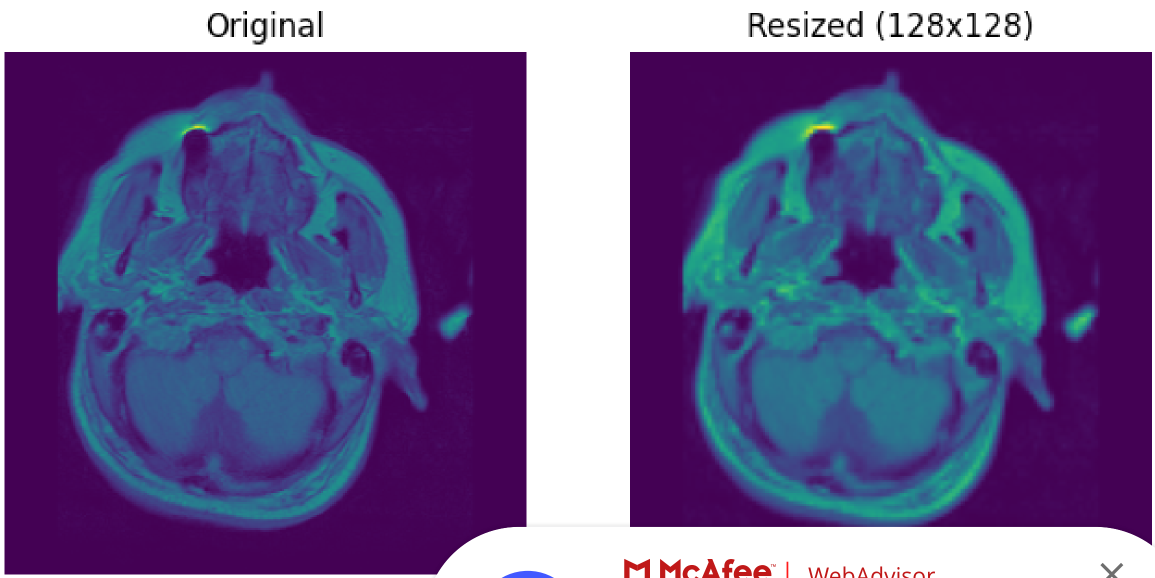
The following is a basic code I've constructed just to resize the image and output it. This is going to require a lot more work, but I just wanted to take one shot at it to see how it goes.

```
#Imports for the specific code
from PIL import Image
import requests
from io import BytesIO
import matplotlib.pyplot as plt
```

```
#load the URL for my GitHub
url = "https://raw.githubusercontent.com/Aditsmishra2005/APS360---Project/a1
result = requests.get(url)
photo = Image.open(BytesIO(result.content))

photo_resized = photo.resize((128,128))
fig, axes = plt.subplots(1, 2, figsize=(8, 4))

#Duisplay the Original for a reference
axes[0].imshow(photo)
axes[0].set_title("Original")
axes[0].axis("off")

#Display the resized for a reference
axes[1].imshow(photo_resized)
axes[1].set_title("Resized (128x128)")
axes[1].axis("off")

plt.show()
```



Okay following the intial documentation shown above I decided to construct my model, my base model is an ANN and I planned to do some basic data augmentation to increase the data quantity I have. I planned to use the Lab Three framework to import my dataset from google drive.

```
import torch
import torchvision
import torchvision.transforms as transforms
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
import numpy as np
```

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call
```

Now I load the dataset, and to do this I basically uploaded all the images from my dataset to the drive.

```
import torchvision.datasets as d
data = d.ImageFolder('/content/drive/My Drive/Colab Notebooks/parkinsons_dat
```

```
paths = [sample[0] for sample in data.samples]  # or data.imgs
labels = [sample[1] for sample in data.samples]
```

Now I plan to just check that the data is imported.

```
print(len(data)) # with this I can see that the amount of datasets are compl
```

```
1662
```

This next portion is the deletion portion if the rotated images are too many then I do this, but I'm only doubling my dataset. So only run it if I need to delete data.

```
base_path = '/content/drive/My Drive/Colab Notebooks/parkinsons_dataset1'#se
classes = ['normal', 'parkinson'] #Adjusting the classes as needed

for cls in classes:
    class_directory = os.path.join(base_path, cls)
    for name in os.listdir(class_directory):
        if '_rot' in name:
            file_path = os.path.join(class_directory, name)
            print(f"Deleting {file_path}")
            os.remove(file_path)
```

Doubling the dataset by performing roations, this is my main form of augmentation. I will say that this was largely Perplexity generated. I know I would normall have to disclose this, but I did modify the code slightly. Not very familiar with heavy data augmentation.

```
from PIL import Image
import os
import random

# setting the correct path
base_path = '/content/drive/My Drive/Colab Notebooks/parkinsons_dataset1'
classes = ['normal', 'parkinson']   # names of the two classes I have

angle_range = (-30, 30)  # Can't rotate it too much, because in medical imag

for cls in classes: #makes sense
    class_directory = os.path.join(base_path, cls)
    for name in os.listdir(class_directory):
        if name.endswith('.jpg') or name.endswith('.png'):
            img_path = os.path.join(class_directory, name)
            img = Image.open(img_path)#grab original image
            angle = random.randint(*angle_range)#rotate using the angle rang
            rotated_img = img.rotate(angle)
            new_fname = f"{os.path.splitext(name)[0]}_rot{angle}{os.path.spl
            rotated_img.save(os.path.join(class_directory, new_fname))
```

Check the new total dataset amounts!

```
data = d.ImageFolder('/content/drive/My Drive/Colab Notebooks/parkinsons_dat
```

```
print(len(data)) #data has officially doubled now
```

```
1662
```

The next portion is going to be me r
going to replace the images all in the

```
target_size = (128, 128) #Looking at 128x128 so a total of 16,384 features
for cls in classes:
    class_directory = os.path.join(base_path, cls)
    for name in os.listdir(class_directory):
        if name.endswith('.jpg') or name.endswith('.png'):
            img_path = os.path.join(class_directory, name)
            img = Image.open(img_path)
            img_resized = img.resize(target_size)

            img_resized.save(img_path)#save the resized image to the appropr
```

Now that all my data is processed and ready I'm going to seperate it using SK learn. I'm going to set aside a certain amount of my data to test on, and this will be used for the later verification of my models.

```
X = []
y = []

for img, label in data:
    img_arr = np.array(img).astype(np.float32) / 255.0  # scale to [0, 1]
    X.append(img_arr.flatten())
    y.append(label)

X = np.array(X)
y = np.array(y)
```

In the above I've normalized for the SVM to take in as an input

```
for cls in classes:
    class_dir = os.path.join(base_path, cls)
    images = [f for f in os.listdir(class_dir) if f.endswith('.jpg') or f.en

plt.figure(figsize=(10,3))
for i, img_name in enumerate(images[:3]):  # first 3 images
        img_path = os.path.join(class_dir, img_name)
        img = Image.open(img_path)
        plt.subplot(1,3,i+1)
        plt.imshow(img)
        plt.title(f"{cls}")
        plt.axis('off')
plt.show()
```

Showing the example images of the data that will be processed.

```
from sklearn.model_selection import train_test_split

X_trainval, X_test, y_trainval, y_test = train_test_split(X, y, test_size=0.
X_train, X_val, y_train, y_val = train_test_split(X_trainval, y_trainval, te
```

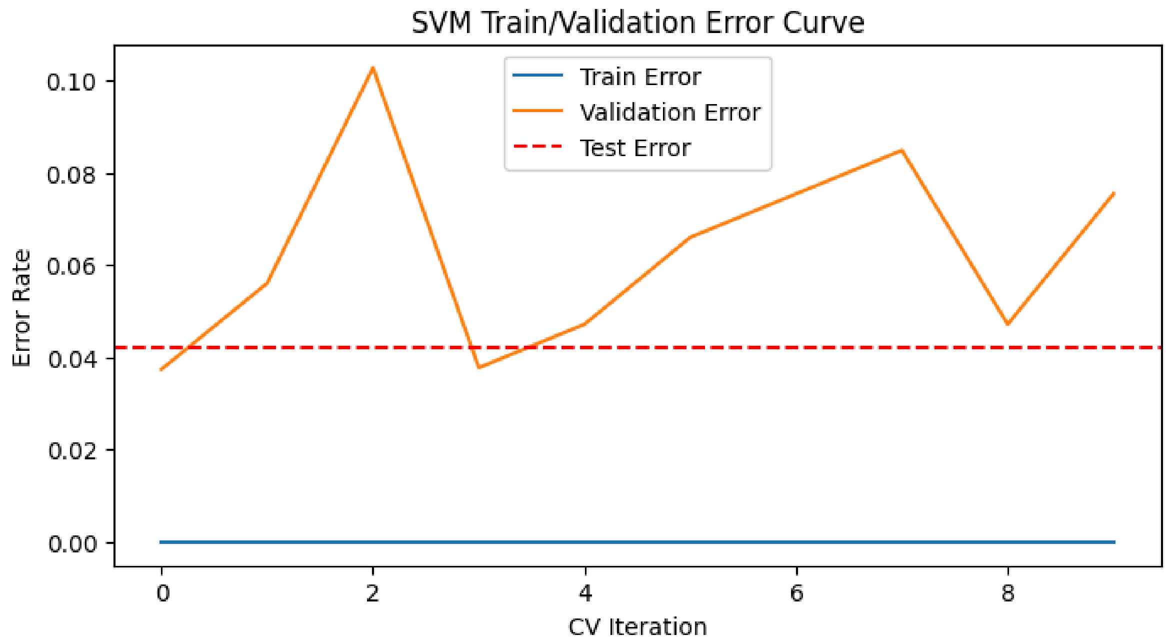
Now that I've split my data, my main goal is going to be to now create a baseline model. I've decided to change my model. Specifically because the ANN doesn't seem to be a good idea for training images. On the other hand due to the nature of the classification task I was thinking of using SVM. This however is different to my proposal, and it will be altered in the progress report.

```
#Starting the code for the SVM also use other imports that I know are good f
from sklearn import svm
from sklearn.metrics import accuracy_score
from sklearn.model_selection import StratifiedKFold
```

```
clf = svm.SVC(kernel='linear', probability=True)#using a linear model on the
cv = StratifiedKFold(n_splits=10, shuffle=True, random_state=24)#use shuffle

train_errs = []
val_errs = []

for train_idx, valid_idx in cv.split(X_train, y_train):
    clf.fit(X_train[train_idx], y_train[train_idx])
    y_train_pred = clf.predict(X_train[train_idx])
    y_valid_pred = clf.predict(X_train[valid_idx])
    train_errs.append(1 - accuracy_score(y_train[train_idx], y_train_pred))
    val_errs.append(1 - accura

# Final fit and test accuracy
clf.fit(X_train, y_train)
y_test_pred = clf.predict(X_test)
```

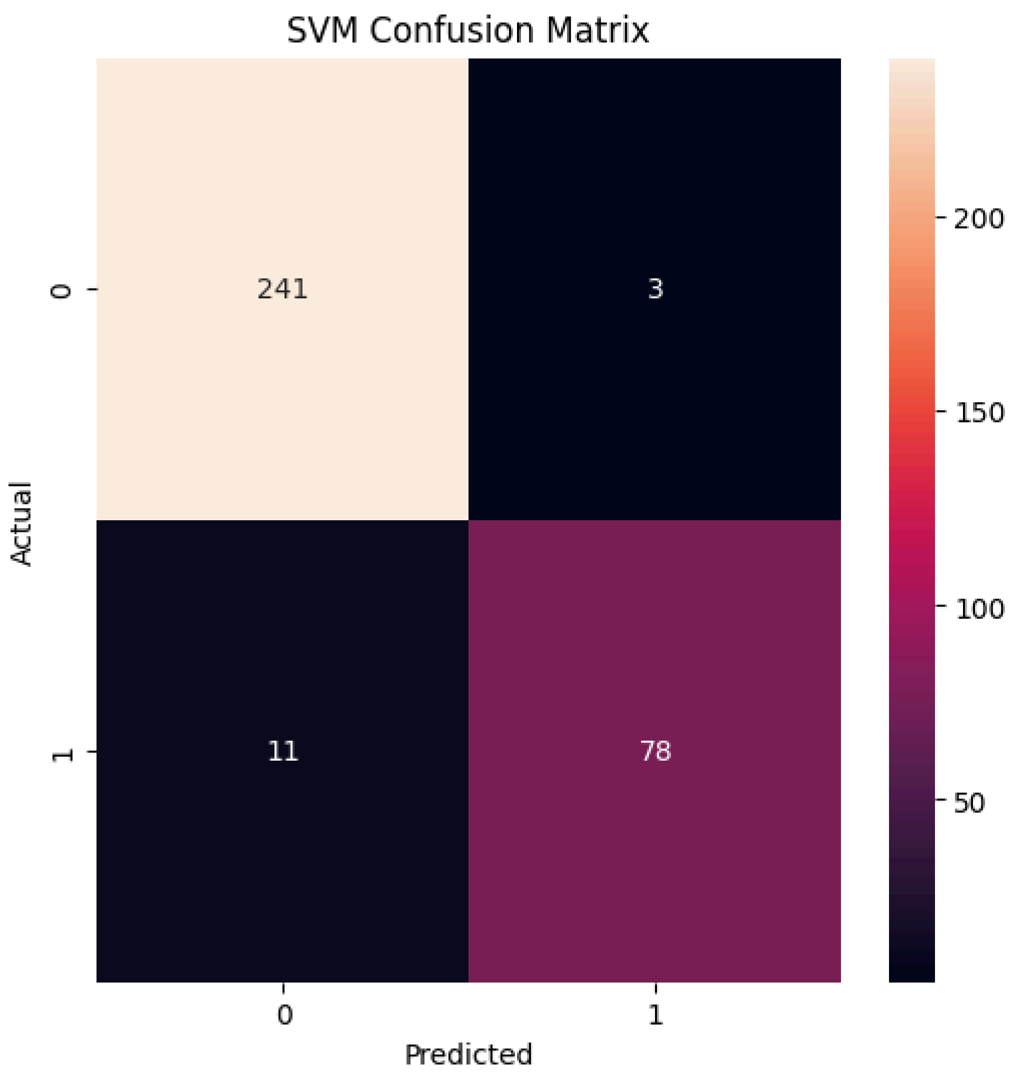
```
test_accuracy = accuracy_score(y_test, y_test_pred)
```

```
plt.figure(figsize=(8,4))
plt.plot(range(len(train_errs)), train_errs, label='Train Error')
plt.plot(range(len(val_errs)), val_errs, label='Validation Error')
plt.axhline(1 - test_accuracy, color='r', linestyle='--', label='Test Error'
plt.xlabel('CV Iteration')
plt.ylabel('Error Rate')
plt.title('SVM Train/Validation Error Curve')
plt.legend()
plt.show()

print("Accuracy Score:", test_accuracy)
```




```
Accuracy Score: 0.9579579579579579
```

```
from sklearn.metrics import confusion_matrix
import seaborn as sns

cm = confusion_matrix(y_test, y_test_pred)
plt.figure(figsize=(6,6))
sns.heatmap(cm, annot=True, fmt='d')
plt.title('SVM Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```



The next section will focus on the creation of the Primary model which we will tune to fit the dataset.

```
from torchvision import datasets, transforms
from torch.utils.data import DataLoader, random_split

transform = transforms.Compose([
    transforms.Resize((128, 128)),
    transforms.ToTensor(),
    transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5)),
])

data_dir = '/content/drive/My Drive/Colab Notebooks/parkinsons_dataset1'
# Assumes each class has its own subfolder
full_dataset = datasets.ImageFolder(root=data_dir, transform=transform)
```

```
train_len = int(0.8 * len(full
val_len = len(full_dataset) -
train_ds, val_ds = random_spl
```

```
train_loader = DataLoader(train_ds, batch_size=16, shuffle=True)
val_loader = DataLoader(val_ds, batch_size=16, shuffle=False)
```

The above is all stuff we have done prior in terms of splitting the data. I could've done a better job potentially with the splitting

```
import torch.nn as nn
import torch.nn.functional as F

class ParkinsonNet(nn.Module):
    def __init__(self, num_classes=2):
        super(ParkinsonNet, self).__init__()
        self.name = "parkinsonnet"
        self.conv1 = nn.Conv2d(3, 32, kernel_size=3, padding=1)
        self.pool1 = nn.MaxPool2d(2, 2)
        self.conv2 = nn.Conv2d(32, 64, kernel_size=3, padding=1)
        self.pool2 = nn.MaxPool2d(2, 2)
        self.conv3 = nn.Conv2d(64, 128, kernel_size=3, padding=1)
        self.fc1 = nn.Linear(128*32*32, 128)
        self.fc2 = nn.Linear(128, 64)
        self.fc_out = nn.Linear(64, num_classes)

    def forward(self, x):
        x = F.relu(self.conv1(x))
        x = self.pool1(x)
        x = F.relu(self.conv2(x))
        x = self.pool2(x)
        x = F.relu(self.conv3(x))
        x = x.view(x.size(0), -1)
        x = F.relu(self.fc1(x))
        x = F.relu(self.fc2(x))
        x = self.fc_out(x)
        return x
```

Setting up the architecture for my model.

```
def trainnet(net, batchsize, learning_rate, epoch, train_dataset, val_datase
    optimizer = optim.SGD (net.parameters(), lr=learning_rate, momentum=0.7)
    loss_func = nn.CrossEntropyLoss()

    train_error = np.zeros(epoch)
    train_loss = np.zeros(epoch)
    val_error = np.zeros(epoch)
    val_loss = np.zeros(epoch)

    train_loader = torch.utils.data.DataLoader(train_dataset, batch_size=bat
    val_loader = torch.utils.da

    for e in range(epoch):
        total_train_samples =
        train_loss_sum = 0.0
```

```
            train_error_sum = 0
            for images, labels in train_loader:
                optimizer.zero_grad()
                output = net(images)
                loss = loss_func(output, labels)
                loss.backward()
                optimizer.step()
                train_loss_sum += loss.item() * images.size(0)
                _, predicted = torch.max(output.data, 1)
                train_error_sum += (predicted != labels).sum().item()
                total_train_samples += labels.size(0)
            train_loss[e] = train_loss_sum / total_train_samples
            train_error[e] = train_error_sum / total_train_samples
            # Validation after each epoch
            val_error[e], val_loss[e] = evaluate(net, val_loader, loss_func)
            print(f"Epoch {e+1}: Train loss: {train_loss[e]:.4f}, Train error: {
            model_path = get_model_name(net.name, batchsize, learning_rate, e +
            torch.save(net.state_dict(), model_path)
        np.savetxt("{}_train_err.csv".format(model_path), train_error)
        np.savetxt("{}_train_loss.csv".format(model_path), train_loss)
        np.savetxt("{}_val_err.csv".format(model_path), val_error)
        np.savetxt("{}_val_loss.csv".format(model_path), val_loss)
```

Training net code from the model. I don't have the evaluate function added because I didn't think it was needed just yet.

```
model = ParkinsonNet()
trainnet(model, 16, 0.001, 20, train_ds, val_ds)
```

```
Epoch 1: Train loss: 0.6736, Train error: 0.4281, Val loss: 0.6267, Val error
Epoch 2: Train loss: 0.5869, Train error: 0.2566, Val loss: 0.6199, Val error
Epoch 3: Train loss: 0.5809, Train error: 0.2566, Val loss: 0.6185, Val error
Epoch 4: Train loss: 0.5791, Train error: 0.2566, Val loss: 0.6148, Val error
Epoch 5: Train loss: 0.5745, Train error: 0.2566, Val loss: 0.6239, Val error
Epoch 6: Train loss: 0.5702, Train error: 0.2566, Val loss: 0.6089, Val error
Epoch 7: Train loss: 0.5651, Train error: 0.2566, Val loss: 0.6084, Val error
Epoch 8: Train loss: 0.5589, Train error: 0.2566, Val loss: 0.5979, Val error
Epoch 9: Train loss: 0.5487, Train error: 0.2566, Val loss: 0.5954, Val error
Epoch 10: Train loss: 0.5343, Train error: 0.2566, Val loss: 0.6122, Val erro
Epoch 11: Train loss: 0.5167, Train error: 0.2566, Val loss: 0.5508, Val erro
Epoch 12: Train loss: 0.4918, Train error: 0.2408, Val loss: 0.5242, Val erro
Epoch 13: Train loss: 0.4568, Train error: 0.2137, Val loss: 0.5031, Val erro
Epoch 14: Train loss: 0.4149, Train error: 0.1768, Val loss: 0.5436, Val erro
Epoch 15: Train loss: 0.3668, Train error: 0.1527, Val loss: 0.5970, Val erro
Epoch 16: Train loss: 0.3340, Train error: 0.1369, Val loss: 0.3432, Val erro
Epoch 17: Train loss: 0.2956, Train error: 0.1257, Val loss: 0.3745, Val erro
Epoch 18: Train loss: 0.2600, Train error: 0.1084, Val loss: 0.3168, Val erro
Epoch 19: Train loss: 0.2375, Train error: 0.0986, Val loss: 0.5985, Val erro
Epoch 20: Train loss: 0.2505, Train error: 0.0978, Val loss: 0.4118, Val erro
```

Running the model over 20 epochs

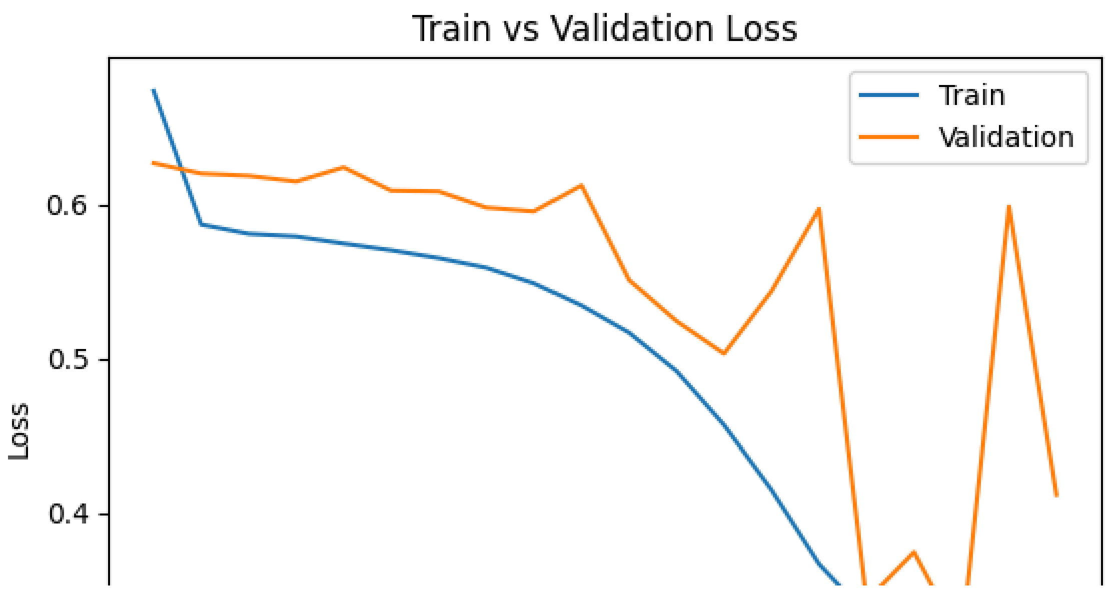
```
# Model function taken directly from Lab2 to help with data checkpoints and
def get_model_name(name, batch_size, learning_rate, epoch):
    """ Generate a name for the model consisting of all the hyperparameter v

    Args:
        config: Configuration object containing the hyperparameters
    Returns:
        path: A string with the hyperparameter name and value concatenated
    """
    path = "model_{0}_bs{1}_lr{2}_epoch{3}".format(name,
                                                   batch_size,
                                                   learning_rate,
                                                   epoch)
    return path
```

```
def plot_training_curve(path): #copied Lab 2
    """ Plots the training curve for a model run, given the csv files
    containing the train/validation error/loss.

    Args:
        path: The base path of the csv files produced during training
    """
    import matplotlib.pyplot as plt
    train_error = np.loadtxt("{}_train_err.csv".format(path))
    val_error = np.loadtxt("{}_val_err.csv".format(path))
    train_loss = np.loadtxt("{}_train_loss.csv".format(path))
    val_loss = np.loadtxt("{}_val_loss.csv".format(path))
    plt.title("Train vs Validation Error")
    n = len(train_error) # number of epochs
    plt.plot(range(1,n+1), train_error, label="Train")
    plt.plot(range(1,n+1), val_error, label="Validation")
    plt.xlabel("Epoch")
    plt.ylabel("Error")
    plt.legend(loc='best')
    plt.show()
    plt.title("Train vs Validation Loss")
    plt.plot(range(1,n+1), train_loss, label="Train")
    plt.plot(range(1,n+1), val_loss, label="Validation")
    plt.xlabel("Epoch")
    plt.ylabel("Loss")
    plt.legend(loc='best')
    plt.show()
```

Code to get the model path and graph the model

```
model_path = get_model_name("parkinsonnet", batch_size=16, learning_rate=0.0
plot_training_curve(model_path)
```


Train vs Validation Error
Train
Validation
0.40
0.35
0.30
0.25
0.20
0.15
0.10
Error
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
Epoch


Train vs Validation Loss
Train
Validation
0.6
0.5
0.4
Loss