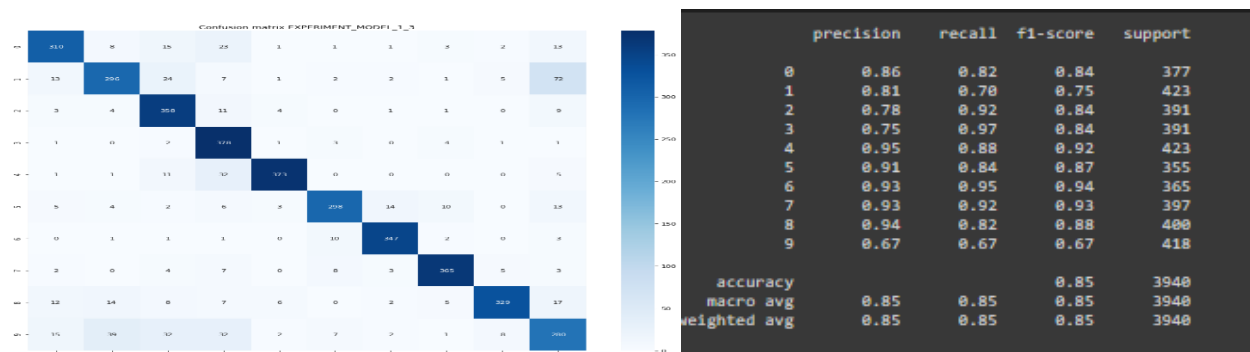
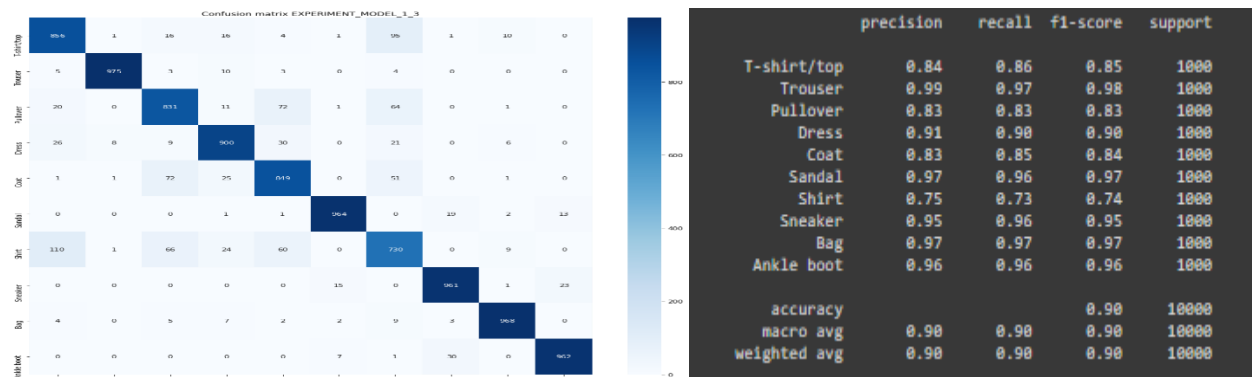
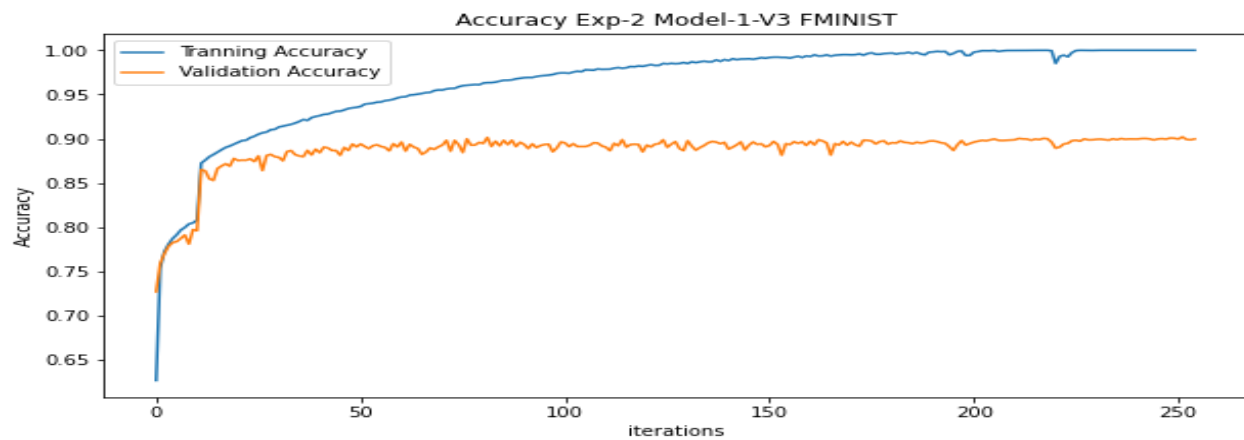
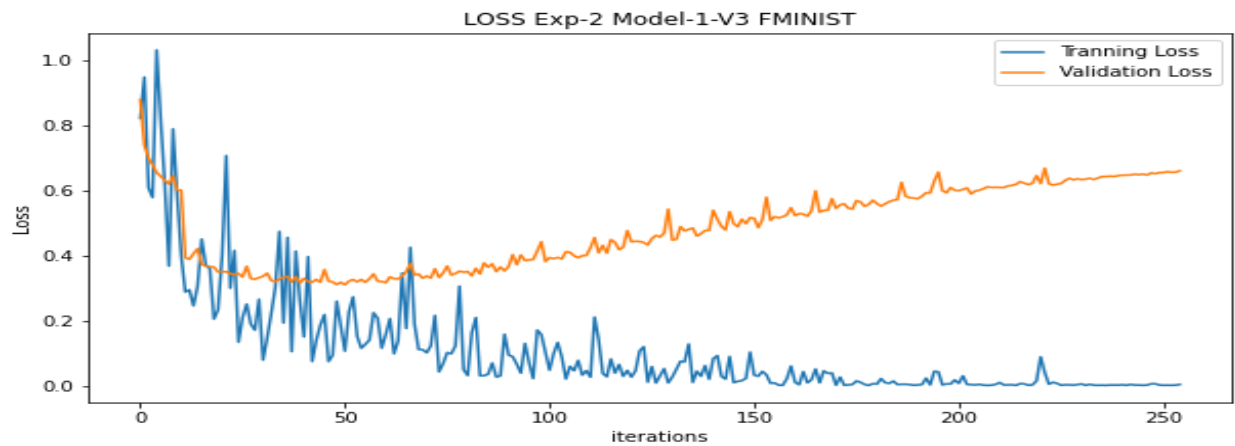


Figure 30: Performance Matrices

3.3.2. Fashion-MNIST

Name	Values
Total dataset	60000
Learning rate	0.01
Batch Size	32
Iteration	478125
Training and Testing Split	80% and 20%
Image Shape	1 * 28 * 28
Epochs	255
Optimizer	SGD

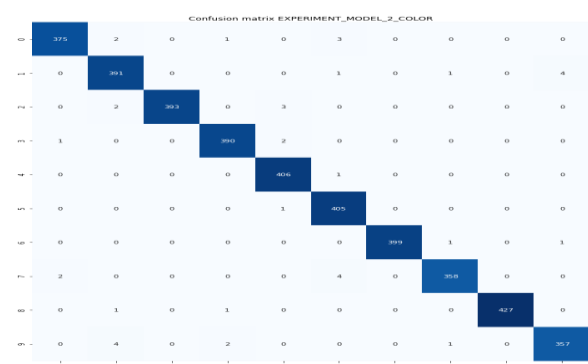
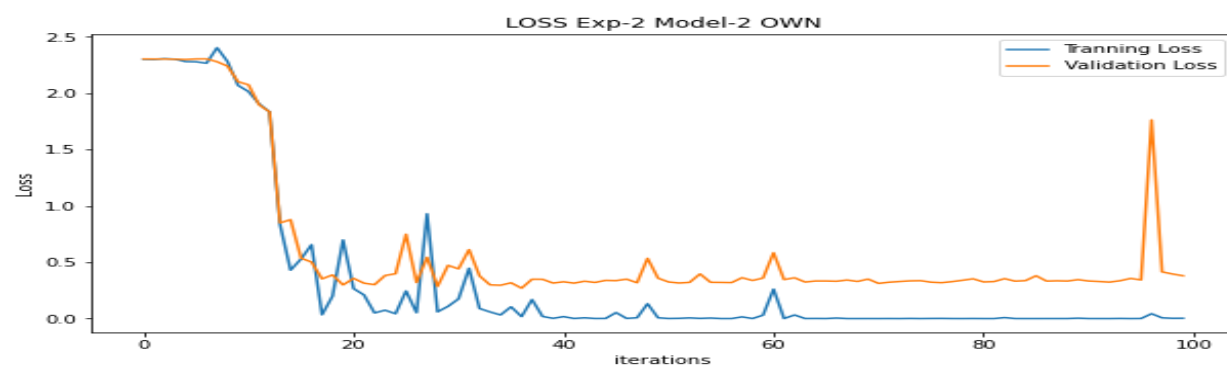


3.4. Experiment 2 – Model 2

3.4.1. Own(training-a)

3.4.1.1. Input Channel 3(RGB-Image)

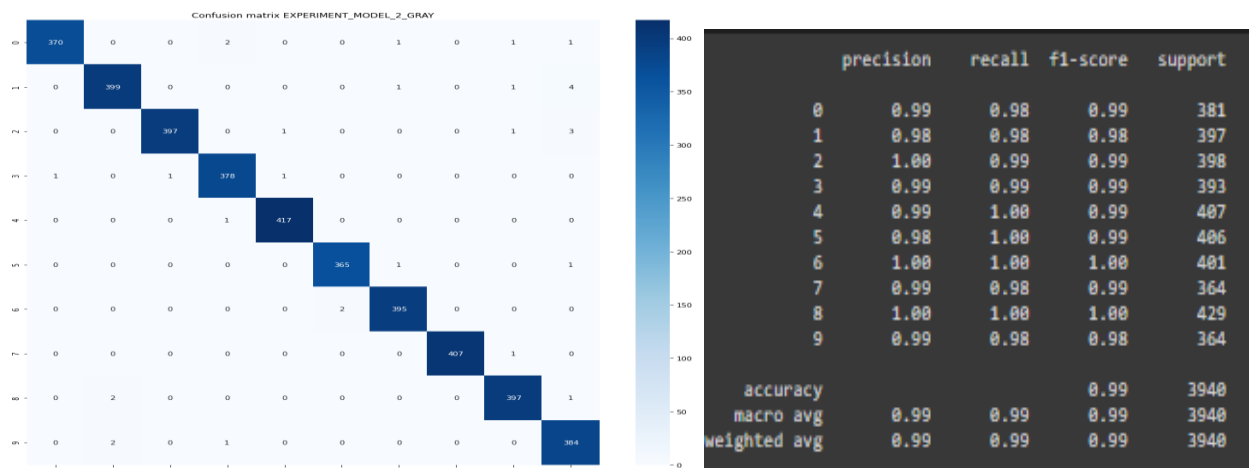
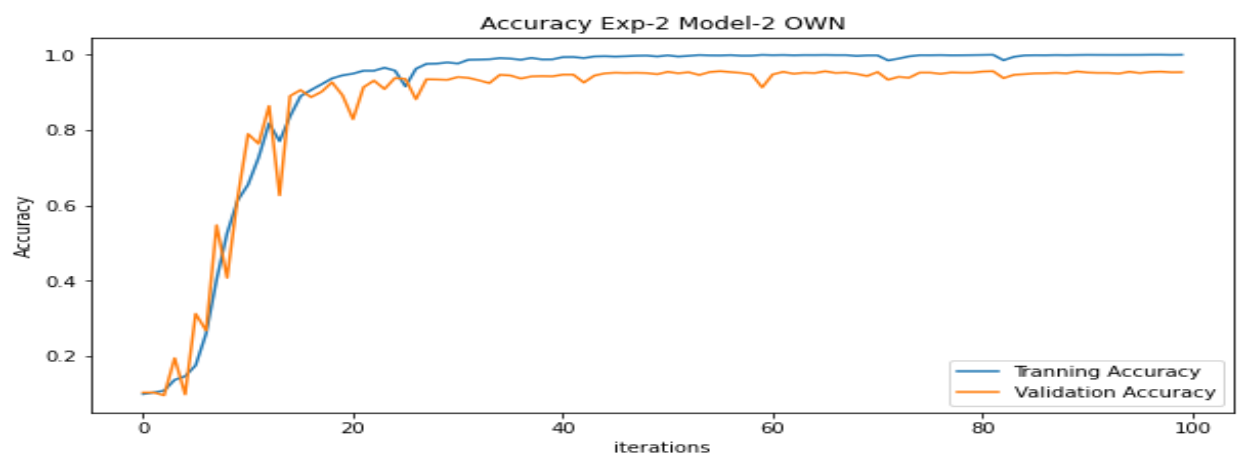
Name	Values
Total dataset	19702
Learning rate	0.01
Batch Size	32
Iteration	49300
Training and Testing Split	80% and 20%
Epochs	100
Image Shape	3 * 128 * 128
Optimizer	SGD



	precision	recall	f1-score	support
0	0.99	0.98	0.99	381
1	0.98	0.98	0.98	397
2	1.00	0.99	0.99	398
3	0.99	0.99	0.99	393
4	0.99	1.00	0.99	407
5	0.98	1.00	0.99	406
6	1.00	1.00	1.00	401
7	0.99	0.98	0.99	364
8	1.00	1.00	1.00	429
9	0.99	0.98	0.98	364
accuracy			0.99	3940
macro avg	0.99	0.99	0.99	3940
weighted avg	0.99	0.99	0.99	3940

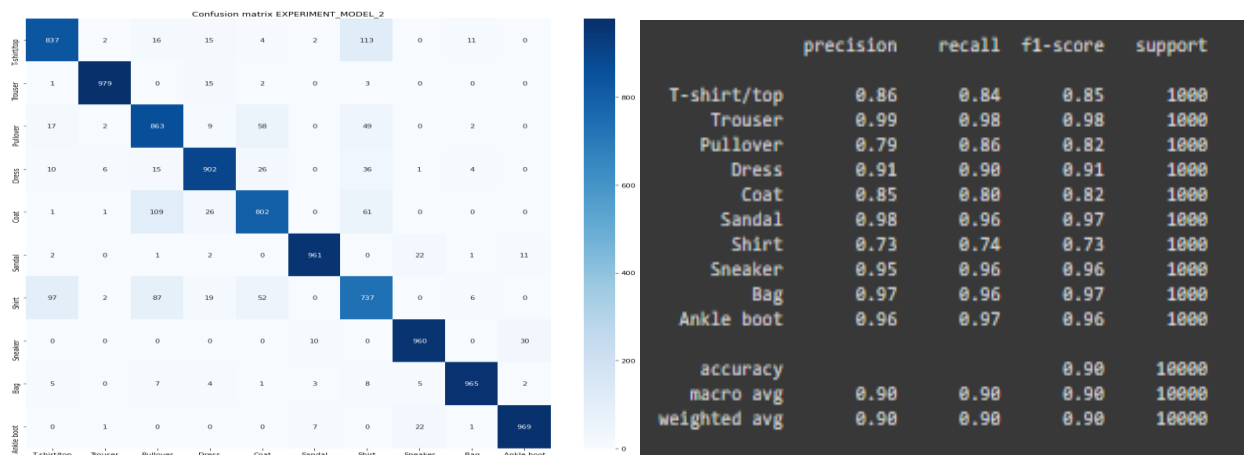
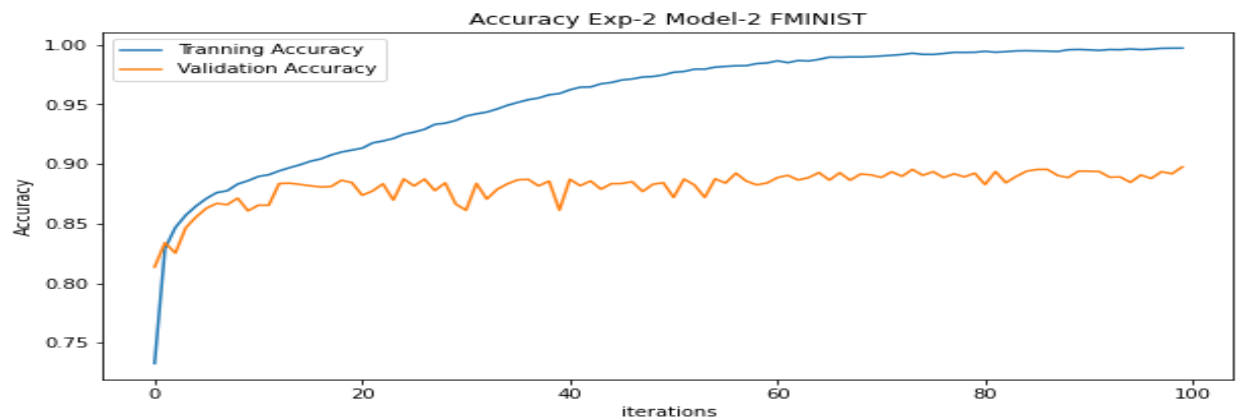
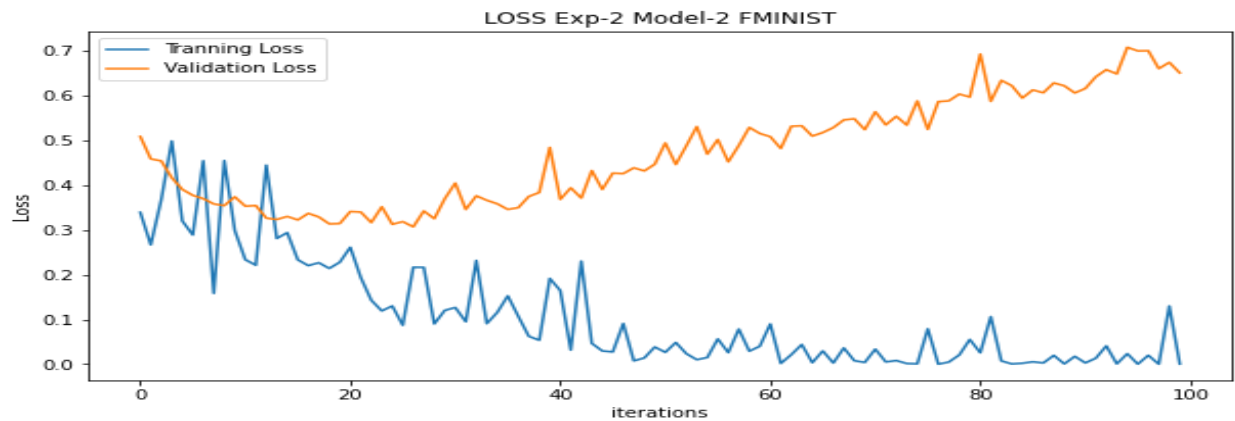
3.4.1.2. Input Channel 1(GRAY-Image)

Name	Values
Total dataset	19702
Learning rate	0.01
Batch Size	32
Iteration	49300
Training and Testing Split	80% and 20%
Epochs	100
Image Shape	1 * 128 * 128
Optimizer	SGD



3.4.2. Fashion-MNIST

Name	Values
Total dataset	60000
Learning rate	0.01
Batch Size	32
Iteration	187500
Training and Testing Split	80% and 20%
Image Shape	1 * 128 * 128
Epochs	100
Optimizer	SGD



3.5. Experiment 2 – Model 3

3.5.1. Own(training-a)

3.5.1.1. Input Channel 3(RGB-Image)

Name	Values
Total dataset	19702
Learning rate	0.001
Batch Size	32
Iteration	12325
Training and Testing Split	80% and 20%
Epochs	25
Image Shape	3 * 224 * 224
Optimizer	SGD



Figure 31: Loss Graph of Model-3

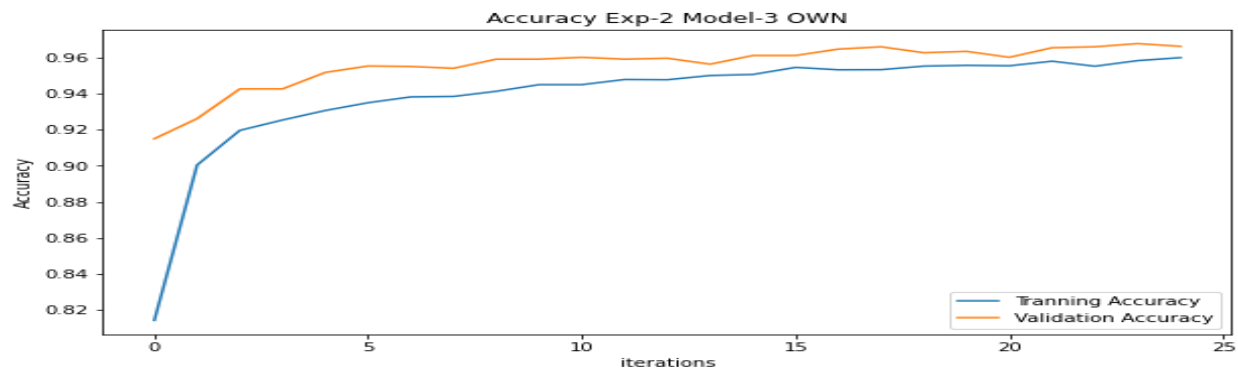


Figure 32:Accuracy Graph of Model 3

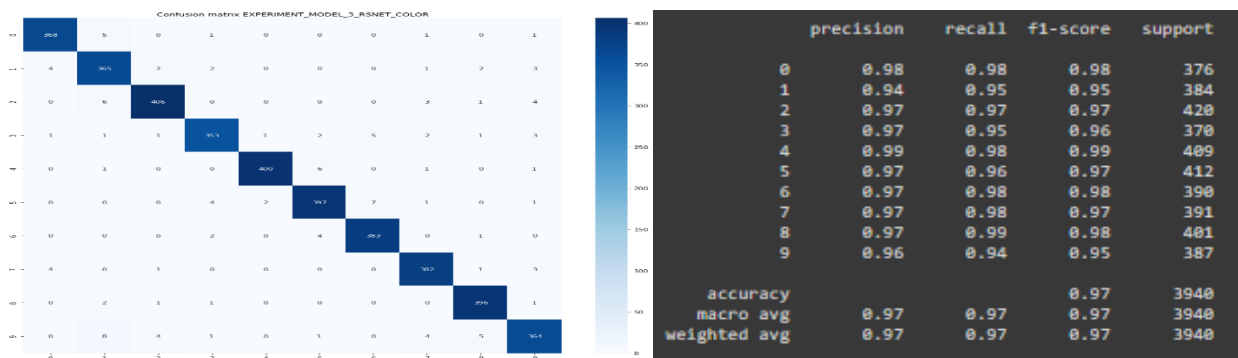
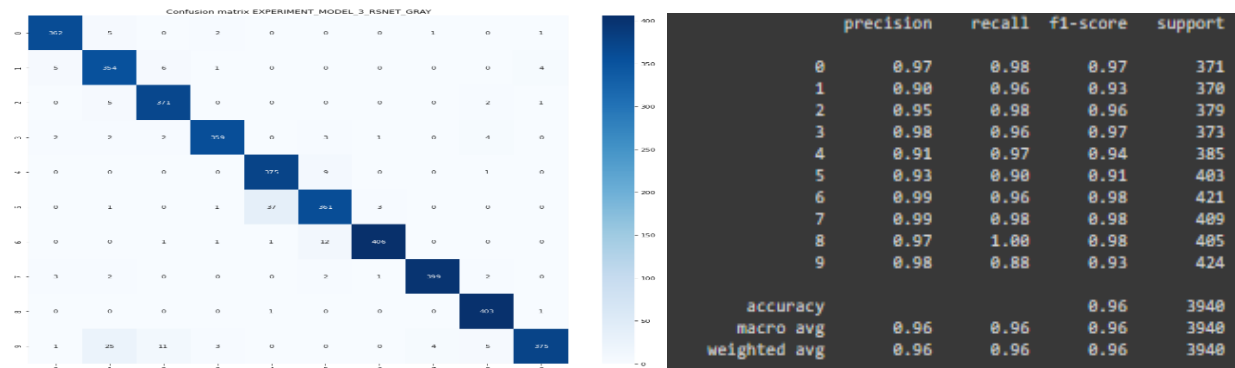
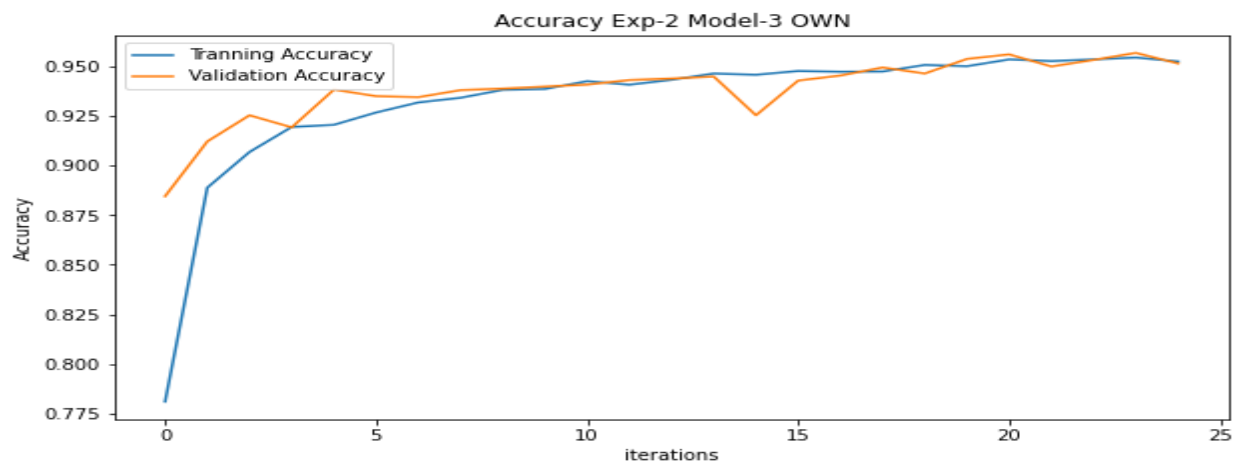


Figure 33: Performance Matrices

3.5.1.2. Input Channel 1(GRAY-Image)

Name	Values
Total dataset	19702
Learning rate	0.01
Batch Size	32
Iteration	49300
Training and Testing Split	80% and 20%
Epochs	100
Image Shape	1 * 244 * 244
Optimizer	SGD



3.5.2. Fashion-MNIST

Name	Values
Total dataset	60000
Learning rate	0.01
Batch Size	32
Iteration	45000
Training and Testing Split	80% and 20%
Image Shape	1 * 224 * 224
Epochs	24
Optimizer	SGD

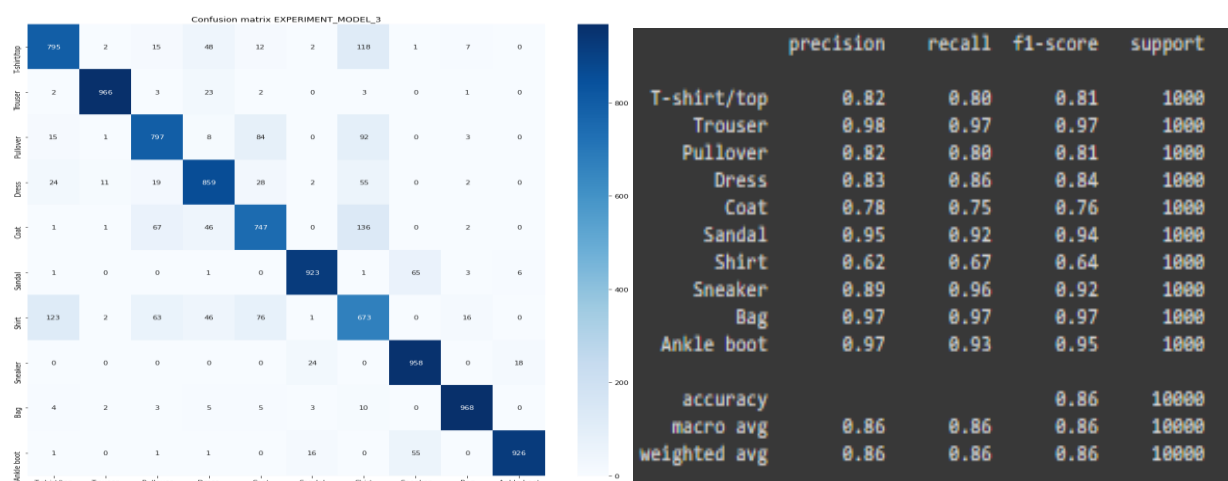
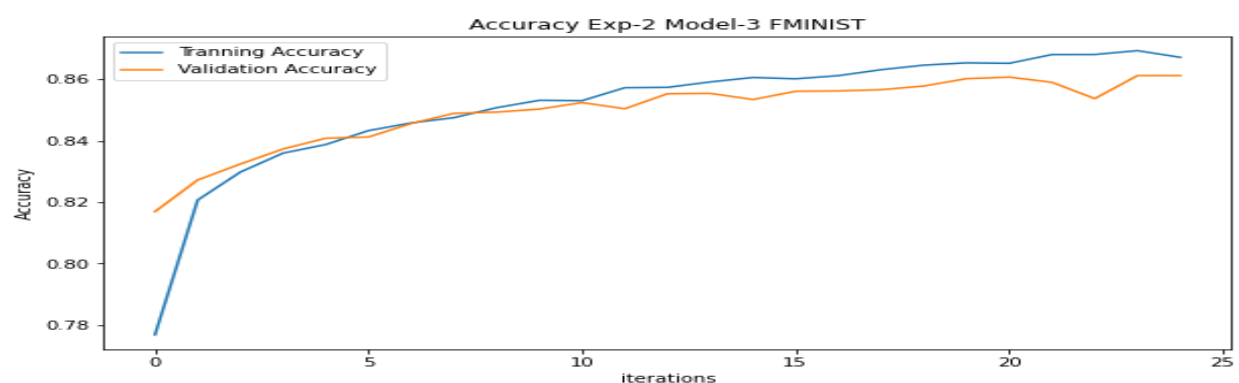
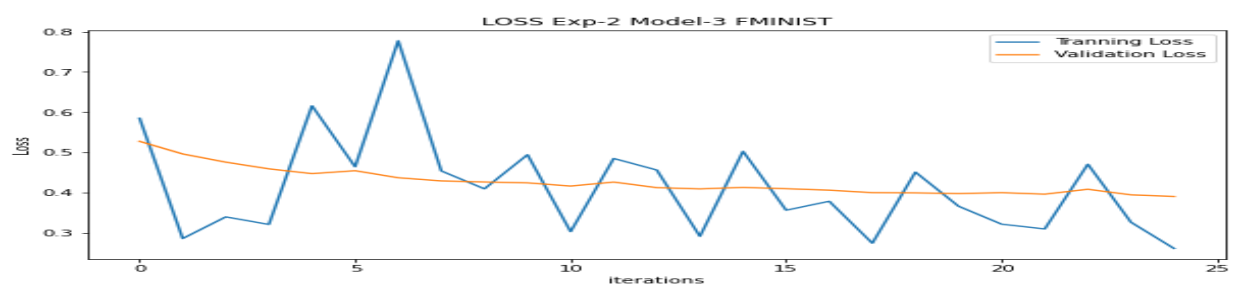


Figure 36: Performance Matrices

4. Reference

Source code

<https://colab.research.google.com/drive/1mAg2xBR7uTMO7a0k6Qjcl9jwMDJJWoyOx?usp=sharing>

<https://colab.research.google.com/drive/1NI0o0kO7aOmjh4enWf-JDu6XxzZnwdYo?usp=sharing>

<https://colab.research.google.com/drive/1FFhvZVv8sMc4jYovDvXp7GbN9pLwuJ4j?usp=sharing>

<https://colab.research.google.com/drive/1pSmIRV21bNGXygJSJgsO4uP7qfid87H5?usp=sharing>

Given Dataset Trained Model

https://drive.google.com/file/d/1-7a44W76z-joInkLC_0ffcdBkPkRY_y8/view?usp=sharing

<https://drive.google.com/file/d/1-8AKgpmagLDT5K6CGmfZ-SrgC5vtxqYG/view?usp=sharing>

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<https://drive.google.com/file/d/1qpsII4q2Xk1mdSrS3KW4K8Pe7ugY8rs3/view?usp=sharing>

F-MNIST Trained Model

https://drive.google.com/file/d/1-92tqY9DwsAHgUikt5B_9dMPc7Oq1sWH/view?usp=sharing

https://drive.google.com/file/d/1GQpI5HSHF_cg8mvBsBxc89ohSa5fDqEv/view?usp=sharing

<https://drive.google.com/file/d/1K73sdUVBVx29VX8cBABH0Alnev920sT0/view?usp=sharing>

https://drive.google.com/file/d/1PBTq5xRgadmgc_MocZIHGhCFY80QBAG2/view?usp=sharing

<https://drive.google.com/file/d/1VzWoWbjjMeptGSLgqqBxSdwiQ28CFmp9/view?usp=sharing>