

1. Describe the input and output for each model, hardware requirement, data statistic, learning curve, metrics (train text val), demo the result, finetuning technique, etc.

Model Architecture (CNN):

- **Input:**
 - o RGB images of size 32x32 pixels
- **Output:**
 - o Softmax probabilities for 10 classes
- **Hardware Requirement:**
 - o GPU recommended for faster training
- **Data Statistic:**
 - o CIFAR-10 dataset with 60,000 32x32 color images in 10 classes
- **Learning Curve:**
 - o Plots of training loss, accuracy, and F1-score over epochs
- **Metrics:**
 - o Classification report, confusion matrix for training, validation, and test sets
- **Demo Result:**
 - o Grid of training images and corresponding labels
- **Fine-tuning Technique:**
 - o Stochastic Gradient Descent (SGD) with CrossEntropyLoss
- **Total params:**
 - o 62,006
- **Epoch number:**
 - o 20

Model Architecture (EfficientNetV2s):

- **Input:**
 - o RGB images of size 224x224 pixels
- **Output:**
 - o Softmax probabilities for 10 custom animal classes
- **Hardware Requirement:**
 - o GPU strongly recommended due to model complexity
- **Data Statistic:**
 - o Custom animal dataset with 10 classes (butterfly, cat, chicken, cow, dog, elephant, horse, sheep, spider, squirrel)
- **Learning Curve:**
 - o Plots of training loss, accuracy, and F1-score over epochs
- **Metrics:**
 - o Classification report, confusion matrix for training, validation, and test sets
- **Demo Result:**
 - o Grid of training images and corresponding labels
- **Fine-tuning Technique:**
 - o Transfer learning with pre-trained EfficientNetV2s model, SGD optimizer with learning rate scheduler
- **Total params:**
 - o 20,190,298
- **Epoch number:**
 - o 20

2. List key features for each function, including input and output. (cheat sheet)

Image Classification (Basic): CIFAR10

Data Loading:

```
trainvalset = torchvision.datasets.CIFAR10(root='./data', train=True, download=True, transform=transform)
trainset, valset = torch.utils.data.random_split(trainvalset, [40000, 10000])

trainloader = torch.utils.data.DataLoader(trainset, batch_size=batch_size, shuffle=True)
valloader = torch.utils.data.DataLoader(valset, batch_size=batch_size, shuffle=False)

testset = torchvision.datasets.CIFAR10(root='./data', train=False, download=True, transform=transform)
testloader = torch.utils.data.DataLoader(testset, batch_size=batch_size, shuffle=False)

#classes = ('plane', 'car', 'bird', 'cat', 'deer', 'dog', 'frog', 'horse', 'ship', 'truck')
```

- `torchvision.datasets.CIFAR10`, `torch.utils.data.DataLoader`
- Input:
 - o root (directory to save/download CIFAR-10 dataset)
 - o train (True for training set, False for test set)
 - o download (True to download dataset if not available)
 - o transform (data preprocessing and augmentation)
- Output:
 - o trainloader, valloader, testloader (data loaders for training, validation, and test sets)

Model Architecture (CNN):

```
class CNN(nn.Module):
    def __init__(self):
        super().__init__()
        self.conv1 = nn.Conv2d(3, 6, 5) # 3 input channels, 6 output channels, 5*5 kernel size
        self.pool = nn.MaxPool2d(2, 2) # 2*2 kernel size, 2 strides
        self.conv2 = nn.Conv2d(6, 16, 5)
        self.fc1 = nn.Linear(400, 120) # dense input 400 (16*5), output 120

        self.fc2 = nn.Linear(120, 84) # dense input 120, output 84
        self.fc3 = nn.Linear(84, 10) # dense input 84, output 10
        self.softmax = torch.nn.Softmax(dim=1) # perform softmax at dim[1] (batch,class)

    def forward(self, x):
        x = self.pool(F.relu(self.conv1(x)))
        x = self.pool(F.relu(self.conv2(x)))
        x = torch.flatten(x, start_dim=1) # flatten all dimensions (dim[1]) except batch (dim[0])
        x = F.relu(self.fc1(x))
        x = F.relu(self.fc2(x))
        x = self.fc3(x)
        x = self.softmax(x)
        return x

net = CNN().to(device)
```

- `class CNN(nn.Module)`
- Input:
 - None
- Output:
 - o CNN model with defined layers and softmax activation

Training Loop:

```
1 criterion = nn.CrossEntropyLoss()
2 optimizer = optim.SGD(net.parameters(), lr=1e-2, momentum=0.9)
3
4 epochs = 20
5
6 history_train = {'loss':np.zeros(epochs), 'acc':np.zeros(epochs), 'f1-score':np.zeros(epochs)}
7 history_val = {'loss':np.zeros(epochs), 'acc':np.zeros(epochs), 'f1-score':np.zeros(epochs)}
8 min_val_loss = 1e10
9 PATH = './CNN_CIFAR10.pth'
10
11 for epoch in range(epochs): # Loop over the dataset multiple times
12
13     print(f'epoch {epoch + 1} \nTraining ...')
14     y_predict = list()
15     y_labels = list()
16     training_loss = 0.0
17     n = 0
18     net.train()
19     for data in tqdm(trainloader):
20         # get the inputs; data is a List of [inputs, labels]
21         inputs, labels = data
22         inputs = inputs.to(device)
23         labels = labels.to(device)
24
25         # zero the parameter gradients
26         optimizer.zero_grad()
27
28         # forward + backward + optimize
29         outputs = net(inputs) # forward
30         loss = criterion(outputs, labels) # calculate loss from forward pass
31         loss.backward() # just calculate
32         optimizer.step() # update weights here
33
34         # aggregate statistics
35         training_loss += loss.item()
36         n+=1
37
38         y_labels += list(labels.cpu().numpy())
39         y_predict += list(outputs.argmax(dim=1).cpu().numpy())
40
41     # print statistics
42     report = classification_report(y_labels, y_predict, digits = 4, output_dict = True)
43     acc = report["accuracy"]
44     f1 = report["weighted avg"]["f1-score"]
45     support = report["weighted avg"]["support"]
46     training_loss /= n
47     print(f"training loss: {training_loss:.4}, acc: {acc*100:.4}%, f1-score: {f1*100:.4}%, support: {support}")
48     history_train['loss'][epoch] = training_loss
49     history_train['acc'][epoch] = acc
50     history_train['f1-score'][epoch] = f1
51
52     print('validating ...')
53     net.eval()
54     y_predict = list()
55     y_labels = list()
56     validation_loss = 0.0
57     n = 0
58     with torch.no_grad():
59         for data in tqdm(valloader):
60             inputs, labels = data
61             inputs = inputs.to(device)
62             labels = labels.to(device)
63
64             outputs = net(inputs)
65             loss = criterion(outputs, labels)
66             validation_loss += loss.item()
67
68             y_labels += list(labels.cpu().numpy())
69             y_predict += list(outputs.argmax(dim=1).cpu().numpy())
70             n+=1
71
72     # print statistics
73     report = classification_report(y_labels, y_predict, digits = 4, output_dict = True)
74     acc = report["accuracy"]
75     f1 = report["weighted avg"]["f1-score"]
76     support = report["weighted avg"]["support"]
77     validation_loss /= n
78     print(f"validation loss: {validation_loss:.4}, acc: {acc*100:.4}%, f1-score: {f1*100:.4}%, support: {support}")
79     history_val['loss'][epoch] = validation_loss
80     history_val['acc'][epoch] = acc
81     history_val['f1-score'][epoch] = f1
82
83     #save min validation loss
84     if validation_loss < min_val_loss:
85         torch.save(net.state_dict(), PATH)
86         min_val_loss = validation_loss
87
88     print('Finished Training')
```

- Training loop using ``torch.optim.SGD``, ``torch.nn.CrossEntropyLoss``
- Input:
 - o trainloader, valloader, CNN model, CrossEntropyLoss, SGD optimizer, number of epochs
- Output:
 - o Trained CNN model, training and validation history

Evaluation Metrics:

```
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay

print('testing ...')
y_predict = list()
y_labels = list()
test_loss = 0.0
n = 0
with torch.no_grad():
    for data in tqdm(testloader):
        inputs, labels = data
        inputs = inputs.to(device)
        labels = labels.to(device)

        outputs = net(inputs)
        loss = criterion(outputs, labels)
        test_loss += loss.item()

        y_labels += list(labels.cpu().numpy())
        y_predict += list(outputs.argmax(dim=1).cpu().numpy())
        n+=1

# print statistics
test_loss /= n
print(f"testing loss: {test_loss:.4}")

report = classification_report(y_labels, y_predict, digits = 4)
M = confusion_matrix(y_labels, y_predict)
print(report)
disp = ConfusionMatrixDisplay(confusion_matrix=M)
```

- ``classification_report``, ``confusion_matrix``
- Input:
 - o Trained CNN model, testloader
- Output:
 - o Classification report, confusion matrix

Visualization (Matplotlib):

- ``imshow``
- Input:
 - o Trainloader
- Output:
 - o Grid of training images, corresponding labels
 - o Learning curve plots (loss, accuracy, F1-score)

Fine-tuning:

```
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(net.parameters(), lr=1e-2, momentum=0.9)
```

- ``optim.SGD``, ``criterion.CrossEntropyLoss``
- Input:
 - o CNN model, CrossEntropyLoss, SGD optimizer, learning rate, momentum, number of epochs
- Output:
 - o Trained CNN model with saved weight

Image Classification (Advanced): Animal

Data Loading (Custom Dataset):

```
1 class AnimalDataset(Dataset):
2
3     def __init__(self,
4                 img_dir,
5                 transforms=None):
6
7         super().__init__()
8         label_image = ['butterfly', 'cat', 'chicken', 'cow', 'dog', 'elephant', 'horse', 'sheep', 'spider', 'squirrel']
9         self.input_dataset = list()
10        label_num = 0
11        for label in label_image:
12            _, _, files = next(os.walk(os.path.join(img_dir, label)))
13            for image_name in files:
14                input = [os.path.join(img_dir, label, image_name), label_num] # [image_path, label_num]
15                self.input_dataset.append(input)
16                label_num += 1
17
18        self.transforms = transforms
19
20    def __len__(self):
21        return len(self.input_dataset)
22
23    def __getitem__(self, idx):
24        img = Image.open(self.input_dataset[idx][0]).convert('RGB')
25        x = self.transforms(img)
26        y = self.input_dataset[idx][1]
27        return x, y
28
29    trainset = AnimalDataset('./Dataset_animal2/train', transform_train)
30    valset = AnimalDataset('./Dataset_animal2/val', transform)
31    testset = AnimalDataset('./Dataset_animal2/test', transform)
32
33
34    trainloader = torch.utils.data.DataLoader(trainset, batch_size=batch_size, shuffle=True)
35    valloader = torch.utils.data.DataLoader(valset, batch_size=batch_size, shuffle=True)
36    testloader = torch.utils.data.DataLoader(testset, batch_size=batch_size, shuffle=True)
```

- ``class AnimalDataset(Dataset)``
- Input:
 - o `img_dir` (directory containing custom animal dataset), `transforms` (data augmentation)
- Output:
 - o `trainset`, `valset`, `testset` (custom dataset splits)
 - o `trainloader`, `valloader`, `testloader` (data loaders for training, validation, and test sets)

Model Architecture (EfficientNetV2s):

```
pretrain_weight = torchvision.models.EfficientNet_V2_S_Weights.IMAGENET1K_V1
net = torchvision.models.efficientnet_v2_s(weights = pretrain_weight)
net.classifier[1] = nn.Linear(1280, 10)
net = net.to(device)
```

- ``torchvision.models.efficientnet_v2_s``
- Input:
 - o Pre-trained EfficientNetV2s model with weights for ImageNet
- Output:
 - o EfficientNetV2s model with modified classifier for custom animal classes

Training Loop with Transfer Learning:

```
1 criterion = nn.CrossEntropyLoss()
2 optimizer = optim.SGD(net.parameters(), lr=0.02, momentum=0.9)
3 scheduler = lr_scheduler.StepLR(optimizer, step_size=7, gamma=0.5)
4
5 epochs = 20
6
7 history_train = {'loss':np.zeros(epochs), 'acc':np.zeros(epochs), 'f1-score':np.zeros(epochs)}
8 history_val = {'loss':np.zeros(epochs), 'acc':np.zeros(epochs), 'f1-score':np.zeros(epochs)}
9 min_val_loss = 1e10
10 PATH = './Animal10-efficientnetV2s.pth'
11
12 for epoch in range(epochs): # Loop over the dataset multiple times
13
14     print(f'epoch {epoch + 1} \nTraining ...')
15     net.train()
16     y_predict = list()
17     y_labels = list()
18     training_loss = 0.0
19     n = 0
20     with torch.set_grad_enabled(True):
21         for data in tqdm(trainloader):
22
23             # get the inputs; data is a list of [inputs, labels]
24             inputs, labels = data
25             inputs = inputs.to(device)
26             labels = labels.to(device)
27
28             # zero the parameter gradients
29             optimizer.zero_grad()
30
31             # forward + backward + optimize
32             outputs = net(inputs)
33             loss = criterion(outputs, labels)
34             loss.backward()
35             optimizer.step()
36
37             # aggregate statistics
38             training_loss += loss.item()
39             n+=1
40
41             y_labels += list(labels.cpu().numpy())
42             y_predict += list(outputs.argmax(dim=1).cpu().numpy())
43         scheduler.step()
44
45         # print statistics
46         report = classification_report(y_labels, y_predict, digits = 4, output_dict = True)
47         acc = report["accuracy"]
48         f1 = report["weighted avg"]["f1-score"]
49         support = report["weighted avg"]["support"]
50         training_loss /= n
51         print(f"training loss: {training_loss:.4}, acc: {acc*100:.4}%, f1-score: {f1*100:.4}%, support: {support}")
52         history_train['loss'][epoch] = training_loss
53         history_train['acc'][epoch] = acc
54         history_train['f1-score'][epoch] = f1
55
56     print('validating ...')
57     net.eval()
58
59     optimizer.zero_grad()
60
61     y_predict = list()
62     y_labels = list()
63     validation_loss = 0.0
64     n = 0
65     with torch.no_grad():
66         for data in tqdm(valloader):
67             inputs, labels = data
68             inputs = inputs.to(device)
69             labels = labels.to(device)
70
71             outputs = net(inputs)
72             loss = criterion(outputs, labels)
73             validation_loss += loss.item()
74
75             y_labels += list(labels.cpu().numpy())
76             y_predict += list(outputs.argmax(dim=1).cpu().numpy())
77         n+=1
78
79         # print statistics
80         report = classification_report(y_labels, y_predict, digits = 4, output_dict = True)
81         acc = report["accuracy"]
82         f1 = report["weighted avg"]["f1-score"]
83         support = report["weighted avg"]["support"]
84         validation_loss /= n
85         print(f"validation loss: {validation_loss:.4}, acc: {acc*100:.4}%, f1-score: {f1*100:.4}%, support: {support}")
86         history_val['loss'][epoch] = validation_loss
87         history_val['acc'][epoch] = acc
88         history_val['f1-score'][epoch] = f1
89
90         #save min validation loss
91         if validation_loss < min_val_loss:
92             torch.save(net.state_dict(), PATH)
93             min_val_loss = validation_loss
94
95     print('Finished Training')
```

- Training loop using ``torch.optim.SGD``, ``torch.nn.CrossEntropyLoss``, ``torch.optim.lr_scheduler``
- Input:
 - o trainloader, valloader, EfficientNetV2s model, CrossEntropyLoss, SGD optimizer, learning rate scheduler, number of epochs
- Output:
 - o Trained EfficientNetV2s model, training and validation history

Evaluation Metrics:

```
print('testing ...')
y_predict = list()
y_labels = list()
test_loss = 0.0
n = 0
with torch.no_grad():
    for data in tqdm(testloader):
        net.eval()
        inputs, labels = data
        inputs = inputs.to(device)
        labels = labels.to(device)

        outputs = net(inputs)
        loss = criterion(outputs, labels)
        test_loss += loss.item()

        y_labels += list(labels.cpu().numpy())
        y_predict += list(outputs.argmax(dim=1).cpu().numpy())
        n+=1

# print statistics
test_loss /= n
print(f"testing loss: {test_loss:.4}" )

report = classification_report(y_labels, y_predict, digits = 4)
M = confusion_matrix(y_labels, y_predict)
print(report)
disp = ConfusionMatrixDisplay(confusion_matrix=M)
```

- ``classification_report``, ``confusion_matrix``
- Input:
 - o Trained EfficientNetV2s model, testloader
- Output:
 - o Classification report, confusion matrix