Week_9_WinningModel

November 4, 2024

[1]:
```python
# Standard Libraries
import io
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

# Deep Learning and PyTorch
import torch
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
from torch.utils.data import Dataset, DataLoader
from torchvision import models
# Image Processing
from PIL import Image
from torchvision import transforms, models

# File Handling
import h5py

# Metrics and Evaluation
from sklearn.metrics import classification_report, roc_auc_score, roc_curve, auc

# Progress Visualization
from tqdm import tqdm
```

0.1 Create Custom Dataset

[2]:
```python
class MultiInputDataset(Dataset):
    def __init__(self, hdf5_file, csv_file, transform=None):
        # Open the HDF5 file with error handling
        try:
            self.hdf5_file = h5py.File(hdf5_file, 'r')  # Read-only mode
        except Exception as e:
            raise IOError(f"Could not open HDF5 file: {hdf5_file}. Error: {e}")

        # Read the CSV file containing image labels and additional features
```

```
        try:
            self.labels_df = pd.read_csv(csv_file)
        except Exception as e:
            raise IOError(f"Could not read CSV file: {csv_file}. Error: {e}")

        # Ensure that all image IDs from the CSV are present in the HDF5 file
        self.image_ids = self.labels_df['isic_id'].values
        for image_id in self.image_ids:
            if str(image_id) not in self.hdf5_file.keys():
                raise ValueError(f"Image id {image_id} not found in HDF5 file.")

        # Store any transformations to be applied to the images
        self.transform = transform

    def __len__(self):
        # Return the total number of samples in the dataset
        return len(self.labels_df)

    def __getitem__(self, idx):
        # Get the image ID from the CSV file based on index
        image_id = str(self.labels_df.iloc[idx]['isic_id'])

        # Load the image data from the HDF5 file
        image_bytes = self.hdf5_file[image_id][()]

        # Convert the image bytes to a PIL Image
        image = Image.open(io.BytesIO(image_bytes))

        # Apply any specified transformations to the image
        if self.transform:
            image = self.transform(image)

        # Retrieve the label
        label = torch.tensor(self.labels_df.iloc[idx]['target'], dtype=torch.
↪long)  # Adjust dtype if needed

        # Retrieve other features, excluding 'isic_id' and 'target'
        other_variables = self.labels_df.iloc[idx].drop(['isic_id', 'target']).
↪values.astype(float)

        # Convert other variables (metadata) to a tensor
        metadata_tensor = torch.tensor(other_variables, dtype=torch.float32)

        # Return the image, metadata, and label
        return image, metadata_tensor, label
```

[3]:
```python
def get_train_transform(resize_size=(224, 224), crop_size=128,␣
↪rotation_degree=10, normalize_means=(0.5, 0.5, 0.5), normalize_stds=(0.5, 0.
↪5, 0.5)):
    """
    Returns the transformations for the training dataset, including data␣
↪augmentation.

    Args:
        resize_size (tuple): The size to resize the image before cropping.
        crop_size (int): The size of the random crop.
        rotation_degree (int): Maximum degree for random rotation.
        normalize_means (tuple): Means for normalization.
        normalize_stds (tuple): Standard deviations for normalization.

    Returns:
        transforms.Compose: The composed transformations for the training set.
    """
    return transforms.Compose([
        transforms.Resize(resize_size),  # Resize to specified size
        transforms.RandomResizedCrop(crop_size, scale=(0.8, 1.0)),  # Random␣
↪crop with scale
        transforms.RandomRotation(rotation_degree),  # Randomly rotate images
        transforms.ToTensor(),  # Convert image to PyTorch tensor
        transforms.Normalize(normalize_means, normalize_stds)  # Normalize with␣
↪specified means and stds
    ])

def get_normal_transform(resize_size=(224, 224), normalize_means=(0.5, 0.5, 0.
↪5), normalize_stds=(0.5, 0.5, 0.5)):
    """
    Returns the transformations for the validation/test dataset (without data␣
↪augmentation).

    Args:
        resize_size (tuple): The size to resize the image.
        normalize_means (tuple): Means for normalization.
        normalize_stds (tuple): Standard deviations for normalization.

    Returns:
        transforms.Compose: The composed transformations for the validation/
↪test set.
    """
    return transforms.Compose([
        transforms.Resize(resize_size),  # Resize to specified size
        transforms.ToTensor(),  # Convert image to PyTorch tensor
```

```
        transforms.Normalize(normalize_means, normalize_stds)  # Normalize with␣
↪specified means and stds
    ])
```

0.2 Train DataLoader

[4]:
```
device = "cuda" if torch.cuda.is_available() else "cpu"
```

0.3 Model Building

[5]:
```
# CNN Model
class CustomImageFeatureCNN2(nn.Module):
    def __init__(self, feature_input_size, input_image_size=(128, 128)):
        super(CustomImageFeatureCNN2, self).__init__()

        # Image CNN with Batch Normalization
        self.conv1 = nn.Conv2d(in_channels=3, out_channels=32, kernel_size=3,␣
↪padding=1)
        self.bn1 = nn.BatchNorm2d(32)  # Batch normalization after conv1

        self.conv2 = nn.Conv2d(32, 64, kernel_size=3, padding=1)
        self.bn2 = nn.BatchNorm2d(64)  # Batch normalization after conv2

        self.conv3 = nn.Conv2d(64, 128, kernel_size=3, padding=1)
        self.bn3 = nn.BatchNorm2d(128)  # Batch normalization after conv3

        self.pool = nn.MaxPool2d(kernel_size=2, stride=2)  # 2x2 Max pooling

        # Dynamically calculate the flattened size of the feature map
        self.flattened_size = self._get_flattened_size(input_image_size)

        # Fully connected layer after the CNN layers
        self.fc_image = nn.Linear(self.flattened_size, 512)

        # Fully connected layer for metadata (feature data)
        self.fc_metadata = nn.Linear(feature_input_size, 128)

        # Dropout layer to prevent overfitting
        self.dropout = nn.Dropout(0.5)  # 50% dropout

        # Final fully connected layer for binary classification (combined image␣
↪+ feature input)
        self.fc_combined = nn.Linear(512 + 128, 1)  # Change 2 to 1 for binary␣
↪classification

    def _get_flattened_size(self, input_image_size):
```

```
        # Forward pass a dummy image to get the size of the flattened features
        dummy_image = torch.zeros(1, 3, *input_image_size)  # Batch size of 1,␣
↪3 channels (RGB), and input size
        x = self.pool(F.relu(self.bn1(self.conv1(dummy_image))))
        x = self.pool(F.relu(self.bn2(self.conv2(x))))
        x = self.pool(F.relu(self.bn3(self.conv3(x))))
        return x.view(-1).shape[0]  # Flatten and return the size

    def forward(self, image, metadata):
        # Forward pass for the image through the CNN
        x = self.pool(F.relu(self.bn1(self.conv1(image))))  # Conv layer 1 with␣
↪ReLU, BatchNorm, MaxPool
        x = self.pool(F.relu(self.bn2(self.conv2(x))))  # Conv layer 2 with␣
↪ReLU, BatchNorm, MaxPool
        x = self.pool(F.relu(self.bn3(self.conv3(x))))  # Conv layer 3 with␣
↪ReLU, BatchNorm, MaxPool

        # Flatten the feature map to feed into fully connected layer
        x = x.view(x.size(0), -1)  # Flatten feature maps into a 1D vector
        image_features = F.relu(self.fc_image(x))

        # Process metadata (feature data)
        metadata_features = F.relu(self.fc_metadata(metadata))

        # Ensure the batch sizes are consistent
        assert image_features.shape[0] == metadata_features.shape[0], \
            f"Batch sizes do not match! Image batch size: {image_features.
↪shape[0]}, Metadata batch size: {metadata_features.shape[0]}"

        # Concatenate image features and metadata features
        combined_features = torch.cat((image_features, metadata_features),␣
↪dim=1)

        # Dropout and final classification layer
        combined_features = self.dropout(combined_features)
        output = self.fc_combined(combined_features)

        # If you're using BCELoss, uncomment the next line to apply sigmoid
        output = torch.sigmoid(output)

        return output
```

[6]:
```
# Resnet Model
class CustomImageFeatureResNet(nn.Module):
    def __init__(self, feature_input_size, pretrained=True):
        super(CustomImageFeatureResNet, self).__init__()
```

```
        # Load a pretrained ResNet model for image feature extraction (ResNet18␣
↪in this case)
        resnet = models.resnet18(pretrained=pretrained)  # Change to resnet50,␣
↪resnet101 as needed
        self.resnet = nn.Sequential(*list(resnet.children())[:-1])  # Remove␣
↪the final classification layer

        # The output of ResNet18's last conv layer is 512-dimensional (for␣
↪ResNet50, it would be 2048)
        self.fc_image = nn.Linear(resnet.fc.in_features, 512)  # Adjust if␣
↪using ResNet50

        # Fully connected layer for metadata (feature data)
        self.fc_metadata = nn.Linear(feature_input_size, 128)

        # Dropout layer to prevent overfitting
        self.dropout = nn.Dropout(0.5)  # 50% dropout

        # Final fully connected layer for binary classification (combined image␣
↪+ feature input)
        self.fc_combined = nn.Linear(512 + 128, 1)  # For binary classification

    def forward(self, image, metadata):
        # Forward pass for the image through the ResNet (without the final␣
↪classification layer)
        x = self.resnet(image)  # ResNet feature extraction
        x = x.view(x.size(0), -1)  # Flatten the ResNet output
        image_features = F.relu(self.fc_image(x))

        # Process metadata (feature data)
        metadata_features = F.relu(self.fc_metadata(metadata))

        # Ensure the batch sizes are consistent
        assert image_features.shape[0] == metadata_features.shape[0], \
            f"Batch sizes do not match! Image batch size: {image_features.
↪shape[0]}, Metadata batch size: {metadata_features.shape[0]}"

        # Concatenate image features and metadata features
        combined_features = torch.cat((image_features, metadata_features),␣
↪dim=1)

        # Dropout and final classification layer
        combined_features = self.dropout(combined_features)
        output = self.fc_combined(combined_features)
```

```
        # If you're using BCELoss, uncomment the next line to apply sigmoid
        output = torch.sigmoid(output)

        return output
```

[7]:

```
# EfficientNet Model
class CustomImageFeatureEfficientNet(nn.Module):
    def __init__(self, feature_input_size, pretrained=True):
        super(CustomImageFeatureEfficientNet, self).__init__()

        # Load a pretrained EfficientNet model for image feature extraction␣
↪(EfficientNet-B0 in this case)
        efficientnet = models.efficientnet_b0(pretrained=pretrained)  # You can␣
↪change this to another EfficientNet version like B1 or B7
        self.efficientnet = nn.Sequential(*list(efficientnet.children())[:-1]) ␣
↪# Remove the final classification layer

        # The output of EfficientNet-B0's last conv layer is 1280-dimensional
        self.fc_image = nn.Linear(1280, 512)  # Reduce dimension to match your␣
↪custom architecture

        # Fully connected layer for metadata (feature data)
        self.fc_metadata = nn.Linear(feature_input_size, 128)

        # Dropout layer to prevent overfitting
        self.dropout = nn.Dropout(0.5)  # 50% dropout

        # Final fully connected layer for binary classification (combined image␣
↪+ feature input)
        self.fc_combined = nn.Linear(512 + 128, 1)  # For binary classification

    def forward(self, image, metadata):
        # Forward pass for the image through EfficientNet (without the final␣
↪classification layer)
        x = self.efficientnet(image)  # EfficientNet feature extraction
        x = x.view(x.size(0), -1)  # Flatten the EfficientNet output
        image_features = F.relu(self.fc_image(x))

        # Process metadata (feature data)
        metadata_features = F.relu(self.fc_metadata(metadata))

        # Ensure the batch sizes are consistent
        assert image_features.shape[0] == metadata_features.shape[0], \
            f"Batch sizes do not match! Image batch size: {image_features.
↪shape[0]}, Metadata batch size: {metadata_features.shape[0]}"
```

```
        # Concatenate image features and metadata features
        combined_features = torch.cat((image_features, metadata_features),␣
↪dim=1)

        # Dropout and final classification layer
        combined_features = self.dropout(combined_features)
        output = self.fc_combined(combined_features)

        # If you're using BCELoss, uncomment the next line to apply sigmoid
        output = torch.sigmoid(output)

        return output
```

0.4 Model Training

[8]:
```
# Function to compute partial AUC-above-TPR
def score(solution: np.array, submission: np.array, min_tpr: float = 0.80) ->␣
↪float:
    """
    Compute the partial AUC by focusing on a specific range of true positive␣
↪rates (TPR).

    Args:
        solution (np.array): Ground truth binary labels.
        submission (np.array): Model predictions.
        min_tpr (float): Minimum true positive rate to calculate partial AUC.

    Returns:
        float: The calculated partial AUC.

    Raises:
        ValueError: If the min_tpr is not within a valid range.
    """
    # Rescale the target to handle sklearn limitations and flip the predictions
    v_gt = abs(solution - 1)
    v_pred = -1.0 * submission
    max_fpr = abs(1 - min_tpr)

    # Compute ROC curve using sklearn
    fpr, tpr, _ = roc_curve(v_gt, v_pred)
    if max_fpr is None or max_fpr == 1:
        return auc(fpr, tpr)
    if max_fpr <= 0 or max_fpr > 1:
        raise ValueError(f"Expected min_tpr in range [0, 1), got: {min_tpr}")

    # Interpolate for partial AUC
```

```
    stop = np.searchsorted(fpr, max_fpr, "right")
    x_interp = [fpr[stop - 1], fpr[stop]]
    y_interp = [tpr[stop - 1], tpr[stop]]
    tpr = np.append(tpr[:stop], np.interp(max_fpr, x_interp, y_interp))
    fpr = np.append(fpr[:stop], max_fpr)
    partial_auc = auc(fpr, tpr)

    return partial_auc

# Training and validation loop function
def train_and_validate(
    model: nn.Module,
    train_dataloader: torch.utils.data.DataLoader,
    val_dataloader: torch.utils.data.DataLoader,
    criterion: nn.Module,
    optimizer: torch.optim.Optimizer,
    epochs: int,
    device: torch.device,
    best_model_path: str,
    early_stopping_patience: int = 5,
    min_tpr: float = 0.80

) -> nn.Module:
    """
    Train and validate a PyTorch model with early stopping, AUROC, partial AUC,␣
 ↪and error handling.

    Args:
        model (nn.Module): The model to be trained and validated.
        train_dataloader (torch.utils.data.DataLoader): Dataloader for training␣
 ↪data.
        val_dataloader (torch.utils.data.DataLoader): Dataloader for validation␣
 ↪data.
        criterion (nn.Module): Loss function.
        optimizer (torch.optim.Optimizer): Optimizer to update the model.
        epochs (int): Number of training epochs.
        device (torch.device): The device (CPU or GPU) to use.
        early_stopping_patience (int): Early stopping patience.
        min_tpr (float): The minimum true positive rate for calculating partial␣
 ↪AUC.

    Returns:
        nn.Module: The trained model.
    """
    # Initialize tracking variables
    best_val_loss = float('inf')
    best_epoch = 0
```

```
    train_losses = []
    val_losses = []
    train_accuracies = []
    val_accuracies = []
    early_stopping_counter = 0

    # Start the training and validation loop
    for epoch in range(epochs):
        print(f'Epoch {epoch + 1}/{epochs}')

        # Training phase
        model.train()
        running_train_loss = 0.0
        correct_train = 0
        total_train = 0
        all_train_labels = []
        all_train_probs = []

        progress_bar = tqdm(train_dataloader, desc=f'Training Epoch {epoch +␣
↪1}')

        try:
            # Loop through the training batches
            for i, (image, metadata, labels) in enumerate(progress_bar):
                image, metadata, labels = image.to(device), metadata.
↪to(device), labels.float().to(device)
                labels = labels.unsqueeze(1)  # Adjust labels to have the right␣
↪shape for binary classification

                optimizer.zero_grad()

                # Forward pass
                probs = model(image, metadata)

                if probs.shape != labels.shape:
                    raise ValueError(f"Shape mismatch: Predictions shape {probs.
↪shape} does not match labels shape {labels.shape}")

                # Calculate loss and backpropagate
                loss = criterion(probs, labels)
                loss.backward()
                optimizer.step()

                # Update running loss
                running_train_loss += loss.item()

                # Store labels and predictions for accuracy calculations
```

```
                all_train_labels.extend(labels.cpu().detach().numpy())
                all_train_probs.extend(probs.cpu().detach().numpy())

                # Calculate binary predictions for training accuracy
                predicted_train = (probs >= 0.5).float()
                total_train += labels.size(0)
                correct_train += (predicted_train == labels).sum().item()

                # Update progress bar
                progress_bar.set_postfix(train_loss=running_train_loss / (i +␣
↪1))

            # Calculate training accuracy and loss
            train_accuracy = 100 * correct_train / total_train
            train_losses.append(running_train_loss / len(train_dataloader))
            train_accuracies.append(train_accuracy)

        except ValueError as ve:
            print(f"Error during training loop: {ve}")
            break

        # Validation phase
        model.eval()
        running_val_loss = 0.0
        correct = 0
        total = 0
        all_labels = []
        all_probs = []

        progress_bar = tqdm(val_dataloader, desc=f'Validating Epoch {epoch +␣
↪1}')

        with torch.no_grad():
            try:
                # Loop through the validation batches
                for i, (images, metadata, labels) in enumerate(progress_bar):
                    images, metadata, labels = images.to(device), metadata.
↪to(device), labels.float().to(device)
                    labels = labels.unsqueeze(1)

                    probs = model(images, metadata)

                    loss = criterion(probs, labels)
                    running_val_loss += loss.item()

                    all_labels.extend(labels.cpu().detach().numpy())
                    all_probs.extend(probs.cpu().detach().numpy())
```

```
                # Calculate binary predictions for validation accuracy
                predicted = (probs >= 0.5).float()
                total += labels.size(0)
                correct += (predicted == labels).sum().item()

                progress_bar.set_postfix(val_loss=running_val_loss / (i +␣
↪1))

            val_accuracy = 100 * correct / total
            val_loss = running_val_loss / len(val_dataloader)
            val_accuracies.append(val_accuracy)
            val_losses.append(val_loss)

            # Calculate AUROC
            try:
                valid_auroc = roc_auc_score(all_labels, all_probs)
            except ValueError as ve:
                print(f"AUROC Calculation Error: {ve}")
                valid_auroc = 0.0

            # Calculate partial AUC-above-TPR
            try:
                partial_auroc = score(np.array(all_labels), np.
↪array(all_probs), min_tpr=min_tpr)
            except ValueError as ve:
                print(f"Partial AUC Calculation Error: {ve}")
                partial_auroc = 0.0

            print(f'Epoch [{epoch}/{epochs}], Train Loss: {train_losses[-1]:
↪.4f}, Val Loss: {val_loss:.4f}, '
                  f'Val Accuracy: {val_accuracy:.2f}%, Val AUROC:␣
↪{valid_auroc:.4f}, Partial AUROC: {partial_auroc:.4f}')

            # Early stopping based on validation loss
            if val_loss < best_val_loss:
                best_val_loss = val_loss
                best_epoch = epoch + 1
                early_stopping_counter = 0
                torch.save(model.state_dict(), best_model_path)
            else:
                early_stopping_counter += 1

            if early_stopping_counter >= early_stopping_patience:
                print(f"Early stopping triggered at epoch {epoch}")
                break
```

```
            except Exception as e:
                print(f"Error during validation loop: {e}")
                break

    print(f"Best Epoch: {best_epoch}, Best Validation Loss: {best_val_loss:.
↪4f}")
    print('Training Complete')

    # Plot training and validation loss
    plt.figure(figsize=(10, 5))
    plt.plot(train_losses, label='Train Loss')
    plt.plot(val_losses, label='Validation Loss')
    plt.xlabel('Epochs')
    plt.ylabel('Loss')
    plt.title('Training and Validation Loss')
    plt.legend()
    plt.show()

    # Plot training and validation accuracy
    plt.figure(figsize=(10, 5))
    plt.plot(train_accuracies, label='Train Accuracy')
    plt.plot(val_accuracies, label='Validation Accuracy')
    plt.xlabel('Epochs')
    plt.ylabel('Accuracy (%)')
    plt.title('Training and Validation Accuracy')
    plt.legend()
    plt.show()

    # Generate classification report
    try:
        print("Classification Report:")
        print(classification_report(all_labels, (np.array(all_probs) >= 0.5).
↪astype(int), target_names=['Class 0', 'Class 1']))
    except Exception as e:
        print(f"Error generating classification report: {e}")

    return model
```

[9]:
```
# Initialize the dataset
CNN_train_dataset = MultiInputDataset(hdf5_file='../data/raw/train_images.
↪hdf5', csv_file='../data/processed/processed-train-metadata1.csv',␣
↪transform=get_train_transform(resize_size=(128,128)))
CNN_val_dataset = MultiInputDataset(hdf5_file='../data/raw/validation_image.
↪hdf5', csv_file='../data/processed/processed-validation-metadata1.csv',␣
↪transform=get_normal_transform(resize_size=(128,128)))
# Create a DataLoader
```

```
CNN_train_dataloader = DataLoader(CNN_train_dataset,  batch_size=64,␣
↪shuffle=True)
CNN_val_dataloader = DataLoader(CNN_val_dataset,  batch_size=64, shuffle=True)
```

[10]:
```
# Initialize the dataset
resnet_train_dataset = MultiInputDataset(hdf5_file='../data/raw/train_images.
↪hdf5', csv_file='../data/processed/processed-train-metadata1.csv',␣
↪transform=get_train_transform(resize_size=(225,225)))
resnet_val_dataset = MultiInputDataset(hdf5_file='../data/raw/validation_image.
↪hdf5', csv_file='../data/processed/processed-validation-metadata1.csv',␣
↪transform=get_normal_transform(resize_size=(225,225)))
# Create a DataLoader
resnet_train_dataloader = DataLoader(resnet_train_dataset,  batch_size=64,␣
↪shuffle=True)
resnet_val_dataloader = DataLoader(resnet_val_dataset,  batch_size=64,␣
↪shuffle=True)
```

[11]:
```
# Initialize the dataset
effnet_train_dataset = MultiInputDataset(hdf5_file='../data/raw/train_images.
↪hdf5', csv_file='../data/processed/processed-train-metadata1.csv',␣
↪transform=get_train_transform(resize_size=(224,224)))
effnet_val_dataset = MultiInputDataset(hdf5_file='../data/raw/validation_image.
↪hdf5', csv_file='../data/processed/processed-validation-metadata1.csv',␣
↪transform=get_normal_transform(resize_size=(224,224)))
# Create a DataLoader
effnet_train_dataloader = DataLoader(effnet_train_dataset,  batch_size=64,␣
↪shuffle=True)
effnet_val_dataloader = DataLoader(effnet_val_dataset,  batch_size=64,␣
↪shuffle=True)
```

0.5 Model 1

[12]:
```
model1 = CustomImageFeatureCNN2(feature_input_size=9)  # Assuming 9 features␣
↪for metadata
model1.to(device)
# Initialize optimizer
optimizer = optim.Adam(model1.parameters(), lr=0.001)
# Define the loss function with the class weights
criterion = nn.BCELoss()  # Binary classification loss
# Set the number of epochs
epochs = 20
best_model_path = "best_model1.pth"
```

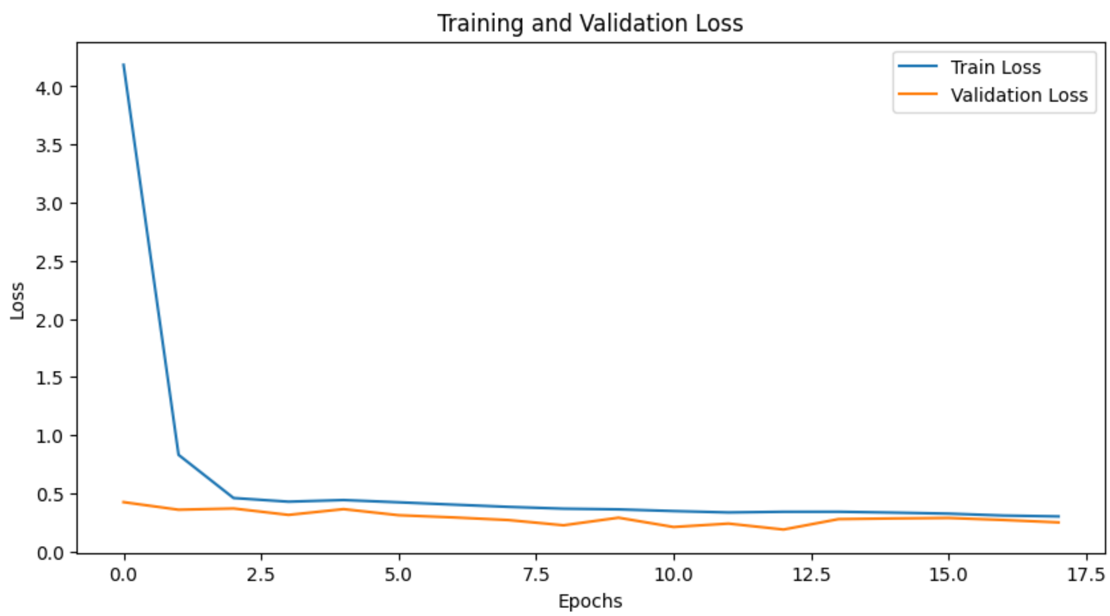
[13]:
```
train_and_validate(model1,CNN_train_dataloader, CNN_val_dataloader, criterion,␣
↪optimizer, epochs, device ,best_model_path)
```

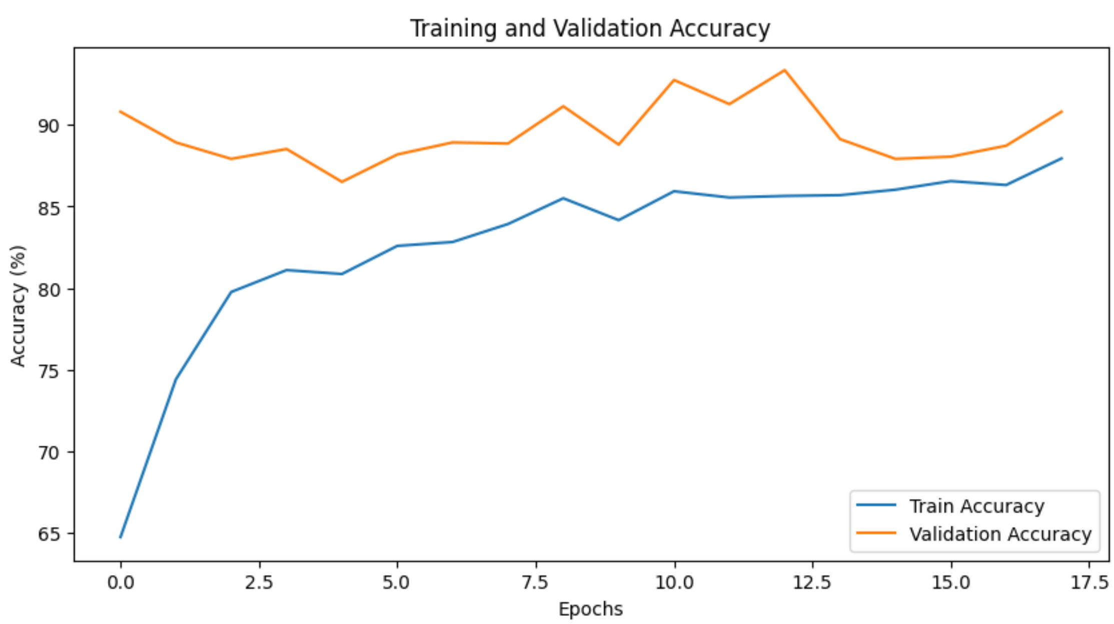
```
Epoch 1/20

Training Epoch 1: 100%|     | 33/33 [01:27<00:00,  2.64s/it,
train_loss=4.18]
Validating Epoch 1: 100%|     | 24/24 [00:25<00:00,  1.06s/it,
val_loss=0.423]

Epoch [0/20], Train Loss: 4.1848, Val Loss: 0.4227, Val Accuracy: 90.81%, Val
AUROC: 0.8038, Partial AUROC: 0.0749
Epoch 2/20

Training Epoch 2: 100%|     | 33/33 [01:19<00:00,  2.40s/it,
train_loss=0.83]
Validating Epoch 2: 100%|     | 24/24 [00:29<00:00,  1.23s/it,
val_loss=0.358]

Epoch [1/20], Train Loss: 0.8297, Val Loss: 0.3575, Val Accuracy: 88.93%, Val
AUROC: 0.7938, Partial AUROC: 0.0599
Epoch 3/20

Training Epoch 3: 100%|     | 33/33 [01:45<00:00,  3.19s/it,
train_loss=0.458]
Validating Epoch 3: 100%|     | 24/24 [00:24<00:00,  1.01s/it,
val_loss=0.368]

Epoch [2/20], Train Loss: 0.4581, Val Loss: 0.3682, Val Accuracy: 87.92%, Val
AUROC: 0.8200, Partial AUROC: 0.0693
Epoch 4/20

Training Epoch 4: 100%|     | 33/33 [01:18<00:00,  2.38s/it,
train_loss=0.427]
Validating Epoch 4: 100%|     | 24/24 [00:24<00:00,  1.04s/it,
val_loss=0.313]

Epoch [3/20], Train Loss: 0.4267, Val Loss: 0.3129, Val Accuracy: 88.52%, Val
AUROC: 0.8165, Partial AUROC: 0.0715
Epoch 5/20

Training Epoch 5: 100%|     | 33/33 [01:24<00:00,  2.57s/it,
train_loss=0.441]
Validating Epoch 5: 100%|     | 24/24 [00:25<00:00,  1.04s/it,
val_loss=0.363]

Epoch [4/20], Train Loss: 0.4409, Val Loss: 0.3627, Val Accuracy: 86.51%, Val
AUROC: 0.8393, Partial AUROC: 0.0821
Epoch 6/20

Training Epoch 6: 100%|     | 33/33 [01:22<00:00,  2.50s/it,
train_loss=0.421]
Validating Epoch 6: 100%|     | 24/24 [00:25<00:00,  1.04s/it,
val_loss=0.31]

Epoch [5/20], Train Loss: 0.4213, Val Loss: 0.3103, Val Accuracy: 88.19%, Val
AUROC: 0.8442, Partial AUROC: 0.0844
```

```
Epoch 7/20

Training Epoch 7: 100%|     | 33/33 [01:22<00:00,  2.49s/it,
train_loss=0.401]
Validating Epoch 7: 100%|     | 24/24 [00:26<00:00,  1.10s/it,
val_loss=0.291]

Epoch [6/20], Train Loss: 0.4014, Val Loss: 0.2913, Val Accuracy: 88.93%, Val
AUROC: 0.8538, Partial AUROC: 0.0917
Epoch 8/20

Training Epoch 8: 100%|     | 33/33 [01:28<00:00,  2.69s/it,
train_loss=0.382]
Validating Epoch 8: 100%|     | 24/24 [00:49<00:00,  2.06s/it,
val_loss=0.269]

Epoch [7/20], Train Loss: 0.3820, Val Loss: 0.2685, Val Accuracy: 88.86%, Val
AUROC: 0.8516, Partial AUROC: 0.0890
Epoch 9/20

Training Epoch 9: 100%|     | 33/33 [01:22<00:00,  2.50s/it,
train_loss=0.367]
Validating Epoch 9: 100%|     | 24/24 [00:32<00:00,  1.37s/it,
val_loss=0.224]

Epoch [8/20], Train Loss: 0.3666, Val Loss: 0.2236, Val Accuracy: 91.14%, Val
AUROC: 0.8624, Partial AUROC: 0.1020
Epoch 10/20

Training Epoch 10: 100%|     | 33/33 [02:13<00:00,  4.04s/it,
train_loss=0.361]
Validating Epoch 10: 100%|     | 24/24 [00:42<00:00,  1.77s/it,
val_loss=0.289]

Epoch [9/20], Train Loss: 0.3605, Val Loss: 0.2888, Val Accuracy: 88.79%, Val
AUROC: 0.8273, Partial AUROC: 0.0790
Epoch 11/20

Training Epoch 11: 100%|     | 33/33 [02:02<00:00,  3.72s/it,
train_loss=0.346]
Validating Epoch 11: 100%|     | 24/24 [00:34<00:00,  1.45s/it,
val_loss=0.209]

Epoch [10/20], Train Loss: 0.3460, Val Loss: 0.2089, Val Accuracy: 92.75%, Val
AUROC: 0.8748, Partial AUROC: 0.1060
Epoch 12/20

Training Epoch 12: 100%|     | 33/33 [01:57<00:00,  3.55s/it,
train_loss=0.334]
Validating Epoch 12: 100%|     | 24/24 [00:54<00:00,  2.26s/it,
val_loss=0.238]

Epoch [11/20], Train Loss: 0.3341, Val Loss: 0.2383, Val Accuracy: 91.28%, Val
AUROC: 0.8747, Partial AUROC: 0.1048
```

```
Epoch 13/20

Training Epoch 13: 100%|     | 33/33 [02:03<00:00,  3.73s/it,
train_loss=0.34]
Validating Epoch 13: 100%|     | 24/24 [00:35<00:00,  1.49s/it,
val_loss=0.187]

Epoch [12/20], Train Loss: 0.3399, Val Loss: 0.1871, Val Accuracy: 93.36%, Val
AUROC: 0.8728, Partial AUROC: 0.1066
Epoch 14/20

Training Epoch 14: 100%|     | 33/33 [01:52<00:00,  3.42s/it,
train_loss=0.34]
Validating Epoch 14: 100%|     | 24/24 [00:35<00:00,  1.48s/it,
val_loss=0.277]

Epoch [13/20], Train Loss: 0.3402, Val Loss: 0.2766, Val Accuracy: 89.13%, Val
AUROC: 0.8791, Partial AUROC: 0.1095
Epoch 15/20

Training Epoch 15: 100%|     | 33/33 [01:56<00:00,  3.55s/it,
train_loss=0.333]
Validating Epoch 15: 100%|     | 24/24 [00:36<00:00,  1.51s/it,
val_loss=0.283]

Epoch [14/20], Train Loss: 0.3327, Val Loss: 0.2826, Val Accuracy: 87.92%, Val
AUROC: 0.8737, Partial AUROC: 0.1035
Epoch 16/20

Training Epoch 16: 100%|     | 33/33 [01:59<00:00,  3.62s/it,
train_loss=0.324]
Validating Epoch 16: 100%|     | 24/24 [00:44<00:00,  1.84s/it,
val_loss=0.287]

Epoch [15/20], Train Loss: 0.3239, Val Loss: 0.2866, Val Accuracy: 88.05%, Val
AUROC: 0.8761, Partial AUROC: 0.1093
Epoch 17/20

Training Epoch 17: 100%|     | 33/33 [02:14<00:00,  4.08s/it,
train_loss=0.307]
Validating Epoch 17: 100%|     | 24/24 [00:35<00:00,  1.50s/it,
val_loss=0.269]

Epoch [16/20], Train Loss: 0.3074, Val Loss: 0.2691, Val Accuracy: 88.72%, Val
AUROC: 0.8842, Partial AUROC: 0.1106
Epoch 18/20

Training Epoch 18: 100%|     | 33/33 [01:55<00:00,  3.51s/it,
train_loss=0.3]
Validating Epoch 18: 100%|     | 24/24 [00:36<00:00,  1.52s/it,
val_loss=0.248]

Epoch [17/20], Train Loss: 0.2999, Val Loss: 0.2485, Val Accuracy: 90.81%, Val
AUROC: 0.8738, Partial AUROC: 0.1037
```

```
Early stopping triggered at epoch 17
Best Epoch: 13, Best Validation Loss: 0.1871
Training Complete
```






```
Classification Report:
              precision    recall  f1-score   support
```

```
     Class 0       0.99      0.92      0.95      1431
     Class 1       0.25      0.68      0.37        59

    accuracy                           0.91      1490
   macro avg       0.62      0.80      0.66      1490
weighted avg       0.96      0.91      0.93      1490
```

[13]:
```
CustomImageFeatureCNN2(
  (conv1): Conv2d(3, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (bn1): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
  (conv2): Conv2d(32, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
  (conv3): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (bn3): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
  (pool): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)
  (fc_image): Linear(in_features=32768, out_features=512, bias=True)
  (fc_metadata): Linear(in_features=9, out_features=128, bias=True)
  (dropout): Dropout(p=0.5, inplace=False)
  (fc_combined): Linear(in_features=640, out_features=1, bias=True)
)
```

0.6 Model 2

[14]:
```
model2 = CustomImageFeatureCNN2(feature_input_size=9)  # Assuming 9 features␣
 ↪for metadata
model2.to(device)
# Initialize optimizer
optimizer = optim.SGD(model2.parameters(), lr=0.001)
# Define the loss function with the class weights
criterion = nn.BCELoss()  # Binary classification loss
# Set the number of epochs
epochs = 20
best_model_path = "best_model2.pth"
```

[15]:
```
train_and_validate(model2,CNN_train_dataloader, CNN_val_dataloader, criterion,␣
 ↪optimizer, epochs, device,best_model_path )
```

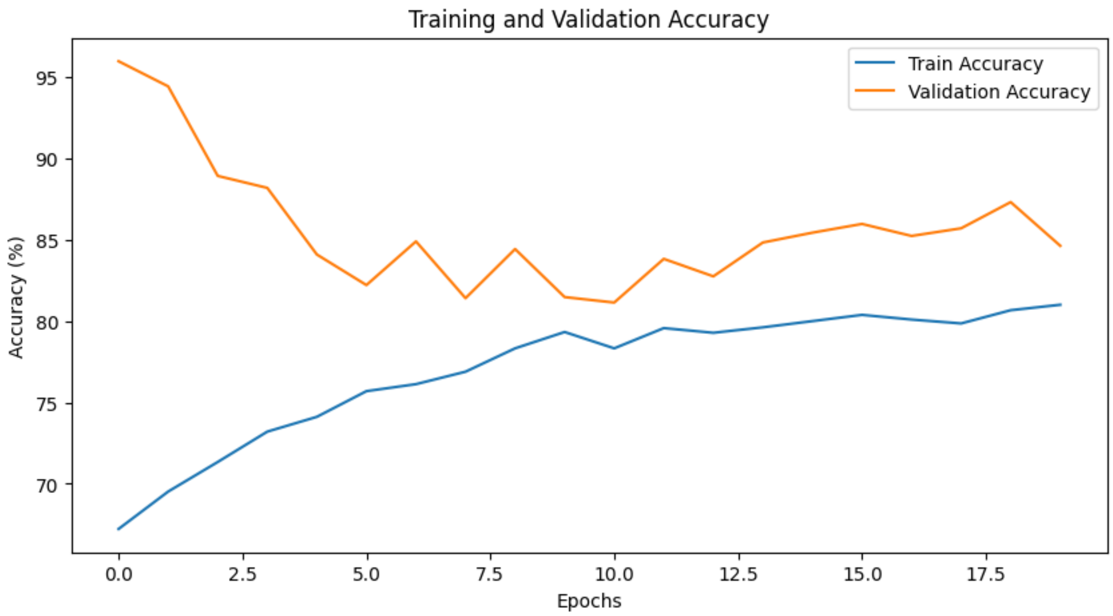
```
Epoch 1/20

Training Epoch 1: 100%|     | 33/33 [01:57<00:00,  3.57s/it,
train_loss=0.628]
Validating Epoch 1: 100%|     | 24/24 [00:41<00:00,  1.75s/it,
val_loss=0.57]
```

```
Epoch [0/20], Train Loss: 0.6278, Val Loss: 0.5701, Val Accuracy: 95.97%, Val
AUROC: 0.7021, Partial AUROC: 0.0547
Epoch 2/20

Training Epoch 2: 100%|     | 33/33 [01:52<00:00,  3.41s/it,
train_loss=0.599]
Validating Epoch 2: 100%|     | 24/24 [00:53<00:00,  2.22s/it,
val_loss=0.496]

Epoch [1/20], Train Loss: 0.5989, Val Loss: 0.4958, Val Accuracy: 94.43%, Val
AUROC: 0.7610, Partial AUROC: 0.0619
Epoch 3/20

Training Epoch 3: 100%|     | 33/33 [02:07<00:00,  3.87s/it,
train_loss=0.577]
Validating Epoch 3: 100%|     | 24/24 [00:38<00:00,  1.62s/it,
val_loss=0.512]

Epoch [2/20], Train Loss: 0.5775, Val Loss: 0.5117, Val Accuracy: 88.93%, Val
AUROC: 0.7735, Partial AUROC: 0.0635
Epoch 4/20

Training Epoch 4: 100%|     | 33/33 [01:56<00:00,  3.52s/it,
train_loss=0.555]
Validating Epoch 4: 100%|     | 24/24 [00:37<00:00,  1.58s/it,
val_loss=0.482]

Epoch [3/20], Train Loss: 0.5548, Val Loss: 0.4821, Val Accuracy: 88.19%, Val
AUROC: 0.7844, Partial AUROC: 0.0660
Epoch 5/20

Training Epoch 5: 100%|     | 33/33 [02:03<00:00,  3.74s/it,
train_loss=0.54]
Validating Epoch 5: 100%|     | 24/24 [00:38<00:00,  1.61s/it,
val_loss=0.495]

Epoch [4/20], Train Loss: 0.5395, Val Loss: 0.4947, Val Accuracy: 84.09%, Val
AUROC: 0.7909, Partial AUROC: 0.0696
Epoch 6/20

Training Epoch 6: 100%|     | 33/33 [01:54<00:00,  3.47s/it,
train_loss=0.525]
Validating Epoch 6: 100%|     | 24/24 [01:05<00:00,  2.74s/it,
val_loss=0.507]

Epoch [5/20], Train Loss: 0.5253, Val Loss: 0.5066, Val Accuracy: 82.21%, Val
AUROC: 0.7962, Partial AUROC: 0.0693
Epoch 7/20

Training Epoch 7: 100%|     | 33/33 [01:56<00:00,  3.53s/it,
train_loss=0.506]
Validating Epoch 7: 100%|     | 24/24 [00:37<00:00,  1.56s/it,
val_loss=0.451]
```

```
Epoch [6/20], Train Loss: 0.5061, Val Loss: 0.4514, Val Accuracy: 84.90%, Val
AUROC: 0.8026, Partial AUROC: 0.0705
Epoch 8/20

Training Epoch 8: 100%|     | 33/33 [01:55<00:00,  3.49s/it,
train_loss=0.497]
Validating Epoch 8: 100%|     | 24/24 [00:39<00:00,  1.64s/it,
val_loss=0.492]

Epoch [7/20], Train Loss: 0.4968, Val Loss: 0.4923, Val Accuracy: 81.41%, Val
AUROC: 0.8021, Partial AUROC: 0.0676
Epoch 9/20

Training Epoch 9: 100%|     | 33/33 [02:03<00:00,  3.75s/it,
train_loss=0.485]
Validating Epoch 9: 100%|     | 24/24 [00:38<00:00,  1.59s/it,
val_loss=0.445]

Epoch [8/20], Train Loss: 0.4849, Val Loss: 0.4452, Val Accuracy: 84.43%, Val
AUROC: 0.8091, Partial AUROC: 0.0722
Epoch 10/20

Training Epoch 10: 100%|     | 33/33 [01:55<00:00,  3.51s/it,
train_loss=0.471]
Validating Epoch 10: 100%|     | 24/24 [01:06<00:00,  2.79s/it,
val_loss=0.484]

Epoch [9/20], Train Loss: 0.4712, Val Loss: 0.4843, Val Accuracy: 81.48%, Val
AUROC: 0.8107, Partial AUROC: 0.0731
Epoch 11/20

Training Epoch 11: 100%|     | 33/33 [01:58<00:00,  3.58s/it,
train_loss=0.477]
Validating Epoch 11: 100%|     | 24/24 [00:38<00:00,  1.61s/it,
val_loss=0.479]

Epoch [10/20], Train Loss: 0.4768, Val Loss: 0.4790, Val Accuracy: 81.14%, Val
AUROC: 0.8137, Partial AUROC: 0.0748
Epoch 12/20

Training Epoch 12: 100%|     | 33/33 [01:58<00:00,  3.59s/it,
train_loss=0.468]
Validating Epoch 12: 100%|     | 24/24 [00:41<00:00,  1.72s/it,
val_loss=0.448]

Epoch [11/20], Train Loss: 0.4682, Val Loss: 0.4476, Val Accuracy: 83.83%, Val
AUROC: 0.8137, Partial AUROC: 0.0701
Epoch 13/20

Training Epoch 13: 100%|     | 33/33 [01:55<00:00,  3.50s/it,
train_loss=0.464]
Validating Epoch 13: 100%|     | 24/24 [00:38<00:00,  1.61s/it,
val_loss=0.452]
```

```
Epoch [12/20], Train Loss: 0.4639, Val Loss: 0.4522, Val Accuracy: 82.75%, Val
AUROC: 0.8171, Partial AUROC: 0.0733
Epoch 14/20

Training Epoch 14: 100%|     | 33/33 [01:56<00:00,  3.54s/it,
train_loss=0.457]
Validating Epoch 14: 100%|     | 24/24 [00:53<00:00,  2.21s/it,
val_loss=0.42]

Epoch [13/20], Train Loss: 0.4574, Val Loss: 0.4204, Val Accuracy: 84.83%, Val
AUROC: 0.8185, Partial AUROC: 0.0722
Epoch 15/20

Training Epoch 15: 100%|     | 33/33 [02:17<00:00,  4.18s/it,
train_loss=0.453]
Validating Epoch 15: 100%|     | 24/24 [00:47<00:00,  1.99s/it,
val_loss=0.428]

Epoch [14/20], Train Loss: 0.4527, Val Loss: 0.4277, Val Accuracy: 85.44%, Val
AUROC: 0.8213, Partial AUROC: 0.0800
Epoch 16/20

Training Epoch 16: 100%|     | 33/33 [02:25<00:00,  4.42s/it,
train_loss=0.45]
Validating Epoch 16: 100%|     | 24/24 [00:45<00:00,  1.91s/it,
val_loss=0.399]

Epoch [15/20], Train Loss: 0.4504, Val Loss: 0.3990, Val Accuracy: 85.97%, Val
AUROC: 0.8235, Partial AUROC: 0.0766
Epoch 17/20

Training Epoch 17: 100%|     | 33/33 [02:16<00:00,  4.14s/it,
train_loss=0.444]
Validating Epoch 17: 100%|     | 24/24 [00:45<00:00,  1.90s/it,
val_loss=0.407]

Epoch [16/20], Train Loss: 0.4443, Val Loss: 0.4070, Val Accuracy: 85.23%, Val
AUROC: 0.8227, Partial AUROC: 0.0734
Epoch 18/20

Training Epoch 18: 100%|     | 33/33 [02:47<00:00,  5.07s/it,
train_loss=0.439]
Validating Epoch 18: 100%|     | 24/24 [00:43<00:00,  1.83s/it,
val_loss=0.406]

Epoch [17/20], Train Loss: 0.4394, Val Loss: 0.4057, Val Accuracy: 85.70%, Val
AUROC: 0.8271, Partial AUROC: 0.0771
Epoch 19/20

Training Epoch 19: 100%|     | 33/33 [01:26<00:00,  2.64s/it,
train_loss=0.439]
Validating Epoch 19: 100%|     | 24/24 [00:26<00:00,  1.12s/it,
val_loss=0.384]
```

```
Epoch [18/20], Train Loss: 0.4394, Val Loss: 0.3842, Val Accuracy: 87.32%, Val
AUROC: 0.8297, Partial AUROC: 0.0800
Epoch 20/20

Training Epoch 20: 100%|      | 33/33 [01:33<00:00,  2.84s/it,
train_loss=0.432]
Validating Epoch 20: 100%|      | 24/24 [00:32<00:00,  1.34s/it,
val_loss=0.415]

Epoch [19/20], Train Loss: 0.4317, Val Loss: 0.4151, Val Accuracy: 84.63%, Val
AUROC: 0.8273, Partial AUROC: 0.0768
Best Epoch: 19, Best Validation Loss: 0.3842
Training Complete
```




```
Classification Report:
              precision    recall  f1-score   support

     Class 0       0.98      0.85      0.91      1431
     Class 1       0.16      0.68      0.26        59

    accuracy                           0.85      1490
   macro avg       0.57      0.77      0.59      1490
weighted avg       0.95      0.85      0.89      1490
```

[15]:
```
CustomImageFeatureCNN2(
  (conv1): Conv2d(3, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (bn1): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
  (conv2): Conv2d(32, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
  (conv3): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (bn3): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
  (pool): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)
  (fc_image): Linear(in_features=32768, out_features=512, bias=True)
  (fc_metadata): Linear(in_features=9, out_features=128, bias=True)
  (dropout): Dropout(p=0.5, inplace=False)
  (fc_combined): Linear(in_features=640, out_features=1, bias=True)
```

```
)
```

0.7 Model 3

[16]:
```
model3 = CustomImageFeatureCNN2(feature_input_size=9)  # Assuming 9 features␣
↪for metadata
model3.to(device)
# Initialize optimizer
optimizer = optim.SGD(model3.parameters(), lr=0.0001,weight_decay=1e-4)
# Define the loss function with the class weights
criterion = nn.BCELoss()  # Binary classification loss
# Set the number of epochs
epochs = 20
batch_size = 32
best_model_path = "best_model3.pth"
```

[17]:
```
CNN_train_dataloader = DataLoader(CNN_train_dataset, batch_size=batch_size,␣
↪shuffle=True)
CNN_val_dataloader = DataLoader(CNN_val_dataset, batch_size=batch_size,␣
↪shuffle=True)
```

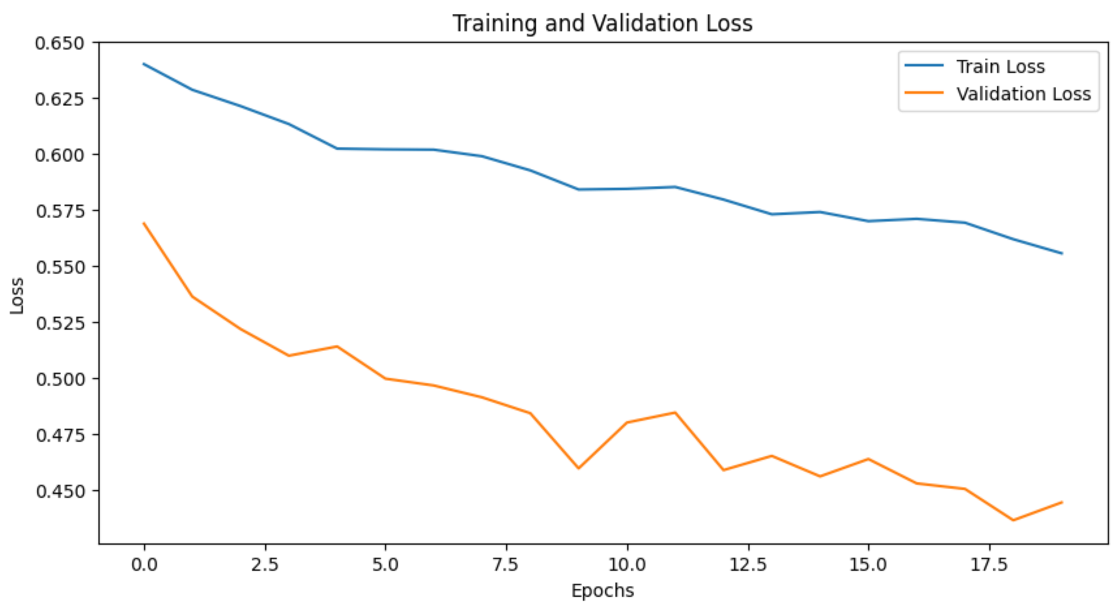
[18]:
```
train_and_validate(model3,CNN_train_dataloader, CNN_val_dataloader, criterion,␣
↪optimizer, epochs, device, best_model_path )
```

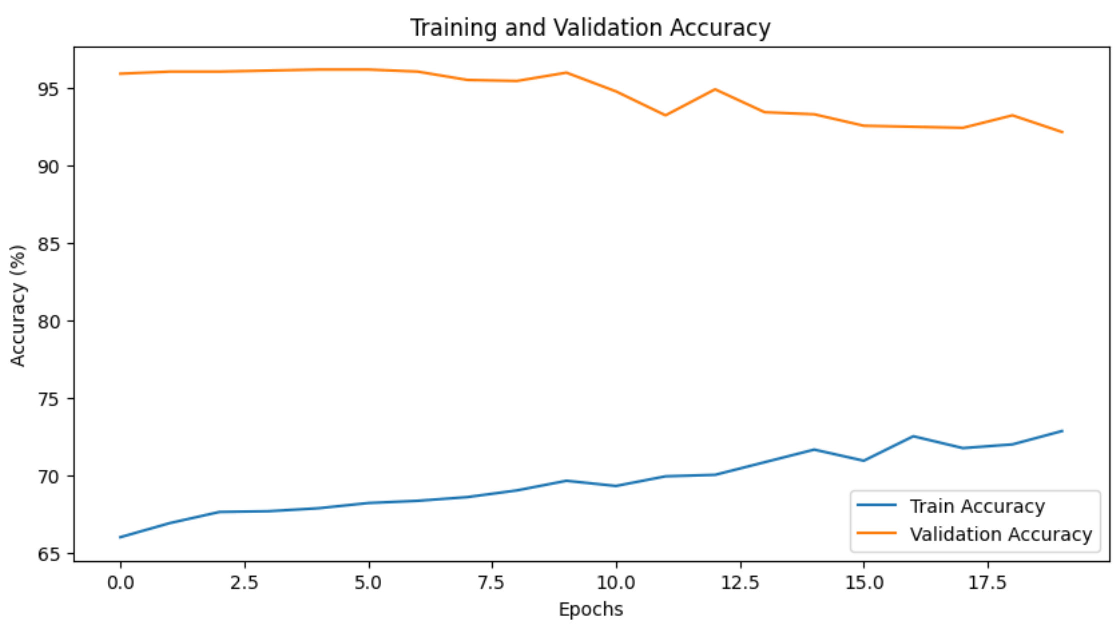
```
Epoch 1/20

Training Epoch 1: 100%|      | 66/66 [01:26<00:00,  1.31s/it,
train_loss=0.64]
Validating Epoch 1: 100%|      | 47/47 [00:37<00:00,  1.25it/s,
val_loss=0.569]

Epoch [0/20], Train Loss: 0.6399, Val Loss: 0.5689, Val Accuracy: 95.91%, Val
AUROC: 0.6144, Partial AUROC: 0.0319
Epoch 2/20

Training Epoch 2: 100%|      | 66/66 [02:27<00:00,  2.24s/it,
train_loss=0.629]
Validating Epoch 2: 100%|      | 47/47 [00:41<00:00,  1.12it/s,
val_loss=0.536]

Epoch [1/20], Train Loss: 0.6285, Val Loss: 0.5364, Val Accuracy: 96.04%, Val
AUROC: 0.6355, Partial AUROC: 0.0391
Epoch 3/20

Training Epoch 3: 100%|      | 66/66 [01:44<00:00,  1.58s/it,
train_loss=0.621]
Validating Epoch 3: 100%|      | 47/47 [00:21<00:00,  2.23it/s,
val_loss=0.522]
```

```
Epoch [2/20], Train Loss: 0.6212, Val Loss: 0.5219, Val Accuracy: 96.04%, Val
AUROC: 0.6689, Partial AUROC: 0.0431
Epoch 4/20

Training Epoch 4: 100%|     | 66/66 [01:39<00:00,  1.51s/it,
train_loss=0.613]
Validating Epoch 4: 100%|     | 47/47 [00:42<00:00,  1.11it/s,
val_loss=0.51]

Epoch [3/20], Train Loss: 0.6132, Val Loss: 0.5100, Val Accuracy: 96.11%, Val
AUROC: 0.6878, Partial AUROC: 0.0471
Epoch 5/20

Training Epoch 5: 100%|     | 66/66 [02:02<00:00,  1.86s/it,
train_loss=0.602]
Validating Epoch 5: 100%|     | 47/47 [00:39<00:00,  1.19it/s,
val_loss=0.514]

Epoch [4/20], Train Loss: 0.6023, Val Loss: 0.5141, Val Accuracy: 96.17%, Val
AUROC: 0.7038, Partial AUROC: 0.0465
Epoch 6/20

Training Epoch 6: 100%|     | 66/66 [02:29<00:00,  2.26s/it,
train_loss=0.602]
Validating Epoch 6: 100%|     | 47/47 [00:25<00:00,  1.88it/s,
val_loss=0.5]

Epoch [5/20], Train Loss: 0.6020, Val Loss: 0.4998, Val Accuracy: 96.17%, Val
AUROC: 0.7137, Partial AUROC: 0.0486
Epoch 7/20

Training Epoch 7: 100%|     | 66/66 [01:10<00:00,  1.07s/it,
train_loss=0.602]
Validating Epoch 7: 100%|     | 47/47 [00:21<00:00,  2.23it/s,
val_loss=0.497]

Epoch [6/20], Train Loss: 0.6018, Val Loss: 0.4968, Val Accuracy: 96.04%, Val
AUROC: 0.7155, Partial AUROC: 0.0510
Epoch 8/20

Training Epoch 8: 100%|     | 66/66 [01:16<00:00,  1.17s/it,
train_loss=0.599]
Validating Epoch 8: 100%|     | 47/47 [00:23<00:00,  2.01it/s,
val_loss=0.491]

Epoch [7/20], Train Loss: 0.5989, Val Loss: 0.4915, Val Accuracy: 95.50%, Val
AUROC: 0.7197, Partial AUROC: 0.0518
Epoch 9/20

Training Epoch 9: 100%|     | 66/66 [01:12<00:00,  1.09s/it,
train_loss=0.593]
Validating Epoch 9: 100%|     | 47/47 [00:25<00:00,  1.86it/s,
val_loss=0.484]
```

```
Epoch [8/20], Train Loss: 0.5926, Val Loss: 0.4844, Val Accuracy: 95.44%, Val
AUROC: 0.7217, Partial AUROC: 0.0523
Epoch 10/20

Training Epoch 10: 100%|     | 66/66 [01:11<00:00,  1.08s/it,
train_loss=0.584]
Validating Epoch 10: 100%|     | 47/47 [00:19<00:00,  2.40it/s,
val_loss=0.46]

Epoch [9/20], Train Loss: 0.5841, Val Loss: 0.4598, Val Accuracy: 95.97%, Val
AUROC: 0.7264, Partial AUROC: 0.0528
Epoch 11/20

Training Epoch 11: 100%|     | 66/66 [01:11<00:00,  1.08s/it,
train_loss=0.584]
Validating Epoch 11: 100%|     | 47/47 [00:22<00:00,  2.07it/s,
val_loss=0.48]

Epoch [10/20], Train Loss: 0.5844, Val Loss: 0.4802, Val Accuracy: 94.77%, Val
AUROC: 0.7367, Partial AUROC: 0.0524
Epoch 12/20

Training Epoch 12: 100%|     | 66/66 [01:11<00:00,  1.08s/it,
train_loss=0.585]
Validating Epoch 12: 100%|     | 47/47 [00:18<00:00,  2.48it/s,
val_loss=0.485]

Epoch [11/20], Train Loss: 0.5852, Val Loss: 0.4847, Val Accuracy: 93.22%, Val
AUROC: 0.7396, Partial AUROC: 0.0542
Epoch 13/20

Training Epoch 13: 100%|     | 66/66 [01:37<00:00,  1.48s/it,
train_loss=0.58]
Validating Epoch 13: 100%|     | 47/47 [00:25<00:00,  1.86it/s,
val_loss=0.459]

Epoch [12/20], Train Loss: 0.5796, Val Loss: 0.4590, Val Accuracy: 94.90%, Val
AUROC: 0.7420, Partial AUROC: 0.0535
Epoch 14/20

Training Epoch 14: 100%|     | 66/66 [01:17<00:00,  1.17s/it,
train_loss=0.573]
Validating Epoch 14: 100%|     | 47/47 [00:22<00:00,  2.12it/s,
val_loss=0.465]

Epoch [13/20], Train Loss: 0.5730, Val Loss: 0.4654, Val Accuracy: 93.42%, Val
AUROC: 0.7402, Partial AUROC: 0.0540
Epoch 15/20

Training Epoch 15: 100%|     | 66/66 [01:23<00:00,  1.27s/it,
train_loss=0.574]
Validating Epoch 15: 100%|     | 47/47 [00:17<00:00,  2.62it/s,
val_loss=0.456]
```

```
Epoch [14/20], Train Loss: 0.5740, Val Loss: 0.4562, Val Accuracy: 93.29%, Val
AUROC: 0.7453, Partial AUROC: 0.0545
Epoch 16/20

Training Epoch 16: 100%|     | 66/66 [01:13<00:00,  1.11s/it,
train_loss=0.57]
Validating Epoch 16: 100%|     | 47/47 [00:18<00:00,  2.48it/s,
val_loss=0.464]

Epoch [15/20], Train Loss: 0.5700, Val Loss: 0.4640, Val Accuracy: 92.55%, Val
AUROC: 0.7510, Partial AUROC: 0.0556
Epoch 17/20

Training Epoch 17: 100%|     | 66/66 [01:10<00:00,  1.07s/it,
train_loss=0.571]
Validating Epoch 17: 100%|     | 47/47 [00:22<00:00,  2.13it/s,
val_loss=0.453]

Epoch [16/20], Train Loss: 0.5710, Val Loss: 0.4531, Val Accuracy: 92.48%, Val
AUROC: 0.7481, Partial AUROC: 0.0542
Epoch 18/20

Training Epoch 18: 100%|     | 66/66 [01:16<00:00,  1.16s/it,
train_loss=0.569]
Validating Epoch 18: 100%|     | 47/47 [00:18<00:00,  2.50it/s,
val_loss=0.451]

Epoch [17/20], Train Loss: 0.5693, Val Loss: 0.4507, Val Accuracy: 92.42%, Val
AUROC: 0.7562, Partial AUROC: 0.0552
Epoch 19/20

Training Epoch 19: 100%|     | 66/66 [01:37<00:00,  1.47s/it,
train_loss=0.562]
Validating Epoch 19: 100%|     | 47/47 [00:17<00:00,  2.66it/s,
val_loss=0.437]

Epoch [18/20], Train Loss: 0.5619, Val Loss: 0.4367, Val Accuracy: 93.22%, Val
AUROC: 0.7566, Partial AUROC: 0.0554
Epoch 20/20

Training Epoch 20: 100%|     | 66/66 [01:16<00:00,  1.16s/it,
train_loss=0.556]
Validating Epoch 20: 100%|     | 47/47 [00:25<00:00,  1.83it/s,
val_loss=0.445]

Epoch [19/20], Train Loss: 0.5557, Val Loss: 0.4446, Val Accuracy: 92.15%, Val
AUROC: 0.7592, Partial AUROC: 0.0553
Best Epoch: 19, Best Validation Loss: 0.4367
Training Complete
```





Classification Report:

	precision	recall	f1-score	support
Class 0	0.97	0.95	0.96	1431
Class 1	0.19	0.31	0.24	59
accuracy			0.92	1490

```
   macro avg       0.58      0.63      0.60      1490
weighted avg       0.94      0.92      0.93      1490
```

[18]:
```
CustomImageFeatureCNN2(
  (conv1): Conv2d(3, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (bn1): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
  (conv2): Conv2d(32, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
  (conv3): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (bn3): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
  (pool): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)
  (fc_image): Linear(in_features=32768, out_features=512, bias=True)
  (fc_metadata): Linear(in_features=9, out_features=128, bias=True)
  (dropout): Dropout(p=0.5, inplace=False)
  (fc_combined): Linear(in_features=640, out_features=1, bias=True)
)
```

0.8 Model 4

[19]:
```
model4 = CustomImageFeatureResNet(feature_input_size=9)  # Assuming 9 features␣
 ↪for metadata
model4.to(device)
# Initialize optimizer
optimizer = optim.Adam(model4.parameters(), lr=0.001)
# Define the loss function with the class weights
criterion = nn.BCELoss()  # Binary classification loss
# Set the number of epochs
epochs = 20
best_model_path = "best_model4.pth"
```

```
/home/jupyter-sohka/.local/lib/python3.10/site-
packages/torchvision/models/_utils.py:208: UserWarning: The parameter
'pretrained' is deprecated since 0.13 and may be removed in the future, please
use 'weights' instead.
  warnings.warn(
/home/jupyter-sohka/.local/lib/python3.10/site-
packages/torchvision/models/_utils.py:223: UserWarning: Arguments other than a
weight enum or `None` for 'weights' are deprecated since 0.13 and may be removed
in the future. The current behavior is equivalent to passing
`weights=ResNet18_Weights.IMAGENET1K_V1`. You can also use
`weights=ResNet18_Weights.DEFAULT` to get the most up-to-date weights.
  warnings.warn(msg)
```

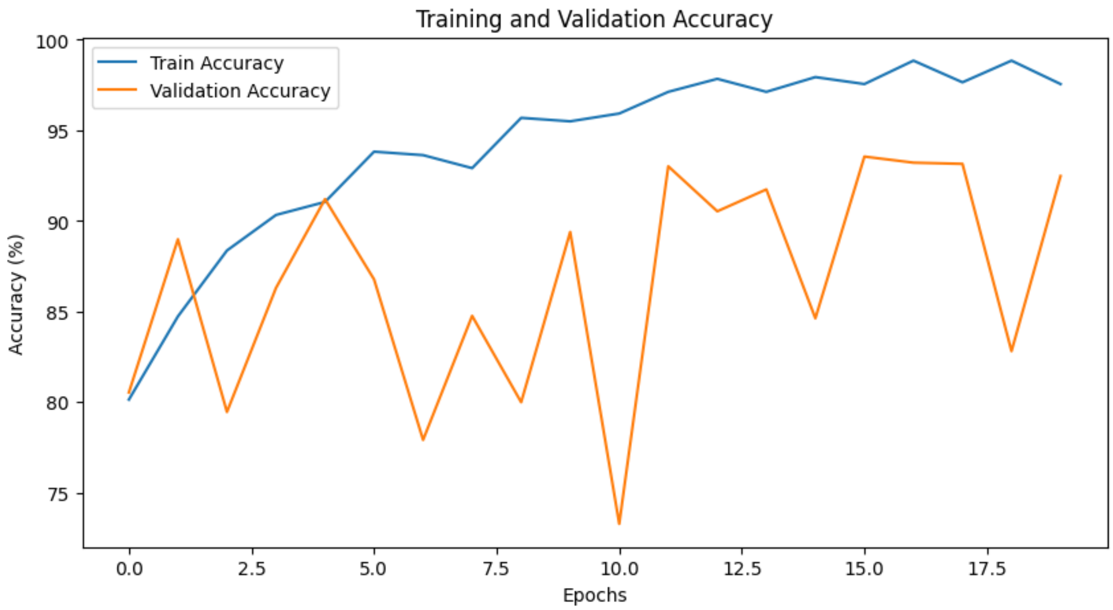
[20]:
```
train_and_validate(model4,resnet_train_dataloader, resnet_val_dataloader,
    criterion, optimizer, epochs, device, best_model_path )
```

```
Epoch 1/20

Training Epoch 1: 100%|      | 33/33 [01:41<00:00,  3.08s/it,
train_loss=0.474]
Validating Epoch 1: 100%|      | 24/24 [01:28<00:00,  3.67s/it,
val_loss=0.567]

Epoch [0/20], Train Loss: 0.4739, Val Loss: 0.5675, Val Accuracy: 80.54%, Val
AUROC: 0.7634, Partial AUROC: 0.0691
Epoch 2/20

Training Epoch 2: 100%|      | 33/33 [01:56<00:00,  3.53s/it,
train_loss=0.351]
Validating Epoch 2: 100%|      | 24/24 [01:22<00:00,  3.43s/it,
val_loss=0.336]

Epoch [1/20], Train Loss: 0.3508, Val Loss: 0.3355, Val Accuracy: 88.99%, Val
AUROC: 0.7413, Partial AUROC: 0.0491
Epoch 3/20

Training Epoch 3: 100%|      | 33/33 [02:23<00:00,  4.34s/it,
train_loss=0.302]
Validating Epoch 3: 100%|      | 24/24 [01:28<00:00,  3.67s/it,
val_loss=0.398]

Epoch [2/20], Train Loss: 0.3015, Val Loss: 0.3976, Val Accuracy: 79.46%, Val
AUROC: 0.8102, Partial AUROC: 0.0917
Epoch 4/20

Training Epoch 4: 100%|      | 33/33 [01:41<00:00,  3.07s/it,
train_loss=0.249]
Validating Epoch 4: 100%|      | 24/24 [01:26<00:00,  3.61s/it,
val_loss=0.32]

Epoch [3/20], Train Loss: 0.2492, Val Loss: 0.3196, Val Accuracy: 86.31%, Val
AUROC: 0.7434, Partial AUROC: 0.0684
Epoch 5/20

Training Epoch 5: 100%|      | 33/33 [01:41<00:00,  3.07s/it,
train_loss=0.228]
Validating Epoch 5: 100%|      | 24/24 [01:27<00:00,  3.65s/it,
val_loss=0.259]

Epoch [4/20], Train Loss: 0.2279, Val Loss: 0.2589, Val Accuracy: 91.21%, Val
AUROC: 0.8385, Partial AUROC: 0.0922
Epoch 6/20

Training Epoch 6: 100%|      | 33/33 [01:44<00:00,  3.15s/it,
train_loss=0.158]
```

```
Validating Epoch 6: 100%|     | 24/24 [01:33<00:00,  3.90s/it,
val_loss=0.366]

Epoch [5/20], Train Loss: 0.1581, Val Loss: 0.3662, Val Accuracy: 86.78%, Val
AUROC: 0.7717, Partial AUROC: 0.0584
Epoch 7/20

Training Epoch 7: 100%|     | 33/33 [01:47<00:00,  3.26s/it,
train_loss=0.17]
Validating Epoch 7: 100%|     | 24/24 [01:25<00:00,  3.57s/it,
val_loss=0.398]

Epoch [6/20], Train Loss: 0.1701, Val Loss: 0.3978, Val Accuracy: 77.92%, Val
AUROC: 0.7380, Partial AUROC: 0.0591
Epoch 8/20

Training Epoch 8: 100%|     | 33/33 [01:43<00:00,  3.15s/it,
train_loss=0.171]
Validating Epoch 8: 100%|     | 24/24 [01:23<00:00,  3.46s/it,
val_loss=0.368]

Epoch [7/20], Train Loss: 0.1706, Val Loss: 0.3679, Val Accuracy: 84.77%, Val
AUROC: 0.7922, Partial AUROC: 0.0746
Epoch 9/20

Training Epoch 9: 100%|     | 33/33 [01:44<00:00,  3.15s/it,
train_loss=0.116]
Validating Epoch 9: 100%|     | 24/24 [01:31<00:00,  3.83s/it,
val_loss=0.456]

Epoch [8/20], Train Loss: 0.1159, Val Loss: 0.4561, Val Accuracy: 80.00%, Val
AUROC: 0.8201, Partial AUROC: 0.0955
Epoch 10/20

Training Epoch 10: 100%|     | 33/33 [01:42<00:00,  3.12s/it,
train_loss=0.118]
Validating Epoch 10: 100%|     | 24/24 [01:23<00:00,  3.49s/it,
val_loss=0.258]

Epoch [9/20], Train Loss: 0.1177, Val Loss: 0.2578, Val Accuracy: 89.40%, Val
AUROC: 0.7430, Partial AUROC: 0.0672
Epoch 11/20

Training Epoch 11: 100%|     | 33/33 [01:52<00:00,  3.42s/it,
train_loss=0.108]
Validating Epoch 11: 100%|     | 24/24 [01:13<00:00,  3.08s/it,
val_loss=0.527]

Epoch [10/20], Train Loss: 0.1078, Val Loss: 0.5266, Val Accuracy: 73.29%, Val
AUROC: 0.7982, Partial AUROC: 0.0709
Epoch 12/20

Training Epoch 12: 100%|     | 33/33 [01:54<00:00,  3.48s/it,
train_loss=0.0786]
```

```
Validating Epoch 12: 100%|     | 24/24 [01:45<00:00,  4.39s/it,
val_loss=0.183]

Epoch [11/20], Train Loss: 0.0786, Val Loss: 0.1828, Val Accuracy: 93.02%, Val
AUROC: 0.8238, Partial AUROC: 0.0840
Epoch 13/20

Training Epoch 13: 100%|     | 33/33 [03:01<00:00,  5.49s/it,
train_loss=0.0714]
Validating Epoch 13: 100%|     | 24/24 [02:20<00:00,  5.87s/it,
val_loss=0.292]

Epoch [12/20], Train Loss: 0.0714, Val Loss: 0.2925, Val Accuracy: 90.54%, Val
AUROC: 0.7638, Partial AUROC: 0.0659
Epoch 14/20

Training Epoch 14: 100%|     | 33/33 [02:38<00:00,  4.81s/it,
train_loss=0.0764]
Validating Epoch 14: 100%|     | 24/24 [02:03<00:00,  5.15s/it,
val_loss=0.233]

Epoch [13/20], Train Loss: 0.0764, Val Loss: 0.2325, Val Accuracy: 91.74%, Val
AUROC: 0.7967, Partial AUROC: 0.0725
Epoch 15/20

Training Epoch 15: 100%|     | 33/33 [02:26<00:00,  4.45s/it,
train_loss=0.0652]
Validating Epoch 15: 100%|     | 24/24 [02:00<00:00,  5.01s/it,
val_loss=0.378]

Epoch [14/20], Train Loss: 0.0652, Val Loss: 0.3783, Val Accuracy: 84.63%, Val
AUROC: 0.7758, Partial AUROC: 0.0631
Epoch 16/20

Training Epoch 16: 100%|     | 33/33 [02:29<00:00,  4.53s/it,
train_loss=0.0704]
Validating Epoch 16: 100%|     | 24/24 [02:06<00:00,  5.27s/it,
val_loss=0.18]

Epoch [15/20], Train Loss: 0.0704, Val Loss: 0.1804, Val Accuracy: 93.56%, Val
AUROC: 0.8074, Partial AUROC: 0.0833
Epoch 17/20

Training Epoch 17: 100%|     | 33/33 [02:20<00:00,  4.27s/it,
train_loss=0.0362]
Validating Epoch 17: 100%|     | 24/24 [01:55<00:00,  4.80s/it,
val_loss=0.242]

Epoch [16/20], Train Loss: 0.0362, Val Loss: 0.2416, Val Accuracy: 93.22%, Val
AUROC: 0.7827, Partial AUROC: 0.0742
Epoch 18/20

Training Epoch 18: 100%|     | 33/33 [02:22<00:00,  4.33s/it,
train_loss=0.0648]
```

```
Validating Epoch 18: 100%|      | 24/24 [02:14<00:00,  5.61s/it,
val_loss=0.246]

Epoch [17/20], Train Loss: 0.0648, Val Loss: 0.2462, Val Accuracy: 93.15%, Val
AUROC: 0.7440, Partial AUROC: 0.0623
Epoch 19/20

Training Epoch 19: 100%|      | 33/33 [02:14<00:00,  4.09s/it,
train_loss=0.0355]
Validating Epoch 19: 100%|      | 24/24 [01:29<00:00,  3.73s/it,
val_loss=0.416]

Epoch [18/20], Train Loss: 0.0355, Val Loss: 0.4160, Val Accuracy: 82.82%, Val
AUROC: 0.7396, Partial AUROC: 0.0643
Epoch 20/20

Training Epoch 20: 100%|      | 33/33 [02:31<00:00,  4.60s/it,
train_loss=0.0653]
Validating Epoch 20: 100%|      | 24/24 [02:36<00:00,  6.51s/it,
val_loss=0.229]

Epoch [19/20], Train Loss: 0.0653, Val Loss: 0.2292, Val Accuracy: 92.48%, Val
AUROC: 0.7764, Partial AUROC: 0.0750
Best Epoch: 16, Best Validation Loss: 0.1804
Training Complete
```




```
Classification Report:
              precision    recall  f1-score   support

     Class 0       0.98      0.95      0.96      1431
     Class 1       0.24      0.42      0.31        59

    accuracy                           0.92      1490
   macro avg       0.61      0.68      0.63      1490
weighted avg       0.95      0.92      0.93      1490
```

[20]:
```
CustomImageFeatureResNet(
  (resnet): Sequential(
    (0): Conv2d(3, 64, kernel_size=(7, 7), stride=(2, 2), padding=(3, 3),
bias=False)
    (1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (2): ReLU(inplace=True)
    (3): MaxPool2d(kernel_size=3, stride=2, padding=1, dilation=1,
ceil_mode=False)
    (4): Sequential(
      (0): BasicBlock(
        (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), bias=False)
        (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
        (relu): ReLU(inplace=True)
```

```
        (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), bias=False)
        (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      )
      (1): BasicBlock(
        (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), bias=False)
        (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), bias=False)
        (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      )
    )
    (5): Sequential(
      (0): BasicBlock(
        (conv1): Conv2d(64, 128, kernel_size=(3, 3), stride=(2, 2), padding=(1,
1), bias=False)
        (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), bias=False)
        (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
        (downsample): Sequential(
          (0): Conv2d(64, 128, kernel_size=(1, 1), stride=(2, 2), bias=False)
          (1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
        )
      )
      (1): BasicBlock(
        (conv1): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), bias=False)
        (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), bias=False)
        (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      )
    )
    (6): Sequential(
```

```
      (0): BasicBlock(
        (conv1): Conv2d(128, 256, kernel_size=(3, 3), stride=(2, 2), padding=(1,
1), bias=False)
        (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), bias=False)
        (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
        (downsample): Sequential(
          (0): Conv2d(128, 256, kernel_size=(1, 1), stride=(2, 2), bias=False)
          (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
        )
      )
      (1): BasicBlock(
        (conv1): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), bias=False)
        (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), bias=False)
        (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      )
    )
    (7): Sequential(
      (0): BasicBlock(
        (conv1): Conv2d(256, 512, kernel_size=(3, 3), stride=(2, 2), padding=(1,
1), bias=False)
        (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), bias=False)
        (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
        (downsample): Sequential(
          (0): Conv2d(256, 512, kernel_size=(1, 1), stride=(2, 2), bias=False)
          (1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
        )
      )
      (1): BasicBlock(
        (conv1): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1,
```

```
1), bias=False)
        (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), bias=False)
        (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      )
    )
    (8): AdaptiveAvgPool2d(output_size=(1, 1))
  )
  (fc_image): Linear(in_features=512, out_features=512, bias=True)
  (fc_metadata): Linear(in_features=9, out_features=128, bias=True)
  (dropout): Dropout(p=0.5, inplace=False)
  (fc_combined): Linear(in_features=640, out_features=1, bias=True)
)
```

0.9 Model 5

[21]:
```python
model5 = CustomImageFeatureResNet(feature_input_size=9)  # Assuming 9 features␣
 ↪for metadata
model5.to(device)
# Initialize optimizer
optimizer = optim.SGD(model5.parameters(), lr=0.001)
# Define the loss function with the class weights
criterion = nn.BCELoss()  # Binary classification loss
# Set the number of epochs
epochs = 20
best_model_path = "best_model5.pth"
```

```
/home/jupyter-sohka/.local/lib/python3.10/site-
packages/torchvision/models/_utils.py:208: UserWarning: The parameter
'pretrained' is deprecated since 0.13 and may be removed in the future, please
use 'weights' instead.
  warnings.warn(
/home/jupyter-sohka/.local/lib/python3.10/site-
packages/torchvision/models/_utils.py:223: UserWarning: Arguments other than a
weight enum or `None` for 'weights' are deprecated since 0.13 and may be removed
in the future. The current behavior is equivalent to passing
`weights=ResNet18_Weights.IMAGENET1K_V1`. You can also use
`weights=ResNet18_Weights.DEFAULT` to get the most up-to-date weights.
  warnings.warn(msg)
```

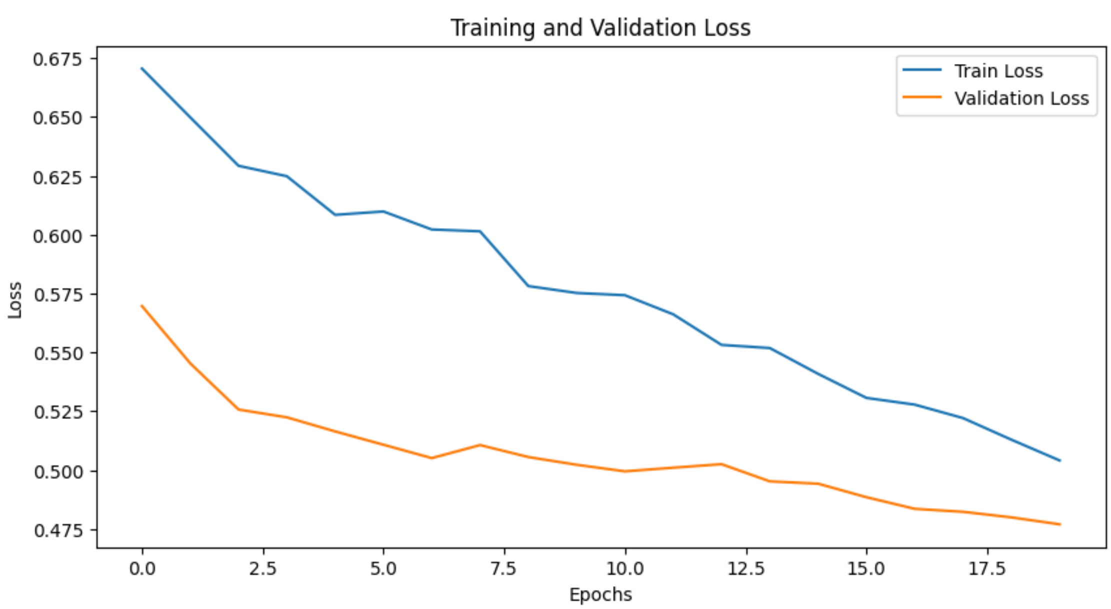
[22]:
```python
train_and_validate(model5,resnet_train_dataloader, resnet_val_dataloader,␣
 ↪criterion, optimizer, epochs, device, best_model_path )
```

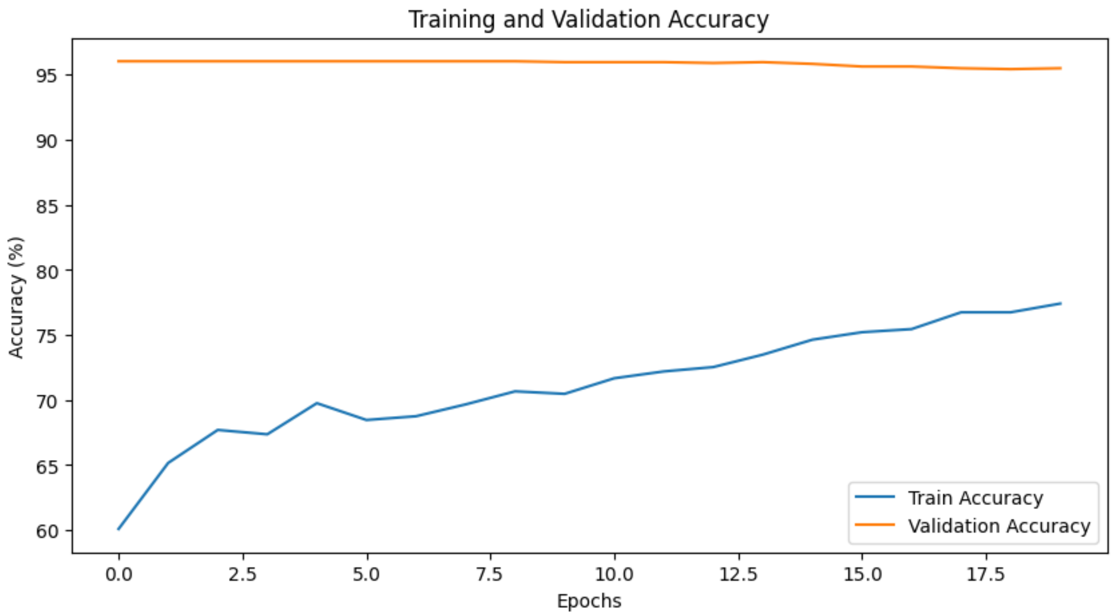
```
Epoch 1/20

Training Epoch 1: 100%|     | 33/33 [02:46<00:00,  5.05s/it,
train_loss=0.671]
Validating Epoch 1: 100%|     | 24/24 [01:58<00:00,  4.95s/it,
val_loss=0.57]

Epoch [0/20], Train Loss: 0.6705, Val Loss: 0.5696, Val Accuracy: 96.04%, Val
AUROC: 0.5256, Partial AUROC: 0.0269
Epoch 2/20

Training Epoch 2: 100%|     | 33/33 [03:04<00:00,  5.59s/it,
train_loss=0.65]
Validating Epoch 2: 100%|     | 24/24 [02:28<00:00,  6.17s/it,
val_loss=0.545]

Epoch [1/20], Train Loss: 0.6498, Val Loss: 0.5453, Val Accuracy: 96.04%, Val
AUROC: 0.5536, Partial AUROC: 0.0261
Epoch 3/20

Training Epoch 3: 100%|     | 33/33 [02:30<00:00,  4.55s/it,
train_loss=0.629]
Validating Epoch 3: 100%|     | 24/24 [01:56<00:00,  4.85s/it,
val_loss=0.526]

Epoch [2/20], Train Loss: 0.6292, Val Loss: 0.5257, Val Accuracy: 96.04%, Val
AUROC: 0.5678, Partial AUROC: 0.0274
Epoch 4/20

Training Epoch 4: 100%|     | 33/33 [02:06<00:00,  3.85s/it,
train_loss=0.625]
Validating Epoch 4: 100%|     | 24/24 [01:27<00:00,  3.65s/it,
val_loss=0.522]

Epoch [3/20], Train Loss: 0.6248, Val Loss: 0.5224, Val Accuracy: 96.04%, Val
AUROC: 0.5870, Partial AUROC: 0.0279
Epoch 5/20

Training Epoch 5: 100%|     | 33/33 [01:43<00:00,  3.13s/it,
train_loss=0.608]
Validating Epoch 5: 100%|     | 24/24 [01:28<00:00,  3.68s/it,
val_loss=0.516]

Epoch [4/20], Train Loss: 0.6084, Val Loss: 0.5164, Val Accuracy: 96.04%, Val
AUROC: 0.6024, Partial AUROC: 0.0290
Epoch 6/20

Training Epoch 6: 100%|     | 33/33 [01:48<00:00,  3.28s/it,
train_loss=0.61]
Validating Epoch 6: 100%|     | 24/24 [01:31<00:00,  3.79s/it,
val_loss=0.511]

Epoch [5/20], Train Loss: 0.6098, Val Loss: 0.5107, Val Accuracy: 96.04%, Val
AUROC: 0.6146, Partial AUROC: 0.0297
```

```
Epoch 7/20

Training Epoch 7: 100%|     | 33/33 [01:38<00:00,  2.99s/it,
train_loss=0.602]
Validating Epoch 7: 100%|     | 24/24 [01:26<00:00,  3.58s/it,
val_loss=0.505]

Epoch [6/20], Train Loss: 0.6022, Val Loss: 0.5051, Val Accuracy: 96.04%, Val
AUROC: 0.6275, Partial AUROC: 0.0301
Epoch 8/20

Training Epoch 8: 100%|     | 33/33 [01:37<00:00,  2.94s/it,
train_loss=0.601]
Validating Epoch 8: 100%|     | 24/24 [01:27<00:00,  3.64s/it,
val_loss=0.511]

Epoch [7/20], Train Loss: 0.6014, Val Loss: 0.5106, Val Accuracy: 96.04%, Val
AUROC: 0.6324, Partial AUROC: 0.0306
Epoch 9/20

Training Epoch 9: 100%|     | 33/33 [01:42<00:00,  3.11s/it,
train_loss=0.578]
Validating Epoch 9: 100%|     | 24/24 [01:26<00:00,  3.60s/it,
val_loss=0.506]

Epoch [8/20], Train Loss: 0.5781, Val Loss: 0.5055, Val Accuracy: 96.04%, Val
AUROC: 0.6483, Partial AUROC: 0.0316
Epoch 10/20

Training Epoch 10: 100%|     | 33/33 [01:36<00:00,  2.93s/it,
train_loss=0.575]
Validating Epoch 10: 100%|     | 24/24 [01:20<00:00,  3.36s/it,
val_loss=0.502]

Epoch [9/20], Train Loss: 0.5752, Val Loss: 0.5022, Val Accuracy: 95.97%, Val
AUROC: 0.6594, Partial AUROC: 0.0322
Epoch 11/20

Training Epoch 11: 100%|     | 33/33 [01:37<00:00,  2.96s/it,
train_loss=0.574]
Validating Epoch 11: 100%|     | 24/24 [01:27<00:00,  3.64s/it,
val_loss=0.499]

Epoch [10/20], Train Loss: 0.5743, Val Loss: 0.4994, Val Accuracy: 95.97%, Val
AUROC: 0.6636, Partial AUROC: 0.0331
Epoch 12/20

Training Epoch 12: 100%|     | 33/33 [01:39<00:00,  3.00s/it,
train_loss=0.566]
Validating Epoch 12: 100%|     | 24/24 [01:31<00:00,  3.82s/it,
val_loss=0.501]

Epoch [11/20], Train Loss: 0.5661, Val Loss: 0.5010, Val Accuracy: 95.97%, Val
AUROC: 0.6720, Partial AUROC: 0.0331
```

```
Epoch 13/20

Training Epoch 13: 100%|     | 33/33 [01:36<00:00,  2.91s/it,
train_loss=0.553]
Validating Epoch 13: 100%|     | 24/24 [01:20<00:00,  3.34s/it,
val_loss=0.502]

Epoch [12/20], Train Loss: 0.5532, Val Loss: 0.5025, Val Accuracy: 95.91%, Val
AUROC: 0.6800, Partial AUROC: 0.0363
Epoch 14/20

Training Epoch 14: 100%|     | 33/33 [01:34<00:00,  2.87s/it,
train_loss=0.552]
Validating Epoch 14: 100%|     | 24/24 [01:24<00:00,  3.51s/it,
val_loss=0.495]

Epoch [13/20], Train Loss: 0.5518, Val Loss: 0.4952, Val Accuracy: 95.97%, Val
AUROC: 0.6843, Partial AUROC: 0.0357
Epoch 15/20

Training Epoch 15: 100%|     | 33/33 [01:36<00:00,  2.92s/it,
train_loss=0.541]
Validating Epoch 15: 100%|     | 24/24 [01:31<00:00,  3.82s/it,
val_loss=0.494]

Epoch [14/20], Train Loss: 0.5409, Val Loss: 0.4942, Val Accuracy: 95.84%, Val
AUROC: 0.6906, Partial AUROC: 0.0363
Epoch 16/20

Training Epoch 16: 100%|     | 33/33 [01:36<00:00,  2.93s/it,
train_loss=0.531]
Validating Epoch 16: 100%|     | 24/24 [01:26<00:00,  3.62s/it,
val_loss=0.488]

Epoch [15/20], Train Loss: 0.5306, Val Loss: 0.4885, Val Accuracy: 95.64%, Val
AUROC: 0.6979, Partial AUROC: 0.0383
Epoch 17/20

Training Epoch 17: 100%|     | 33/33 [01:42<00:00,  3.10s/it,
train_loss=0.528]
Validating Epoch 17: 100%|     | 24/24 [01:19<00:00,  3.30s/it,
val_loss=0.484]

Epoch [16/20], Train Loss: 0.5278, Val Loss: 0.4835, Val Accuracy: 95.64%, Val
AUROC: 0.7056, Partial AUROC: 0.0387
Epoch 18/20

Training Epoch 18: 100%|     | 33/33 [01:43<00:00,  3.14s/it,
train_loss=0.522]
Validating Epoch 18: 100%|     | 24/24 [01:26<00:00,  3.62s/it,
val_loss=0.482]

Epoch [17/20], Train Loss: 0.5221, Val Loss: 0.4823, Val Accuracy: 95.50%, Val
AUROC: 0.7090, Partial AUROC: 0.0380
```

```
Epoch 19/20

Training Epoch 19: 100%|      | 33/33 [02:06<00:00,  3.84s/it,
train_loss=0.513]
Validating Epoch 19: 100%|      | 24/24 [02:38<00:00,  6.59s/it,
val_loss=0.48]

Epoch [18/20], Train Loss: 0.5129, Val Loss: 0.4799, Val Accuracy: 95.44%, Val
AUROC: 0.7179, Partial AUROC: 0.0388
Epoch 20/20

Training Epoch 20: 100%|      | 33/33 [04:20<00:00,  7.89s/it,
train_loss=0.504]
Validating Epoch 20: 100%|      | 24/24 [03:41<00:00,  9.23s/it,
val_loss=0.477]

Epoch [19/20], Train Loss: 0.5041, Val Loss: 0.4769, Val Accuracy: 95.50%, Val
AUROC: 0.7221, Partial AUROC: 0.0398
Best Epoch: 20, Best Validation Loss: 0.4769
Training Complete
```






```
Classification Report:
              precision    recall  f1-score   support

     Class 0       0.96      0.99      0.98      1431
     Class 1       0.30      0.10      0.15        59

    accuracy                           0.96      1490
   macro avg       0.63      0.55      0.56      1490
weighted avg       0.94      0.96      0.94      1490
```

[22]:
```
CustomImageFeatureResNet(
  (resnet): Sequential(
    (0): Conv2d(3, 64, kernel_size=(7, 7), stride=(2, 2), padding=(3, 3),
bias=False)
    (1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (2): ReLU(inplace=True)
    (3): MaxPool2d(kernel_size=3, stride=2, padding=1, dilation=1,
ceil_mode=False)
    (4): Sequential(
      (0): BasicBlock(
        (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), bias=False)
        (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
        (relu): ReLU(inplace=True)
```

```
        (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), bias=False)
        (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      )
      (1): BasicBlock(
        (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), bias=False)
        (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), bias=False)
        (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      )
    )
    (5): Sequential(
      (0): BasicBlock(
        (conv1): Conv2d(64, 128, kernel_size=(3, 3), stride=(2, 2), padding=(1,
1), bias=False)
        (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), bias=False)
        (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
        (downsample): Sequential(
          (0): Conv2d(64, 128, kernel_size=(1, 1), stride=(2, 2), bias=False)
          (1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
        )
      )
      (1): BasicBlock(
        (conv1): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), bias=False)
        (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), bias=False)
        (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      )
    )
    (6): Sequential(
```

```
      (0): BasicBlock(
        (conv1): Conv2d(128, 256, kernel_size=(3, 3), stride=(2, 2), padding=(1,
1), bias=False)
        (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), bias=False)
        (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
        (downsample): Sequential(
          (0): Conv2d(128, 256, kernel_size=(1, 1), stride=(2, 2), bias=False)
          (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
        )
      )
      (1): BasicBlock(
        (conv1): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), bias=False)
        (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), bias=False)
        (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      )
    )
    (7): Sequential(
      (0): BasicBlock(
        (conv1): Conv2d(256, 512, kernel_size=(3, 3), stride=(2, 2), padding=(1,
1), bias=False)
        (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), bias=False)
        (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
        (downsample): Sequential(
          (0): Conv2d(256, 512, kernel_size=(1, 1), stride=(2, 2), bias=False)
          (1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
        )
      )
      (1): BasicBlock(
        (conv1): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1,
```

```
1), bias=False)
        (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), bias=False)
        (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      )
    )
    (8): AdaptiveAvgPool2d(output_size=(1, 1))
  )
  (fc_image): Linear(in_features=512, out_features=512, bias=True)
  (fc_metadata): Linear(in_features=9, out_features=128, bias=True)
  (dropout): Dropout(p=0.5, inplace=False)
  (fc_combined): Linear(in_features=640, out_features=1, bias=True)
)
```

0.10 Model 6

[23]:
```
model6 = CustomImageFeatureResNet(feature_input_size=9)  # Assuming 9 features␣
↪for metadata
model6.to(device)
# Initialize optimizer
optimizer = optim.SGD(model6.parameters(), lr=0.0001,weight_decay=1e-4)
# Define the loss function with the class weights
criterion = nn.BCELoss()  # Binary classification loss
# Set the number of epochs
epochs = 20
batch_size = 32
best_model_path = "best_model6.pth"
```

```
/home/jupyter-sohka/.local/lib/python3.10/site-
packages/torchvision/models/_utils.py:208: UserWarning: The parameter
'pretrained' is deprecated since 0.13 and may be removed in the future, please
use 'weights' instead.
  warnings.warn(
/home/jupyter-sohka/.local/lib/python3.10/site-
packages/torchvision/models/_utils.py:223: UserWarning: Arguments other than a
weight enum or `None` for 'weights' are deprecated since 0.13 and may be removed
in the future. The current behavior is equivalent to passing
`weights=ResNet18_Weights.IMAGENET1K_V1`. You can also use
`weights=ResNet18_Weights.DEFAULT` to get the most up-to-date weights.
  warnings.warn(msg)
```

[24]:
```
resnet_train_dataloader = DataLoader(resnet_train_dataset,␣
↪batch_size=batch_size, shuffle=True)
```

```
resnet_val_dataloader = DataLoader(resnet_val_dataset, batch_size=batch_size,␣
 ↪shuffle=True)
```

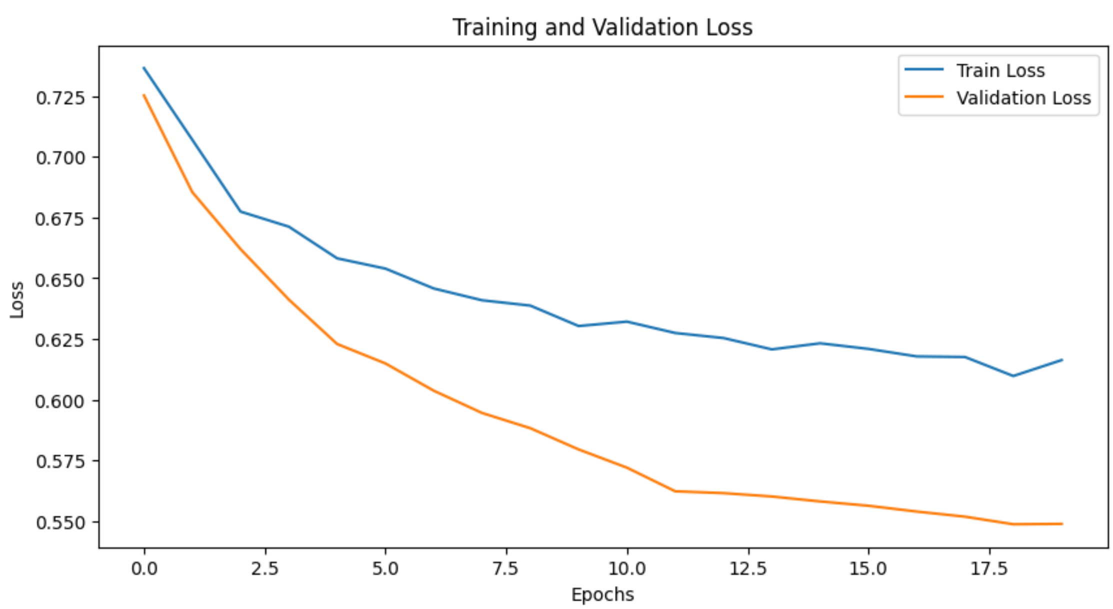
[25]:
```
train_and_validate(model6,resnet_train_dataloader, resnet_val_dataloader,␣
 ↪criterion, optimizer, epochs, device, best_model_path )
```

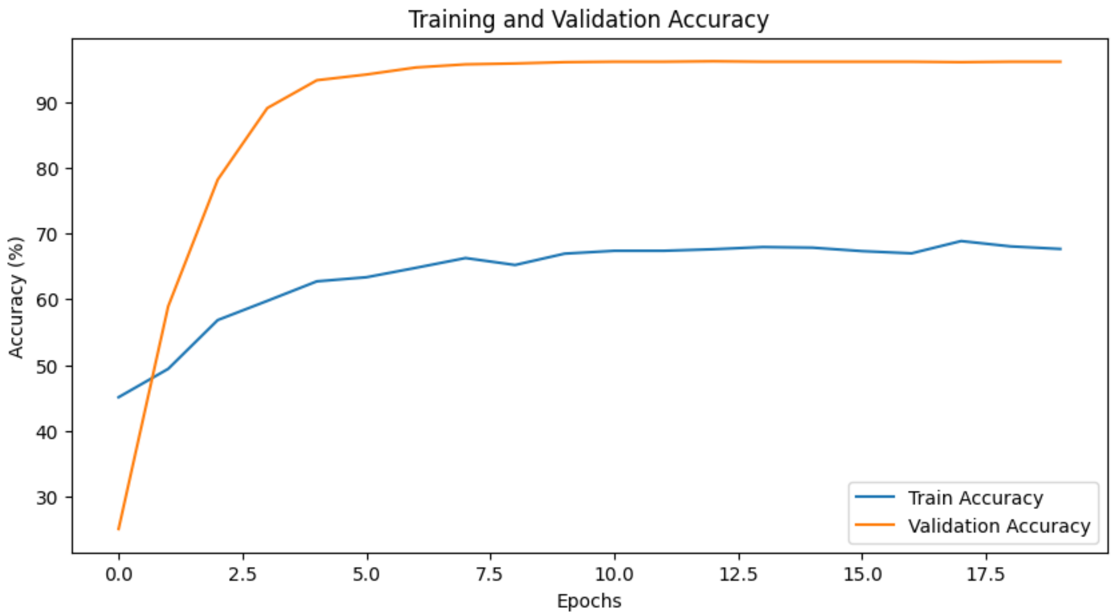
```
Epoch 1/20

Training Epoch 1: 100%|     | 66/66 [04:24<00:00,  4.01s/it,
train_loss=0.736]
Validating Epoch 1: 100%|     | 47/47 [03:12<00:00,  4.10s/it,
val_loss=0.725]

Epoch [0/20], Train Loss: 0.7365, Val Loss: 0.7252, Val Accuracy: 25.10%, Val
AUROC: 0.5898, Partial AUROC: 0.0350
Epoch 2/20

Training Epoch 2: 100%|     | 66/66 [03:58<00:00,  3.61s/it,
train_loss=0.707]
Validating Epoch 2: 100%|     | 47/47 [01:51<00:00,  2.37s/it,
val_loss=0.685]

Epoch [1/20], Train Loss: 0.7070, Val Loss: 0.6855, Val Accuracy: 58.93%, Val
AUROC: 0.5779, Partial AUROC: 0.0277
Epoch 3/20

Training Epoch 3: 100%|     | 66/66 [02:02<00:00,  1.86s/it,
train_loss=0.677]
Validating Epoch 3: 100%|     | 47/47 [01:38<00:00,  2.09s/it,
val_loss=0.662]

Epoch [2/20], Train Loss: 0.6774, Val Loss: 0.6620, Val Accuracy: 78.19%, Val
AUROC: 0.5870, Partial AUROC: 0.0325
Epoch 4/20

Training Epoch 4: 100%|     | 66/66 [03:15<00:00,  2.96s/it,
train_loss=0.671]
Validating Epoch 4: 100%|     | 47/47 [02:23<00:00,  3.05s/it,
val_loss=0.641]

Epoch [3/20], Train Loss: 0.6712, Val Loss: 0.6412, Val Accuracy: 89.06%, Val
AUROC: 0.5699, Partial AUROC: 0.0250
Epoch 5/20

Training Epoch 5: 100%|     | 66/66 [02:03<00:00,  1.87s/it,
train_loss=0.658]
Validating Epoch 5: 100%|     | 47/47 [02:26<00:00,  3.11s/it,
val_loss=0.623]

Epoch [4/20], Train Loss: 0.6582, Val Loss: 0.6230, Val Accuracy: 93.29%, Val
AUROC: 0.5709, Partial AUROC: 0.0260
Epoch 6/20
```

```
Training Epoch 6: 100%|     | 66/66 [01:52<00:00,  1.70s/it,
train_loss=0.654]
Validating Epoch 6: 100%|     | 47/47 [01:51<00:00,  2.37s/it,
val_loss=0.615]

Epoch [5/20], Train Loss: 0.6540, Val Loss: 0.6150, Val Accuracy: 94.16%, Val
AUROC: 0.5798, Partial AUROC: 0.0272
Epoch 7/20

Training Epoch 7: 100%|     | 66/66 [03:23<00:00,  3.08s/it,
train_loss=0.646]
Validating Epoch 7: 100%|     | 47/47 [02:47<00:00,  3.56s/it,
val_loss=0.604]

Epoch [6/20], Train Loss: 0.6458, Val Loss: 0.6037, Val Accuracy: 95.23%, Val
AUROC: 0.5714, Partial AUROC: 0.0252
Epoch 8/20

Training Epoch 8: 100%|     | 66/66 [03:55<00:00,  3.57s/it,
train_loss=0.641]
Validating Epoch 8: 100%|     | 47/47 [02:46<00:00,  3.54s/it,
val_loss=0.595]

Epoch [7/20], Train Loss: 0.6410, Val Loss: 0.5946, Val Accuracy: 95.70%, Val
AUROC: 0.5800, Partial AUROC: 0.0254
Epoch 9/20

Training Epoch 9: 100%|     | 66/66 [03:54<00:00,  3.56s/it,
train_loss=0.639]
Validating Epoch 9: 100%|     | 47/47 [02:10<00:00,  2.77s/it,
val_loss=0.588]

Epoch [8/20], Train Loss: 0.6388, Val Loss: 0.5883, Val Accuracy: 95.84%, Val
AUROC: 0.5818, Partial AUROC: 0.0252
Epoch 10/20

Training Epoch 10: 100%|     | 66/66 [01:42<00:00,  1.56s/it,
train_loss=0.63]
Validating Epoch 10: 100%|     | 47/47 [01:23<00:00,  1.79s/it,
val_loss=0.58]

Epoch [9/20], Train Loss: 0.6303, Val Loss: 0.5796, Val Accuracy: 96.04%, Val
AUROC: 0.5932, Partial AUROC: 0.0282
Epoch 11/20

Training Epoch 11: 100%|     | 66/66 [02:21<00:00,  2.15s/it,
train_loss=0.632]
Validating Epoch 11: 100%|     | 47/47 [02:06<00:00,  2.70s/it,
val_loss=0.572]

Epoch [10/20], Train Loss: 0.6322, Val Loss: 0.5721, Val Accuracy: 96.11%, Val
AUROC: 0.5961, Partial AUROC: 0.0276
Epoch 12/20
```

```
Training Epoch 12: 100%|     | 66/66 [02:24<00:00,  2.18s/it,
train_loss=0.627]
Validating Epoch 12: 100%|     | 47/47 [01:39<00:00,  2.12s/it,
val_loss=0.562]

Epoch [11/20], Train Loss: 0.6275, Val Loss: 0.5623, Val Accuracy: 96.11%, Val
AUROC: 0.5920, Partial AUROC: 0.0263
Epoch 13/20

Training Epoch 13: 100%|     | 66/66 [02:33<00:00,  2.32s/it,
train_loss=0.625]
Validating Epoch 13: 100%|     | 47/47 [02:05<00:00,  2.66s/it,
val_loss=0.562]

Epoch [12/20], Train Loss: 0.6254, Val Loss: 0.5616, Val Accuracy: 96.17%, Val
AUROC: 0.6024, Partial AUROC: 0.0301
Epoch 14/20

Training Epoch 14: 100%|     | 66/66 [02:30<00:00,  2.28s/it,
train_loss=0.621]
Validating Epoch 14: 100%|     | 47/47 [02:00<00:00,  2.57s/it,
val_loss=0.56]

Epoch [13/20], Train Loss: 0.6207, Val Loss: 0.5602, Val Accuracy: 96.11%, Val
AUROC: 0.6045, Partial AUROC: 0.0297
Epoch 15/20

Training Epoch 15: 100%|     | 66/66 [01:46<00:00,  1.61s/it,
train_loss=0.623]
Validating Epoch 15: 100%|     | 47/47 [01:25<00:00,  1.82s/it,
val_loss=0.558]

Epoch [14/20], Train Loss: 0.6232, Val Loss: 0.5582, Val Accuracy: 96.11%, Val
AUROC: 0.6009, Partial AUROC: 0.0285
Epoch 16/20

Training Epoch 16: 100%|     | 66/66 [01:38<00:00,  1.49s/it,
train_loss=0.621]
Validating Epoch 16: 100%|     | 47/47 [01:22<00:00,  1.76s/it,
val_loss=0.556]

Epoch [15/20], Train Loss: 0.6209, Val Loss: 0.5564, Val Accuracy: 96.11%, Val
AUROC: 0.6137, Partial AUROC: 0.0289
Epoch 17/20

Training Epoch 17: 100%|     | 66/66 [01:48<00:00,  1.64s/it,
train_loss=0.618]
Validating Epoch 17: 100%|     | 47/47 [01:18<00:00,  1.67s/it,
val_loss=0.554]

Epoch [16/20], Train Loss: 0.6179, Val Loss: 0.5540, Val Accuracy: 96.11%, Val
AUROC: 0.6156, Partial AUROC: 0.0277
Epoch 18/20
```

```
Training Epoch 18: 100%|     | 66/66 [01:44<00:00,  1.59s/it,
train_loss=0.618]
Validating Epoch 18: 100%|     | 47/47 [01:22<00:00,  1.76s/it,
val_loss=0.552]

Epoch [17/20], Train Loss: 0.6176, Val Loss: 0.5519, Val Accuracy: 96.04%, Val
AUROC: 0.6092, Partial AUROC: 0.0260
Epoch 19/20

Training Epoch 19: 100%|     | 66/66 [01:44<00:00,  1.59s/it,
train_loss=0.61]
Validating Epoch 19: 100%|     | 47/47 [01:19<00:00,  1.70s/it,
val_loss=0.549]

Epoch [18/20], Train Loss: 0.6098, Val Loss: 0.5488, Val Accuracy: 96.11%, Val
AUROC: 0.6211, Partial AUROC: 0.0298
Epoch 20/20

Training Epoch 20: 100%|     | 66/66 [01:59<00:00,  1.82s/it,
train_loss=0.616]
Validating Epoch 20: 100%|     | 47/47 [01:23<00:00,  1.78s/it,
val_loss=0.549]

Epoch [19/20], Train Loss: 0.6163, Val Loss: 0.5489, Val Accuracy: 96.11%, Val
AUROC: 0.6246, Partial AUROC: 0.0306
Best Epoch: 19, Best Validation Loss: 0.5488
Training Complete
```






```
Classification Report:
              precision    recall  f1-score   support

     Class 0       0.96      1.00      0.98      1431
     Class 1       1.00      0.02      0.03        59

    accuracy                           0.96      1490
   macro avg       0.98      0.51      0.51      1490
weighted avg       0.96      0.96      0.94      1490
```

[25]:
```
CustomImageFeatureResNet(
  (resnet): Sequential(
    (0): Conv2d(3, 64, kernel_size=(7, 7), stride=(2, 2), padding=(3, 3),
bias=False)
    (1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (2): ReLU(inplace=True)
    (3): MaxPool2d(kernel_size=3, stride=2, padding=1, dilation=1,
ceil_mode=False)
    (4): Sequential(
      (0): BasicBlock(
        (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), bias=False)
        (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
        (relu): ReLU(inplace=True)
```

```
        (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), bias=False)
        (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      )
      (1): BasicBlock(
        (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), bias=False)
        (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), bias=False)
        (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      )
    )
    (5): Sequential(
      (0): BasicBlock(
        (conv1): Conv2d(64, 128, kernel_size=(3, 3), stride=(2, 2), padding=(1,
1), bias=False)
        (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), bias=False)
        (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
        (downsample): Sequential(
          (0): Conv2d(64, 128, kernel_size=(1, 1), stride=(2, 2), bias=False)
          (1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
        )
      )
      (1): BasicBlock(
        (conv1): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), bias=False)
        (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), bias=False)
        (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      )
    )
    (6): Sequential(
```

```
      (0): BasicBlock(
        (conv1): Conv2d(128, 256, kernel_size=(3, 3), stride=(2, 2), padding=(1,
1), bias=False)
        (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), bias=False)
        (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
        (downsample): Sequential(
          (0): Conv2d(128, 256, kernel_size=(1, 1), stride=(2, 2), bias=False)
          (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
        )
      )
      (1): BasicBlock(
        (conv1): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), bias=False)
        (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), bias=False)
        (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      )
    )
    (7): Sequential(
      (0): BasicBlock(
        (conv1): Conv2d(256, 512, kernel_size=(3, 3), stride=(2, 2), padding=(1,
1), bias=False)
        (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), bias=False)
        (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
        (downsample): Sequential(
          (0): Conv2d(256, 512, kernel_size=(1, 1), stride=(2, 2), bias=False)
          (1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
        )
      )
      (1): BasicBlock(
        (conv1): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1,
```

```
1), bias=False)
        (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), bias=False)
        (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      )
    )
    (8): AdaptiveAvgPool2d(output_size=(1, 1))
  )
  (fc_image): Linear(in_features=512, out_features=512, bias=True)
  (fc_metadata): Linear(in_features=9, out_features=128, bias=True)
  (dropout): Dropout(p=0.5, inplace=False)
  (fc_combined): Linear(in_features=640, out_features=1, bias=True)
)
```

0.11 Model 7

[26]:
```python
model7 =  CustomImageFeatureEfficientNet(feature_input_size=9)  # Assuming 9␣
 ↪features for metadata
model7.to(device)
# Initialize optimizer
optimizer = optim.Adam(model7.parameters(), lr= 1.1621608010269284e-05)
# Define the loss function with the class weights
criterion = nn.BCELoss()  # Binary classification loss
# Set the number of epochs
epochs = 20
batch_size = 16
best_model_path = "best_model7.pth"
```

```
/home/jupyter-sohka/.local/lib/python3.10/site-
packages/torchvision/models/_utils.py:208: UserWarning: The parameter
'pretrained' is deprecated since 0.13 and may be removed in the future, please
use 'weights' instead.
  warnings.warn(
/home/jupyter-sohka/.local/lib/python3.10/site-
packages/torchvision/models/_utils.py:223: UserWarning: Arguments other than a
weight enum or `None` for 'weights' are deprecated since 0.13 and may be removed
in the future. The current behavior is equivalent to passing
`weights=EfficientNet_B0_Weights.IMAGENET1K_V1`. You can also use
`weights=EfficientNet_B0_Weights.DEFAULT` to get the most up-to-date weights.
  warnings.warn(msg)
```

[27]:
```python
effnet_train_dataloader = DataLoader(effnet_train_dataset, ␣
 ↪batch_size=batch_size, shuffle=True)
```

```
effnet_val_dataloader = DataLoader(effnet_val_dataset,  batch_size=batch_size,␣
↪shuffle=True)
```

[28]:
```
train_and_validate(model7,effnet_train_dataloader, effnet_val_dataloader,␣
↪criterion, optimizer, epochs, device, best_model_path )
```

```
Epoch 1/20

Training Epoch 1: 100%|      | 131/131 [01:47<00:00,  1.21it/s,
train_loss=0.665]
Validating Epoch 1: 100%|      | 94/94 [01:39<00:00,  1.06s/it,
val_loss=0.624]

Epoch [0/20], Train Loss: 0.6653, Val Loss: 0.6238, Val Accuracy: 85.03%, Val
AUROC: 0.5190, Partial AUROC: 0.0248
Epoch 2/20

Training Epoch 2: 100%|      | 131/131 [01:46<00:00,  1.23it/s,
train_loss=0.608]
Validating Epoch 2: 100%|      | 94/94 [01:15<00:00,  1.25it/s,
val_loss=0.561]

Epoch [1/20], Train Loss: 0.6077, Val Loss: 0.5613, Val Accuracy: 91.28%, Val
AUROC: 0.6415, Partial AUROC: 0.0523
Epoch 3/20

Training Epoch 3: 100%|      | 131/131 [02:12<00:00,  1.01s/it,
train_loss=0.545]
Validating Epoch 3: 100%|      | 94/94 [01:15<00:00,  1.24it/s,
val_loss=0.526]

Epoch [2/20], Train Loss: 0.5450, Val Loss: 0.5263, Val Accuracy: 89.33%, Val
AUROC: 0.7150, Partial AUROC: 0.0620
Epoch 4/20

Training Epoch 4: 100%|      | 131/131 [01:50<00:00,  1.19it/s,
train_loss=0.496]
Validating Epoch 4: 100%|      | 94/94 [01:14<00:00,  1.27it/s,
val_loss=0.448]

Epoch [3/20], Train Loss: 0.4959, Val Loss: 0.4483, Val Accuracy: 90.40%, Val
AUROC: 0.7604, Partial AUROC: 0.0666
Epoch 5/20

Training Epoch 5: 100%|      | 131/131 [01:44<00:00,  1.26it/s,
train_loss=0.447]
Validating Epoch 5: 100%|      | 94/94 [01:13<00:00,  1.28it/s,
val_loss=0.414]

Epoch [4/20], Train Loss: 0.4469, Val Loss: 0.4141, Val Accuracy: 89.26%, Val
AUROC: 0.7891, Partial AUROC: 0.0740
Epoch 6/20
```

```
Training Epoch 6: 100%|     | 131/131 [01:46<00:00,  1.23it/s,
train_loss=0.413]
Validating Epoch 6: 100%|     | 94/94 [01:17<00:00,  1.21it/s,
val_loss=0.44]

Epoch [5/20], Train Loss: 0.4128, Val Loss: 0.4404, Val Accuracy: 84.70%, Val
AUROC: 0.8196, Partial AUROC: 0.0824
Epoch 7/20

Training Epoch 7: 100%|     | 131/131 [01:45<00:00,  1.24it/s,
train_loss=0.373]
Validating Epoch 7: 100%|     | 94/94 [00:52<00:00,  1.79it/s,
val_loss=0.412]

Epoch [6/20], Train Loss: 0.3726, Val Loss: 0.4124, Val Accuracy: 85.84%, Val
AUROC: 0.8262, Partial AUROC: 0.0850
Epoch 8/20

Training Epoch 8: 100%|     | 131/131 [01:43<00:00,  1.27it/s,
train_loss=0.365]
Validating Epoch 8: 100%|     | 94/94 [01:13<00:00,  1.27it/s,
val_loss=0.368]

Epoch [7/20], Train Loss: 0.3649, Val Loss: 0.3682, Val Accuracy: 87.38%, Val
AUROC: 0.8312, Partial AUROC: 0.0893
Epoch 9/20

Training Epoch 9: 100%|     | 131/131 [01:40<00:00,  1.30it/s,
train_loss=0.334]
Validating Epoch 9: 100%|     | 94/94 [01:14<00:00,  1.25it/s,
val_loss=0.342]

Epoch [8/20], Train Loss: 0.3337, Val Loss: 0.3420, Val Accuracy: 87.65%, Val
AUROC: 0.8349, Partial AUROC: 0.0849
Epoch 10/20

Training Epoch 10: 100%|     | 131/131 [01:47<00:00,  1.22it/s,
train_loss=0.307]
Validating Epoch 10: 100%|     | 94/94 [01:04<00:00,  1.47it/s,
val_loss=0.356]

Epoch [9/20], Train Loss: 0.3074, Val Loss: 0.3557, Val Accuracy: 85.17%, Val
AUROC: 0.8424, Partial AUROC: 0.0945
Epoch 11/20

Training Epoch 11: 100%|     | 131/131 [01:42<00:00,  1.27it/s,
train_loss=0.312]
Validating Epoch 11: 100%|     | 94/94 [01:17<00:00,  1.21it/s,
val_loss=0.339]

Epoch [10/20], Train Loss: 0.3117, Val Loss: 0.3386, Val Accuracy: 86.38%, Val
AUROC: 0.8504, Partial AUROC: 0.0984
Epoch 12/20
```

```
Training Epoch 12: 100%|     | 131/131 [01:47<00:00,  1.22it/s,
train_loss=0.288]
Validating Epoch 12: 100%|     | 94/94 [01:00<00:00,  1.54it/s,
val_loss=0.348]
```

Epoch [11/20], Train Loss: 0.2876, Val Loss: 0.3480, Val Accuracy: 84.77%, Val AUROC: 0.8519, Partial AUROC: 0.1023
Epoch 13/20

```
Training Epoch 13: 100%|     | 131/131 [02:07<00:00,  1.03it/s,
train_loss=0.26]
Validating Epoch 13: 100%|     | 94/94 [01:12<00:00,  1.29it/s,
val_loss=0.312]
```

Epoch [12/20], Train Loss: 0.2600, Val Loss: 0.3124, Val Accuracy: 85.64%, Val AUROC: 0.8514, Partial AUROC: 0.0994
Epoch 14/20

```
Training Epoch 14: 100%|     | 131/131 [02:17<00:00,  1.05s/it,
train_loss=0.257]
Validating Epoch 14: 100%|     | 94/94 [00:53<00:00,  1.75it/s,
val_loss=0.283]
```

Epoch [13/20], Train Loss: 0.2573, Val Loss: 0.2826, Val Accuracy: 89.19%, Val AUROC: 0.8584, Partial AUROC: 0.1038
Epoch 15/20

```
Training Epoch 15: 100%|     | 131/131 [01:52<00:00,  1.17it/s,
train_loss=0.258]
Validating Epoch 15: 100%|     | 94/94 [01:06<00:00,  1.42it/s,
val_loss=0.274]
```

Epoch [14/20], Train Loss: 0.2578, Val Loss: 0.2743, Val Accuracy: 88.99%, Val AUROC: 0.8578, Partial AUROC: 0.1049
Epoch 16/20

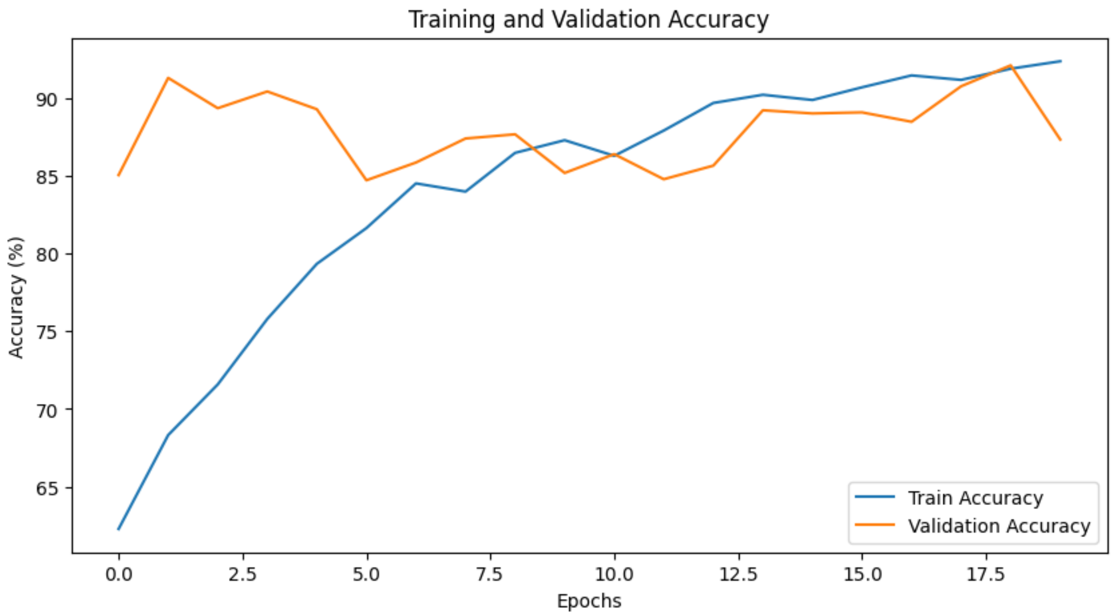
```
Training Epoch 16: 100%|     | 131/131 [01:47<00:00,  1.21it/s,
train_loss=0.241]
Validating Epoch 16: 100%|     | 94/94 [01:12<00:00,  1.29it/s,
val_loss=0.267]
```

Epoch [15/20], Train Loss: 0.2406, Val Loss: 0.2668, Val Accuracy: 89.06%, Val AUROC: 0.8513, Partial AUROC: 0.1010
Epoch 17/20

```
Training Epoch 17: 100%|     | 131/131 [01:45<00:00,  1.24it/s,
train_loss=0.229]
Validating Epoch 17: 100%|     | 94/94 [01:02<00:00,  1.51it/s,
val_loss=0.277]
```

Epoch [16/20], Train Loss: 0.2286, Val Loss: 0.2768, Val Accuracy: 88.46%, Val AUROC: 0.8439, Partial AUROC: 0.0954
Epoch 18/20

```
Training Epoch 18: 100%|      | 131/131 [01:46<00:00,  1.23it/s,
train_loss=0.231]
Validating Epoch 18: 100%|      | 94/94 [00:58<00:00,  1.61it/s,
val_loss=0.241]

Epoch [17/20], Train Loss: 0.2313, Val Loss: 0.2406, Val Accuracy: 90.74%, Val
AUROC: 0.8417, Partial AUROC: 0.0939
Epoch 19/20

Training Epoch 19: 100%|      | 131/131 [01:42<00:00,  1.28it/s,
train_loss=0.211]
Validating Epoch 19: 100%|      | 94/94 [01:04<00:00,  1.45it/s,
val_loss=0.217]

Epoch [18/20], Train Loss: 0.2109, Val Loss: 0.2166, Val Accuracy: 92.08%, Val
AUROC: 0.8535, Partial AUROC: 0.1034
Epoch 20/20

Training Epoch 20: 100%|      | 131/131 [01:47<00:00,  1.22it/s,
train_loss=0.204]
Validating Epoch 20: 100%|      | 94/94 [00:51<00:00,  1.84it/s,
val_loss=0.281]

Epoch [19/20], Train Loss: 0.2044, Val Loss: 0.2810, Val Accuracy: 87.32%, Val
AUROC: 0.8402, Partial AUROC: 0.0970
Best Epoch: 19, Best Validation Loss: 0.2166
Training Complete
```




```
Classification Report:
              precision    recall  f1-score   support

     Class 0       0.98      0.88      0.93      1431
     Class 1       0.18      0.64      0.29        59

    accuracy                           0.87      1490
   macro avg       0.58      0.76      0.61      1490
weighted avg       0.95      0.87      0.90      1490
```

[28]:
```
CustomImageFeatureEfficientNet(
  (efficientnet): Sequential(
    (0): Sequential(
      (0): Conv2dNormActivation(
        (0): Conv2d(3, 32, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1),
bias=False)
        (1): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
        (2): SiLU(inplace=True)
      )
      (1): Sequential(
        (0): MBConv(
          (block): Sequential(
            (0): Conv2dNormActivation(
              (0): Conv2d(32, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), groups=32, bias=False)
```

```
              (1): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (1): SqueezeExcitation(
              (avgpool): AdaptiveAvgPool2d(output_size=1)
              (fc1): Conv2d(32, 8, kernel_size=(1, 1), stride=(1, 1))
              (fc2): Conv2d(8, 32, kernel_size=(1, 1), stride=(1, 1))
              (activation): SiLU(inplace=True)
              (scale_activation): Sigmoid()
            )
            (2): Conv2dNormActivation(
              (0): Conv2d(32, 16, kernel_size=(1, 1), stride=(1, 1), bias=False)
              (1): BatchNorm2d(16, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            )
          )
          (stochastic_depth): StochasticDepth(p=0.0, mode=row)
        )
      )
      (2): Sequential(
        (0): MBConv(
          (block): Sequential(
            (0): Conv2dNormActivation(
              (0): Conv2d(16, 96, kernel_size=(1, 1), stride=(1, 1), bias=False)
              (1): BatchNorm2d(96, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (1): Conv2dNormActivation(
              (0): Conv2d(96, 96, kernel_size=(3, 3), stride=(2, 2), padding=(1,
1), groups=96, bias=False)
              (1): BatchNorm2d(96, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (2): SqueezeExcitation(
              (avgpool): AdaptiveAvgPool2d(output_size=1)
              (fc1): Conv2d(96, 4, kernel_size=(1, 1), stride=(1, 1))
              (fc2): Conv2d(4, 96, kernel_size=(1, 1), stride=(1, 1))
              (activation): SiLU(inplace=True)
              (scale_activation): Sigmoid()
            )
            (3): Conv2dNormActivation(
              (0): Conv2d(96, 24, kernel_size=(1, 1), stride=(1, 1), bias=False)
              (1): BatchNorm2d(24, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
```

```
          )
        )
        (stochastic_depth): StochasticDepth(p=0.0125, mode=row)
      )
      (1): MBConv(
        (block): Sequential(
          (0): Conv2dNormActivation(
            (0): Conv2d(24, 144, kernel_size=(1, 1), stride=(1, 1),
bias=False)
            (1): BatchNorm2d(144, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            (2): SiLU(inplace=True)
          )
          (1): Conv2dNormActivation(
            (0): Conv2d(144, 144, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), groups=144, bias=False)
            (1): BatchNorm2d(144, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            (2): SiLU(inplace=True)
          )
          (2): SqueezeExcitation(
            (avgpool): AdaptiveAvgPool2d(output_size=1)
            (fc1): Conv2d(144, 6, kernel_size=(1, 1), stride=(1, 1))
            (fc2): Conv2d(6, 144, kernel_size=(1, 1), stride=(1, 1))
            (activation): SiLU(inplace=True)
            (scale_activation): Sigmoid()
          )
          (3): Conv2dNormActivation(
            (0): Conv2d(144, 24, kernel_size=(1, 1), stride=(1, 1),
bias=False)
            (1): BatchNorm2d(24, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
          )
        )
        (stochastic_depth): StochasticDepth(p=0.025, mode=row)
      )
    )
    (3): Sequential(
      (0): MBConv(
        (block): Sequential(
          (0): Conv2dNormActivation(
            (0): Conv2d(24, 144, kernel_size=(1, 1), stride=(1, 1),
bias=False)
            (1): BatchNorm2d(144, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            (2): SiLU(inplace=True)
          )
```

```
            (1): Conv2dNormActivation(
              (0): Conv2d(144, 144, kernel_size=(5, 5), stride=(2, 2),
padding=(2, 2), groups=144, bias=False)
              (1): BatchNorm2d(144, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (2): SqueezeExcitation(
              (avgpool): AdaptiveAvgPool2d(output_size=1)
              (fc1): Conv2d(144, 6, kernel_size=(1, 1), stride=(1, 1))
              (fc2): Conv2d(6, 144, kernel_size=(1, 1), stride=(1, 1))
              (activation): SiLU(inplace=True)
              (scale_activation): Sigmoid()
            )
            (3): Conv2dNormActivation(
              (0): Conv2d(144, 40, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(40, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            )
          )
          (stochastic_depth): StochasticDepth(p=0.037500000000000006, mode=row)
        )
        (1): MBConv(
          (block): Sequential(
            (0): Conv2dNormActivation(
              (0): Conv2d(40, 240, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(240, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (1): Conv2dNormActivation(
              (0): Conv2d(240, 240, kernel_size=(5, 5), stride=(1, 1),
padding=(2, 2), groups=240, bias=False)
              (1): BatchNorm2d(240, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (2): SqueezeExcitation(
              (avgpool): AdaptiveAvgPool2d(output_size=1)
              (fc1): Conv2d(240, 10, kernel_size=(1, 1), stride=(1, 1))
              (fc2): Conv2d(10, 240, kernel_size=(1, 1), stride=(1, 1))
              (activation): SiLU(inplace=True)
              (scale_activation): Sigmoid()
            )
            (3): Conv2dNormActivation(
```

```
              (0): Conv2d(240, 40, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(40, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            )
          )
          (stochastic_depth): StochasticDepth(p=0.05, mode=row)
        )
      )
      (4): Sequential(
        (0): MBConv(
          (block): Sequential(
            (0): Conv2dNormActivation(
              (0): Conv2d(40, 240, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(240, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (1): Conv2dNormActivation(
              (0): Conv2d(240, 240, kernel_size=(3, 3), stride=(2, 2),
padding=(1, 1), groups=240, bias=False)
              (1): BatchNorm2d(240, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (2): SqueezeExcitation(
              (avgpool): AdaptiveAvgPool2d(output_size=1)
              (fc1): Conv2d(240, 10, kernel_size=(1, 1), stride=(1, 1))
              (fc2): Conv2d(10, 240, kernel_size=(1, 1), stride=(1, 1))
              (activation): SiLU(inplace=True)
              (scale_activation): Sigmoid()
            )
            (3): Conv2dNormActivation(
              (0): Conv2d(240, 80, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(80, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            )
          )
          (stochastic_depth): StochasticDepth(p=0.0625, mode=row)
        )
        (1): MBConv(
          (block): Sequential(
            (0): Conv2dNormActivation(
              (0): Conv2d(80, 480, kernel_size=(1, 1), stride=(1, 1),
bias=False)
```

```
              (1): BatchNorm2d(480, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (1): Conv2dNormActivation(
              (0): Conv2d(480, 480, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), groups=480, bias=False)
              (1): BatchNorm2d(480, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (2): SqueezeExcitation(
              (avgpool): AdaptiveAvgPool2d(output_size=1)
              (fc1): Conv2d(480, 20, kernel_size=(1, 1), stride=(1, 1))
              (fc2): Conv2d(20, 480, kernel_size=(1, 1), stride=(1, 1))
              (activation): SiLU(inplace=True)
              (scale_activation): Sigmoid()
            )
            (3): Conv2dNormActivation(
              (0): Conv2d(480, 80, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(80, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            )
          )
          (stochastic_depth): StochasticDepth(p=0.07500000000000001, mode=row)
        )
        (2): MBConv(
          (block): Sequential(
            (0): Conv2dNormActivation(
              (0): Conv2d(80, 480, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(480, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (1): Conv2dNormActivation(
              (0): Conv2d(480, 480, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), groups=480, bias=False)
              (1): BatchNorm2d(480, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (2): SqueezeExcitation(
              (avgpool): AdaptiveAvgPool2d(output_size=1)
              (fc1): Conv2d(480, 20, kernel_size=(1, 1), stride=(1, 1))
              (fc2): Conv2d(20, 480, kernel_size=(1, 1), stride=(1, 1))
```

```
              (activation): SiLU(inplace=True)
              (scale_activation): Sigmoid()
            )
            (3): Conv2dNormActivation(
              (0): Conv2d(480, 80, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(80, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            )
          )
          (stochastic_depth): StochasticDepth(p=0.08750000000000001, mode=row)
        )
      )
      (5): Sequential(
        (0): MBConv(
          (block): Sequential(
            (0): Conv2dNormActivation(
              (0): Conv2d(80, 480, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(480, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (1): Conv2dNormActivation(
              (0): Conv2d(480, 480, kernel_size=(5, 5), stride=(1, 1),
padding=(2, 2), groups=480, bias=False)
              (1): BatchNorm2d(480, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (2): SqueezeExcitation(
              (avgpool): AdaptiveAvgPool2d(output_size=1)
              (fc1): Conv2d(480, 20, kernel_size=(1, 1), stride=(1, 1))
              (fc2): Conv2d(20, 480, kernel_size=(1, 1), stride=(1, 1))
              (activation): SiLU(inplace=True)
              (scale_activation): Sigmoid()
            )
            (3): Conv2dNormActivation(
              (0): Conv2d(480, 112, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(112, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            )
          )
          (stochastic_depth): StochasticDepth(p=0.1, mode=row)
        )
        (1): MBConv(
```

```
          (block): Sequential(
            (0): Conv2dNormActivation(
              (0): Conv2d(112, 672, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(672, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (1): Conv2dNormActivation(
              (0): Conv2d(672, 672, kernel_size=(5, 5), stride=(1, 1),
padding=(2, 2), groups=672, bias=False)
              (1): BatchNorm2d(672, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (2): SqueezeExcitation(
              (avgpool): AdaptiveAvgPool2d(output_size=1)
              (fc1): Conv2d(672, 28, kernel_size=(1, 1), stride=(1, 1))
              (fc2): Conv2d(28, 672, kernel_size=(1, 1), stride=(1, 1))
              (activation): SiLU(inplace=True)
              (scale_activation): Sigmoid()
            )
            (3): Conv2dNormActivation(
              (0): Conv2d(672, 112, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(112, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            )
          )
          (stochastic_depth): StochasticDepth(p=0.1125, mode=row)
        )
        (2): MBConv(
          (block): Sequential(
            (0): Conv2dNormActivation(
              (0): Conv2d(112, 672, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(672, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (1): Conv2dNormActivation(
              (0): Conv2d(672, 672, kernel_size=(5, 5), stride=(1, 1),
padding=(2, 2), groups=672, bias=False)
              (1): BatchNorm2d(672, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
```

```
            (2): SqueezeExcitation(
              (avgpool): AdaptiveAvgPool2d(output_size=1)
              (fc1): Conv2d(672, 28, kernel_size=(1, 1), stride=(1, 1))
              (fc2): Conv2d(28, 672, kernel_size=(1, 1), stride=(1, 1))
              (activation): SiLU(inplace=True)
              (scale_activation): Sigmoid()
            )
            (3): Conv2dNormActivation(
              (0): Conv2d(672, 112, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(112, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            )
          )
          (stochastic_depth): StochasticDepth(p=0.125, mode=row)
        )
      )
      (6): Sequential(
        (0): MBConv(
          (block): Sequential(
            (0): Conv2dNormActivation(
              (0): Conv2d(112, 672, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(672, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (1): Conv2dNormActivation(
              (0): Conv2d(672, 672, kernel_size=(5, 5), stride=(2, 2),
padding=(2, 2), groups=672, bias=False)
              (1): BatchNorm2d(672, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (2): SqueezeExcitation(
              (avgpool): AdaptiveAvgPool2d(output_size=1)
              (fc1): Conv2d(672, 28, kernel_size=(1, 1), stride=(1, 1))
              (fc2): Conv2d(28, 672, kernel_size=(1, 1), stride=(1, 1))
              (activation): SiLU(inplace=True)
              (scale_activation): Sigmoid()
            )
            (3): Conv2dNormActivation(
              (0): Conv2d(672, 192, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            )
```

```
          )
          (stochastic_depth): StochasticDepth(p=0.1375, mode=row)
        )
        (1): MBConv(
          (block): Sequential(
            (0): Conv2dNormActivation(
              (0): Conv2d(192, 1152, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(1152, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (1): Conv2dNormActivation(
              (0): Conv2d(1152, 1152, kernel_size=(5, 5), stride=(1, 1),
padding=(2, 2), groups=1152, bias=False)
              (1): BatchNorm2d(1152, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (2): SqueezeExcitation(
              (avgpool): AdaptiveAvgPool2d(output_size=1)
              (fc1): Conv2d(1152, 48, kernel_size=(1, 1), stride=(1, 1))
              (fc2): Conv2d(48, 1152, kernel_size=(1, 1), stride=(1, 1))
              (activation): SiLU(inplace=True)
              (scale_activation): Sigmoid()
            )
            (3): Conv2dNormActivation(
              (0): Conv2d(1152, 192, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            )
          )
          (stochastic_depth): StochasticDepth(p=0.15000000000000002, mode=row)
        )
        (2): MBConv(
          (block): Sequential(
            (0): Conv2dNormActivation(
              (0): Conv2d(192, 1152, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(1152, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (1): Conv2dNormActivation(
              (0): Conv2d(1152, 1152, kernel_size=(5, 5), stride=(1, 1),
padding=(2, 2), groups=1152, bias=False)
```

```
              (1): BatchNorm2d(1152, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (2): SqueezeExcitation(
              (avgpool): AdaptiveAvgPool2d(output_size=1)
              (fc1): Conv2d(1152, 48, kernel_size=(1, 1), stride=(1, 1))
              (fc2): Conv2d(48, 1152, kernel_size=(1, 1), stride=(1, 1))
              (activation): SiLU(inplace=True)
              (scale_activation): Sigmoid()
            )
            (3): Conv2dNormActivation(
              (0): Conv2d(1152, 192, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            )
          )
          (stochastic_depth): StochasticDepth(p=0.1625, mode=row)
        )
        (3): MBConv(
          (block): Sequential(
            (0): Conv2dNormActivation(
              (0): Conv2d(192, 1152, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(1152, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (1): Conv2dNormActivation(
              (0): Conv2d(1152, 1152, kernel_size=(5, 5), stride=(1, 1),
padding=(2, 2), groups=1152, bias=False)
              (1): BatchNorm2d(1152, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (2): SqueezeExcitation(
              (avgpool): AdaptiveAvgPool2d(output_size=1)
              (fc1): Conv2d(1152, 48, kernel_size=(1, 1), stride=(1, 1))
              (fc2): Conv2d(48, 1152, kernel_size=(1, 1), stride=(1, 1))
              (activation): SiLU(inplace=True)
              (scale_activation): Sigmoid()
            )
            (3): Conv2dNormActivation(
              (0): Conv2d(1152, 192, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True,
```

```
track_running_stats=True)
            )
          )
          (stochastic_depth): StochasticDepth(p=0.17500000000000002, mode=row)
        )
      )
      (7): Sequential(
        (0): MBConv(
          (block): Sequential(
            (0): Conv2dNormActivation(
              (0): Conv2d(192, 1152, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(1152, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (1): Conv2dNormActivation(
              (0): Conv2d(1152, 1152, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), groups=1152, bias=False)
              (1): BatchNorm2d(1152, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (2): SqueezeExcitation(
              (avgpool): AdaptiveAvgPool2d(output_size=1)
              (fc1): Conv2d(1152, 48, kernel_size=(1, 1), stride=(1, 1))
              (fc2): Conv2d(48, 1152, kernel_size=(1, 1), stride=(1, 1))
              (activation): SiLU(inplace=True)
              (scale_activation): Sigmoid()
            )
            (3): Conv2dNormActivation(
              (0): Conv2d(1152, 320, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(320, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            )
          )
          (stochastic_depth): StochasticDepth(p=0.1875, mode=row)
        )
      )
      (8): Conv2dNormActivation(
        (0): Conv2d(320, 1280, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (1): BatchNorm2d(1280, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
        (2): SiLU(inplace=True)
      )
    )
```

```
    (1): AdaptiveAvgPool2d(output_size=1)
  )
  (fc_image): Linear(in_features=1280, out_features=512, bias=True)
  (fc_metadata): Linear(in_features=9, out_features=128, bias=True)
  (dropout): Dropout(p=0.5, inplace=False)
  (fc_combined): Linear(in_features=640, out_features=1, bias=True)
)
```

0.12 Model 8

[29]:
```
model8 = CustomImageFeatureEfficientNet(feature_input_size=9)  # Assuming 9␣
↪features for metadata
model8.to(device)
# Initialize optimizer
optimizer = optim.SGD(model8.parameters(), lr=0.01)
# Define the loss function with the class weights
criterion = nn.BCELoss()  # Binary classification loss
# Set the number of epochs
epochs = 20
best_model_path = "best_model8.pth"
```

```
/home/jupyter-sohka/.local/lib/python3.10/site-
packages/torchvision/models/_utils.py:208: UserWarning: The parameter
'pretrained' is deprecated since 0.13 and may be removed in the future, please
use 'weights' instead.
  warnings.warn(
/home/jupyter-sohka/.local/lib/python3.10/site-
packages/torchvision/models/_utils.py:223: UserWarning: Arguments other than a
weight enum or `None` for 'weights' are deprecated since 0.13 and may be removed
in the future. The current behavior is equivalent to passing
`weights=EfficientNet_B0_Weights.IMAGENET1K_V1`. You can also use
`weights=EfficientNet_B0_Weights.DEFAULT` to get the most up-to-date weights.
  warnings.warn(msg)
```

[31]:
```
train_and_validate(model8,effnet_train_dataloader, effnet_val_dataloader,␣
↪criterion, optimizer, epochs, device, best_model_path )
```

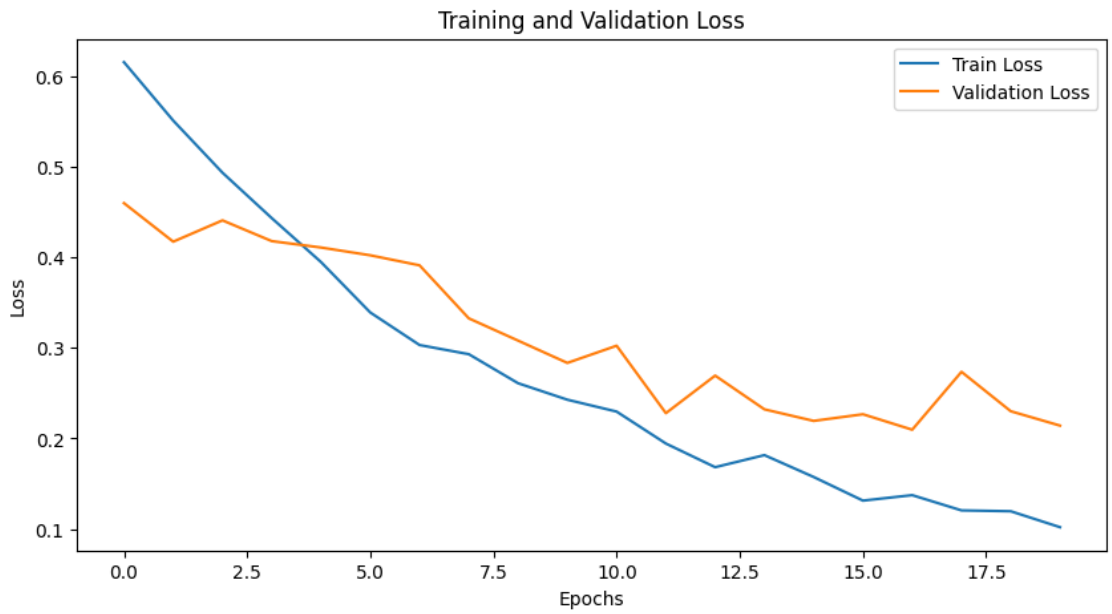
```
Epoch 1/20

Training Epoch 1: 100%|      | 131/131 [01:39<00:00,  1.31it/s,
train_loss=0.616]
Validating Epoch 1: 100%|      | 94/94 [00:51<00:00,  1.82it/s,
val_loss=0.46]

Epoch [0/20], Train Loss: 0.6159, Val Loss: 0.4601, Val Accuracy: 95.37%, Val
AUROC: 0.6985, Partial AUROC: 0.0364
Epoch 2/20
```

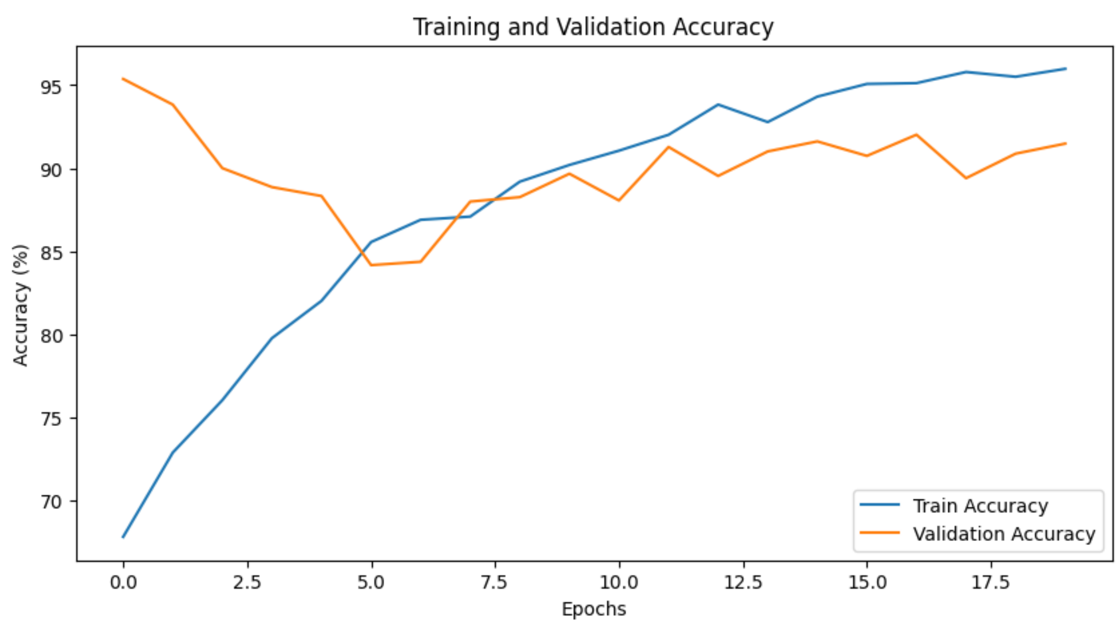
```
Training Epoch 2: 100%|     | 131/131 [01:43<00:00,  1.27it/s,
train_loss=0.551]
Validating Epoch 2: 100%|     | 94/94 [00:50<00:00,  1.85it/s,
val_loss=0.417]

Epoch [1/20], Train Loss: 0.5513, Val Loss: 0.4175, Val Accuracy: 93.83%, Val
AUROC: 0.7256, Partial AUROC: 0.0514
Epoch 3/20

Training Epoch 3: 100%|     | 131/131 [01:36<00:00,  1.35it/s,
train_loss=0.494]
Validating Epoch 3: 100%|     | 94/94 [00:50<00:00,  1.85it/s,
val_loss=0.441]

Epoch [2/20], Train Loss: 0.4937, Val Loss: 0.4410, Val Accuracy: 90.00%, Val
AUROC: 0.7560, Partial AUROC: 0.0557
Epoch 4/20

Training Epoch 4: 100%|     | 131/131 [01:37<00:00,  1.35it/s,
train_loss=0.444]
Validating Epoch 4: 100%|     | 94/94 [00:52<00:00,  1.80it/s,
val_loss=0.418]

Epoch [3/20], Train Loss: 0.4435, Val Loss: 0.4181, Val Accuracy: 88.86%, Val
AUROC: 0.8098, Partial AUROC: 0.0727
Epoch 5/20

Training Epoch 5: 100%|     | 131/131 [01:37<00:00,  1.34it/s,
train_loss=0.395]
Validating Epoch 5: 100%|     | 94/94 [00:52<00:00,  1.79it/s,
val_loss=0.411]

Epoch [4/20], Train Loss: 0.3950, Val Loss: 0.4110, Val Accuracy: 88.32%, Val
AUROC: 0.8227, Partial AUROC: 0.0769
Epoch 6/20

Training Epoch 6: 100%|     | 131/131 [01:46<00:00,  1.23it/s,
train_loss=0.339]
Validating Epoch 6: 100%|     | 94/94 [00:51<00:00,  1.83it/s,
val_loss=0.402]

Epoch [5/20], Train Loss: 0.3392, Val Loss: 0.4024, Val Accuracy: 84.16%, Val
AUROC: 0.8389, Partial AUROC: 0.0866
Epoch 7/20

Training Epoch 7: 100%|     | 131/131 [01:40<00:00,  1.30it/s,
train_loss=0.303]
Validating Epoch 7: 100%|     | 94/94 [00:52<00:00,  1.80it/s,
val_loss=0.391]

Epoch [6/20], Train Loss: 0.3032, Val Loss: 0.3913, Val Accuracy: 84.36%, Val
AUROC: 0.8484, Partial AUROC: 0.0918
Epoch 8/20
```

```
Training Epoch 8: 100%|     | 131/131 [01:39<00:00,  1.32it/s,
train_loss=0.293]
Validating Epoch 8: 100%|     | 94/94 [00:52<00:00,  1.78it/s,
val_loss=0.333]

Epoch [7/20], Train Loss: 0.2931, Val Loss: 0.3327, Val Accuracy: 87.99%, Val
AUROC: 0.8634, Partial AUROC: 0.1028
Epoch 9/20

Training Epoch 9: 100%|     | 131/131 [01:41<00:00,  1.29it/s,
train_loss=0.261]
Validating Epoch 9: 100%|     | 94/94 [00:54<00:00,  1.73it/s,
val_loss=0.308]

Epoch [8/20], Train Loss: 0.2610, Val Loss: 0.3081, Val Accuracy: 88.26%, Val
AUROC: 0.8684, Partial AUROC: 0.1020
Epoch 10/20

Training Epoch 10: 100%|     | 131/131 [01:46<00:00,  1.23it/s,
train_loss=0.243]
Validating Epoch 10: 100%|     | 94/94 [00:51<00:00,  1.81it/s,
val_loss=0.283]

Epoch [9/20], Train Loss: 0.2428, Val Loss: 0.2835, Val Accuracy: 89.66%, Val
AUROC: 0.8852, Partial AUROC: 0.1167
Epoch 11/20

Training Epoch 11: 100%|     | 131/131 [01:38<00:00,  1.32it/s,
train_loss=0.23]
Validating Epoch 11: 100%|     | 94/94 [00:51<00:00,  1.84it/s,
val_loss=0.303]

Epoch [10/20], Train Loss: 0.2297, Val Loss: 0.3025, Val Accuracy: 88.05%, Val
AUROC: 0.8682, Partial AUROC: 0.1011
Epoch 12/20

Training Epoch 12: 100%|     | 131/131 [01:39<00:00,  1.32it/s,
train_loss=0.194]
Validating Epoch 12: 100%|     | 94/94 [01:00<00:00,  1.57it/s,
val_loss=0.228]

Epoch [11/20], Train Loss: 0.1944, Val Loss: 0.2279, Val Accuracy: 91.28%, Val
AUROC: 0.8819, Partial AUROC: 0.1166
Epoch 13/20

Training Epoch 13: 100%|     | 131/131 [01:37<00:00,  1.34it/s,
train_loss=0.168]
Validating Epoch 13: 100%|     | 94/94 [00:55<00:00,  1.69it/s,
val_loss=0.269]

Epoch [12/20], Train Loss: 0.1682, Val Loss: 0.2695, Val Accuracy: 89.53%, Val
AUROC: 0.8395, Partial AUROC: 0.0838
Epoch 14/20
```

```
Training Epoch 14: 100%|     | 131/131 [01:38<00:00,  1.33it/s,
train_loss=0.182]
Validating Epoch 14: 100%|     | 94/94 [00:51<00:00,  1.81it/s,
val_loss=0.232]

Epoch [13/20], Train Loss: 0.1816, Val Loss: 0.2322, Val Accuracy: 91.01%, Val
AUROC: 0.8722, Partial AUROC: 0.1132
Epoch 15/20

Training Epoch 15: 100%|     | 131/131 [01:38<00:00,  1.33it/s,
train_loss=0.157]
Validating Epoch 15: 100%|     | 94/94 [00:50<00:00,  1.84it/s,
val_loss=0.219]

Epoch [14/20], Train Loss: 0.1574, Val Loss: 0.2194, Val Accuracy: 91.61%, Val
AUROC: 0.8603, Partial AUROC: 0.1037
Epoch 16/20

Training Epoch 16: 100%|     | 131/131 [01:37<00:00,  1.34it/s,
train_loss=0.131]
Validating Epoch 16: 100%|     | 94/94 [00:51<00:00,  1.83it/s,
val_loss=0.227]

Epoch [15/20], Train Loss: 0.1313, Val Loss: 0.2267, Val Accuracy: 90.74%, Val
AUROC: 0.8573, Partial AUROC: 0.1118
Epoch 17/20

Training Epoch 17: 100%|     | 131/131 [01:38<00:00,  1.33it/s,
train_loss=0.137]
Validating Epoch 17: 100%|     | 94/94 [00:56<00:00,  1.66it/s,
val_loss=0.21]

Epoch [16/20], Train Loss: 0.1373, Val Loss: 0.2097, Val Accuracy: 92.01%, Val
AUROC: 0.8591, Partial AUROC: 0.1083
Epoch 18/20

Training Epoch 18: 100%|     | 131/131 [01:39<00:00,  1.32it/s,
train_loss=0.12]
Validating Epoch 18: 100%|     | 94/94 [00:51<00:00,  1.82it/s,
val_loss=0.274]

Epoch [17/20], Train Loss: 0.1205, Val Loss: 0.2736, Val Accuracy: 89.40%, Val
AUROC: 0.8619, Partial AUROC: 0.1053
Epoch 19/20

Training Epoch 19: 100%|     | 131/131 [01:37<00:00,  1.34it/s,
train_loss=0.12]
Validating Epoch 19: 100%|     | 94/94 [00:50<00:00,  1.85it/s,
val_loss=0.23]

Epoch [18/20], Train Loss: 0.1195, Val Loss: 0.2301, Val Accuracy: 90.87%, Val
AUROC: 0.8657, Partial AUROC: 0.1158
Epoch 20/20
```

```
Training Epoch 20: 100%|      | 131/131 [01:37<00:00,  1.34it/s,
train_loss=0.102]
Validating Epoch 20: 100%|      | 94/94 [00:51<00:00,  1.82it/s,
val_loss=0.214]

Epoch [19/20], Train Loss: 0.1019, Val Loss: 0.2142, Val Accuracy: 91.48%, Val
AUROC: 0.8567, Partial AUROC: 0.1095
Best Epoch: 17, Best Validation Loss: 0.2097
Training Complete
```





```
Classification Report:
              precision    recall  f1-score   support

     Class 0       0.98      0.93      0.95      1431
     Class 1       0.25      0.56      0.34        59

    accuracy                           0.91      1490
   macro avg       0.61      0.74      0.65      1490
weighted avg       0.95      0.91      0.93      1490
```

[31]:
```
CustomImageFeatureEfficientNet(
  (efficientnet): Sequential(
    (0): Sequential(
      (0): Conv2dNormActivation(
        (0): Conv2d(3, 32, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1),
bias=False)
        (1): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
        (2): SiLU(inplace=True)
      )
      (1): Sequential(
        (0): MBConv(
          (block): Sequential(
            (0): Conv2dNormActivation(
              (0): Conv2d(32, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), groups=32, bias=False)
              (1): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (1): SqueezeExcitation(
              (avgpool): AdaptiveAvgPool2d(output_size=1)
              (fc1): Conv2d(32, 8, kernel_size=(1, 1), stride=(1, 1))
              (fc2): Conv2d(8, 32, kernel_size=(1, 1), stride=(1, 1))
              (activation): SiLU(inplace=True)
              (scale_activation): Sigmoid()
            )
            (2): Conv2dNormActivation(
              (0): Conv2d(32, 16, kernel_size=(1, 1), stride=(1, 1), bias=False)
              (1): BatchNorm2d(16, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            )
          )
          (stochastic_depth): StochasticDepth(p=0.0, mode=row)
```

```
        )
      )
      (2): Sequential(
        (0): MBConv(
          (block): Sequential(
            (0): Conv2dNormActivation(
              (0): Conv2d(16, 96, kernel_size=(1, 1), stride=(1, 1), bias=False)
              (1): BatchNorm2d(96, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (1): Conv2dNormActivation(
              (0): Conv2d(96, 96, kernel_size=(3, 3), stride=(2, 2), padding=(1,
1), groups=96, bias=False)
              (1): BatchNorm2d(96, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (2): SqueezeExcitation(
              (avgpool): AdaptiveAvgPool2d(output_size=1)
              (fc1): Conv2d(96, 4, kernel_size=(1, 1), stride=(1, 1))
              (fc2): Conv2d(4, 96, kernel_size=(1, 1), stride=(1, 1))
              (activation): SiLU(inplace=True)
              (scale_activation): Sigmoid()
            )
            (3): Conv2dNormActivation(
              (0): Conv2d(96, 24, kernel_size=(1, 1), stride=(1, 1), bias=False)
              (1): BatchNorm2d(24, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            )
          )
          (stochastic_depth): StochasticDepth(p=0.0125, mode=row)
        )
        (1): MBConv(
          (block): Sequential(
            (0): Conv2dNormActivation(
              (0): Conv2d(24, 144, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(144, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (1): Conv2dNormActivation(
              (0): Conv2d(144, 144, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), groups=144, bias=False)
              (1): BatchNorm2d(144, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
```

```
              (2): SiLU(inplace=True)
            )
            (2): SqueezeExcitation(
              (avgpool): AdaptiveAvgPool2d(output_size=1)
              (fc1): Conv2d(144, 6, kernel_size=(1, 1), stride=(1, 1))
              (fc2): Conv2d(6, 144, kernel_size=(1, 1), stride=(1, 1))
              (activation): SiLU(inplace=True)
              (scale_activation): Sigmoid()
            )
            (3): Conv2dNormActivation(
              (0): Conv2d(144, 24, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(24, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            )
          )
          (stochastic_depth): StochasticDepth(p=0.025, mode=row)
        )
      )
      (3): Sequential(
        (0): MBConv(
          (block): Sequential(
            (0): Conv2dNormActivation(
              (0): Conv2d(24, 144, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(144, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (1): Conv2dNormActivation(
              (0): Conv2d(144, 144, kernel_size=(5, 5), stride=(2, 2),
padding=(2, 2), groups=144, bias=False)
              (1): BatchNorm2d(144, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (2): SqueezeExcitation(
              (avgpool): AdaptiveAvgPool2d(output_size=1)
              (fc1): Conv2d(144, 6, kernel_size=(1, 1), stride=(1, 1))
              (fc2): Conv2d(6, 144, kernel_size=(1, 1), stride=(1, 1))
              (activation): SiLU(inplace=True)
              (scale_activation): Sigmoid()
            )
            (3): Conv2dNormActivation(
              (0): Conv2d(144, 40, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(40, eps=1e-05, momentum=0.1, affine=True,
```

```
track_running_stats=True)
            )
          )
          (stochastic_depth): StochasticDepth(p=0.037500000000000006, mode=row)
        )
        (1): MBConv(
          (block): Sequential(
            (0): Conv2dNormActivation(
              (0): Conv2d(40, 240, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(240, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (1): Conv2dNormActivation(
              (0): Conv2d(240, 240, kernel_size=(5, 5), stride=(1, 1),
padding=(2, 2), groups=240, bias=False)
              (1): BatchNorm2d(240, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (2): SqueezeExcitation(
              (avgpool): AdaptiveAvgPool2d(output_size=1)
              (fc1): Conv2d(240, 10, kernel_size=(1, 1), stride=(1, 1))
              (fc2): Conv2d(10, 240, kernel_size=(1, 1), stride=(1, 1))
              (activation): SiLU(inplace=True)
              (scale_activation): Sigmoid()
            )
            (3): Conv2dNormActivation(
              (0): Conv2d(240, 40, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(40, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            )
          )
          (stochastic_depth): StochasticDepth(p=0.05, mode=row)
        )
      )
      (4): Sequential(
        (0): MBConv(
          (block): Sequential(
            (0): Conv2dNormActivation(
              (0): Conv2d(40, 240, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(240, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
```

```
            )
            (1): Conv2dNormActivation(
              (0): Conv2d(240, 240, kernel_size=(3, 3), stride=(2, 2),
padding=(1, 1), groups=240, bias=False)
              (1): BatchNorm2d(240, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (2): SqueezeExcitation(
              (avgpool): AdaptiveAvgPool2d(output_size=1)
              (fc1): Conv2d(240, 10, kernel_size=(1, 1), stride=(1, 1))
              (fc2): Conv2d(10, 240, kernel_size=(1, 1), stride=(1, 1))
              (activation): SiLU(inplace=True)
              (scale_activation): Sigmoid()
            )
            (3): Conv2dNormActivation(
              (0): Conv2d(240, 80, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(80, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            )
          )
          (stochastic_depth): StochasticDepth(p=0.0625, mode=row)
        )
        (1): MBConv(
          (block): Sequential(
            (0): Conv2dNormActivation(
              (0): Conv2d(80, 480, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(480, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (1): Conv2dNormActivation(
              (0): Conv2d(480, 480, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), groups=480, bias=False)
              (1): BatchNorm2d(480, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (2): SqueezeExcitation(
              (avgpool): AdaptiveAvgPool2d(output_size=1)
              (fc1): Conv2d(480, 20, kernel_size=(1, 1), stride=(1, 1))
              (fc2): Conv2d(20, 480, kernel_size=(1, 1), stride=(1, 1))
              (activation): SiLU(inplace=True)
              (scale_activation): Sigmoid()
            )
```

```
            (3): Conv2dNormActivation(
              (0): Conv2d(480, 80, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(80, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            )
          )
          (stochastic_depth): StochasticDepth(p=0.07500000000000001, mode=row)
        )
        (2): MBConv(
          (block): Sequential(
            (0): Conv2dNormActivation(
              (0): Conv2d(80, 480, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(480, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (1): Conv2dNormActivation(
              (0): Conv2d(480, 480, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), groups=480, bias=False)
              (1): BatchNorm2d(480, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (2): SqueezeExcitation(
              (avgpool): AdaptiveAvgPool2d(output_size=1)
              (fc1): Conv2d(480, 20, kernel_size=(1, 1), stride=(1, 1))
              (fc2): Conv2d(20, 480, kernel_size=(1, 1), stride=(1, 1))
              (activation): SiLU(inplace=True)
              (scale_activation): Sigmoid()
            )
            (3): Conv2dNormActivation(
              (0): Conv2d(480, 80, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(80, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            )
          )
          (stochastic_depth): StochasticDepth(p=0.08750000000000001, mode=row)
        )
      )
      (5): Sequential(
        (0): MBConv(
          (block): Sequential(
            (0): Conv2dNormActivation(
              (0): Conv2d(80, 480, kernel_size=(1, 1), stride=(1, 1),
```

```
bias=False)
              (1): BatchNorm2d(480, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (1): Conv2dNormActivation(
              (0): Conv2d(480, 480, kernel_size=(5, 5), stride=(1, 1),
padding=(2, 2), groups=480, bias=False)
              (1): BatchNorm2d(480, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (2): SqueezeExcitation(
              (avgpool): AdaptiveAvgPool2d(output_size=1)
              (fc1): Conv2d(480, 20, kernel_size=(1, 1), stride=(1, 1))
              (fc2): Conv2d(20, 480, kernel_size=(1, 1), stride=(1, 1))
              (activation): SiLU(inplace=True)
              (scale_activation): Sigmoid()
            )
            (3): Conv2dNormActivation(
              (0): Conv2d(480, 112, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(112, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            )
          )
          (stochastic_depth): StochasticDepth(p=0.1, mode=row)
        )
        (1): MBConv(
          (block): Sequential(
            (0): Conv2dNormActivation(
              (0): Conv2d(112, 672, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(672, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (1): Conv2dNormActivation(
              (0): Conv2d(672, 672, kernel_size=(5, 5), stride=(1, 1),
padding=(2, 2), groups=672, bias=False)
              (1): BatchNorm2d(672, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (2): SqueezeExcitation(
              (avgpool): AdaptiveAvgPool2d(output_size=1)
              (fc1): Conv2d(672, 28, kernel_size=(1, 1), stride=(1, 1))
```

```
            (fc2): Conv2d(28, 672, kernel_size=(1, 1), stride=(1, 1))
            (activation): SiLU(inplace=True)
            (scale_activation): Sigmoid()
          )
          (3): Conv2dNormActivation(
            (0): Conv2d(672, 112, kernel_size=(1, 1), stride=(1, 1),
bias=False)
            (1): BatchNorm2d(112, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
          )
        )
        (stochastic_depth): StochasticDepth(p=0.1125, mode=row)
      )
      (2): MBConv(
        (block): Sequential(
          (0): Conv2dNormActivation(
            (0): Conv2d(112, 672, kernel_size=(1, 1), stride=(1, 1),
bias=False)
            (1): BatchNorm2d(672, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            (2): SiLU(inplace=True)
          )
          (1): Conv2dNormActivation(
            (0): Conv2d(672, 672, kernel_size=(5, 5), stride=(1, 1),
padding=(2, 2), groups=672, bias=False)
            (1): BatchNorm2d(672, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            (2): SiLU(inplace=True)
          )
          (2): SqueezeExcitation(
            (avgpool): AdaptiveAvgPool2d(output_size=1)
            (fc1): Conv2d(672, 28, kernel_size=(1, 1), stride=(1, 1))
            (fc2): Conv2d(28, 672, kernel_size=(1, 1), stride=(1, 1))
            (activation): SiLU(inplace=True)
            (scale_activation): Sigmoid()
          )
          (3): Conv2dNormActivation(
            (0): Conv2d(672, 112, kernel_size=(1, 1), stride=(1, 1),
bias=False)
            (1): BatchNorm2d(112, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
          )
        )
        (stochastic_depth): StochasticDepth(p=0.125, mode=row)
      )
    )
    (6): Sequential(
```

```
        (0): MBConv(
          (block): Sequential(
            (0): Conv2dNormActivation(
              (0): Conv2d(112, 672, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(672, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (1): Conv2dNormActivation(
              (0): Conv2d(672, 672, kernel_size=(5, 5), stride=(2, 2),
padding=(2, 2), groups=672, bias=False)
              (1): BatchNorm2d(672, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (2): SqueezeExcitation(
              (avgpool): AdaptiveAvgPool2d(output_size=1)
              (fc1): Conv2d(672, 28, kernel_size=(1, 1), stride=(1, 1))
              (fc2): Conv2d(28, 672, kernel_size=(1, 1), stride=(1, 1))
              (activation): SiLU(inplace=True)
              (scale_activation): Sigmoid()
            )
            (3): Conv2dNormActivation(
              (0): Conv2d(672, 192, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            )
          )
          (stochastic_depth): StochasticDepth(p=0.1375, mode=row)
        )
        (1): MBConv(
          (block): Sequential(
            (0): Conv2dNormActivation(
              (0): Conv2d(192, 1152, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(1152, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (1): Conv2dNormActivation(
              (0): Conv2d(1152, 1152, kernel_size=(5, 5), stride=(1, 1),
padding=(2, 2), groups=1152, bias=False)
              (1): BatchNorm2d(1152, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
```

```
            )
            (2): SqueezeExcitation(
              (avgpool): AdaptiveAvgPool2d(output_size=1)
              (fc1): Conv2d(1152, 48, kernel_size=(1, 1), stride=(1, 1))
              (fc2): Conv2d(48, 1152, kernel_size=(1, 1), stride=(1, 1))
              (activation): SiLU(inplace=True)
              (scale_activation): Sigmoid()
            )
            (3): Conv2dNormActivation(
              (0): Conv2d(1152, 192, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            )
          )
          (stochastic_depth): StochasticDepth(p=0.15000000000000002, mode=row)
        )
        (2): MBConv(
          (block): Sequential(
            (0): Conv2dNormActivation(
              (0): Conv2d(192, 1152, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(1152, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (1): Conv2dNormActivation(
              (0): Conv2d(1152, 1152, kernel_size=(5, 5), stride=(1, 1),
padding=(2, 2), groups=1152, bias=False)
              (1): BatchNorm2d(1152, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (2): SqueezeExcitation(
              (avgpool): AdaptiveAvgPool2d(output_size=1)
              (fc1): Conv2d(1152, 48, kernel_size=(1, 1), stride=(1, 1))
              (fc2): Conv2d(48, 1152, kernel_size=(1, 1), stride=(1, 1))
              (activation): SiLU(inplace=True)
              (scale_activation): Sigmoid()
            )
            (3): Conv2dNormActivation(
              (0): Conv2d(1152, 192, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            )
          )
```

```
          (stochastic_depth): StochasticDepth(p=0.1625, mode=row)
        )
        (3): MBConv(
          (block): Sequential(
            (0): Conv2dNormActivation(
              (0): Conv2d(192, 1152, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(1152, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (1): Conv2dNormActivation(
              (0): Conv2d(1152, 1152, kernel_size=(5, 5), stride=(1, 1),
padding=(2, 2), groups=1152, bias=False)
              (1): BatchNorm2d(1152, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (2): SqueezeExcitation(
              (avgpool): AdaptiveAvgPool2d(output_size=1)
              (fc1): Conv2d(1152, 48, kernel_size=(1, 1), stride=(1, 1))
              (fc2): Conv2d(48, 1152, kernel_size=(1, 1), stride=(1, 1))
              (activation): SiLU(inplace=True)
              (scale_activation): Sigmoid()
            )
            (3): Conv2dNormActivation(
              (0): Conv2d(1152, 192, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            )
          )
          (stochastic_depth): StochasticDepth(p=0.17500000000000002, mode=row)
        )
      )
      (7): Sequential(
        (0): MBConv(
          (block): Sequential(
            (0): Conv2dNormActivation(
              (0): Conv2d(192, 1152, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(1152, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (1): Conv2dNormActivation(
              (0): Conv2d(1152, 1152, kernel_size=(3, 3), stride=(1, 1),
```

```
padding=(1, 1), groups=1152, bias=False)
              (1): BatchNorm2d(1152, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (2): SqueezeExcitation(
              (avgpool): AdaptiveAvgPool2d(output_size=1)
              (fc1): Conv2d(1152, 48, kernel_size=(1, 1), stride=(1, 1))
              (fc2): Conv2d(48, 1152, kernel_size=(1, 1), stride=(1, 1))
              (activation): SiLU(inplace=True)
              (scale_activation): Sigmoid()
            )
            (3): Conv2dNormActivation(
              (0): Conv2d(1152, 320, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(320, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            )
          )
          (stochastic_depth): StochasticDepth(p=0.1875, mode=row)
        )
      )
      (8): Conv2dNormActivation(
        (0): Conv2d(320, 1280, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (1): BatchNorm2d(1280, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
        (2): SiLU(inplace=True)
      )
    )
    (1): AdaptiveAvgPool2d(output_size=1)
  )
  (fc_image): Linear(in_features=1280, out_features=512, bias=True)
  (fc_metadata): Linear(in_features=9, out_features=128, bias=True)
  (dropout): Dropout(p=0.5, inplace=False)
  (fc_combined): Linear(in_features=640, out_features=1, bias=True)
)
```

0.13 Model 9

[32]:
```
model9 = CustomImageFeatureEfficientNet(feature_input_size=9)  # Assuming 9␣
↪features for metadata
model9.to(device)
# Initialize optimizer
optimizer = optim.Adam(model9.parameters(), lr=0.001)
# Define the loss function with the class weights
criterion = nn.BCELoss()  # Binary classification loss
# Set the number of epochs
```

```
epochs = 20
batch_sizes = 16
best_model_path = "best_model9.path"
```

```
/home/jupyter-sohka/.local/lib/python3.10/site-
packages/torchvision/models/_utils.py:208: UserWarning: The parameter
'pretrained' is deprecated since 0.13 and may be removed in the future, please
use 'weights' instead.
  warnings.warn(
/home/jupyter-sohka/.local/lib/python3.10/site-
packages/torchvision/models/_utils.py:223: UserWarning: Arguments other than a
weight enum or `None` for 'weights' are deprecated since 0.13 and may be removed
in the future. The current behavior is equivalent to passing
`weights=EfficientNet_B0_Weights.IMAGENET1K_V1`. You can also use
`weights=EfficientNet_B0_Weights.DEFAULT` to get the most up-to-date weights.
  warnings.warn(msg)
```

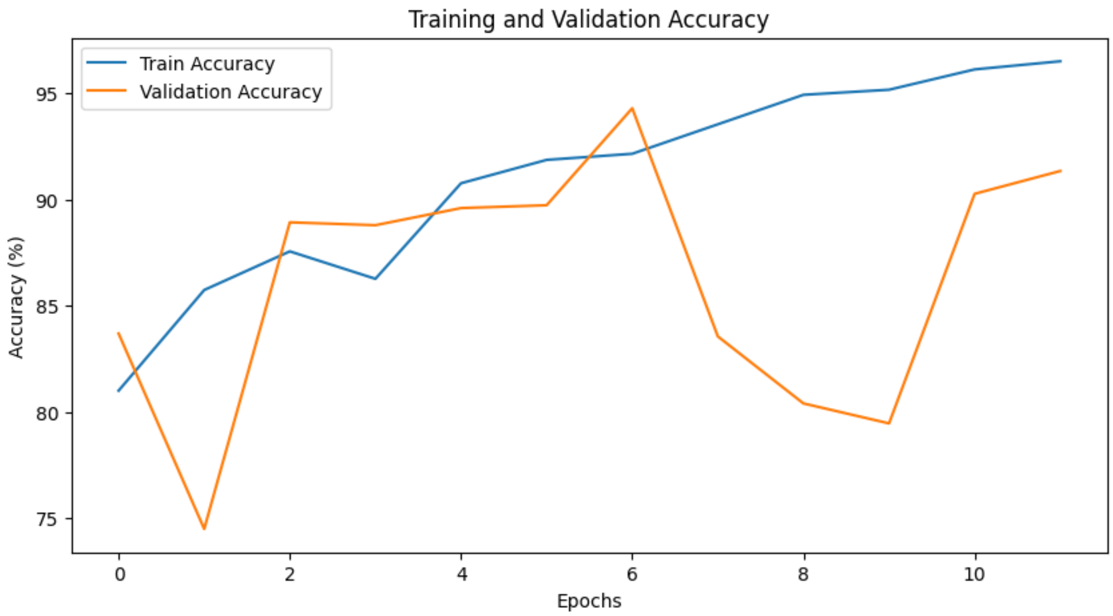
[33]:

```
train_and_validate(model9,effnet_train_dataloader, effnet_val_dataloader,␣
↪criterion, optimizer, epochs, device, best_model_path )
```

```
Epoch 1/20

Training Epoch 1: 100%|      | 131/131 [01:40<00:00,  1.30it/s,
train_loss=0.432]
Validating Epoch 1: 100%|      | 94/94 [00:56<00:00,  1.68it/s,
val_loss=0.376]

Epoch [0/20], Train Loss: 0.4325, Val Loss: 0.3763, Val Accuracy: 83.69%, Val
AUROC: 0.8220, Partial AUROC: 0.0917
Epoch 2/20

Training Epoch 2: 100%|      | 131/131 [01:40<00:00,  1.31it/s,
train_loss=0.347]
Validating Epoch 2: 100%|      | 94/94 [00:50<00:00,  1.87it/s,
val_loss=0.42]

Epoch [1/20], Train Loss: 0.3475, Val Loss: 0.4196, Val Accuracy: 74.50%, Val
AUROC: 0.8406, Partial AUROC: 0.0972
Epoch 3/20

Training Epoch 3: 100%|      | 131/131 [01:40<00:00,  1.30it/s,
train_loss=0.319]
Validating Epoch 3: 100%|      | 94/94 [00:58<00:00,  1.60it/s,
val_loss=0.392]

Epoch [2/20], Train Loss: 0.3192, Val Loss: 0.3923, Val Accuracy: 88.93%, Val
AUROC: 0.7979, Partial AUROC: 0.0693
Epoch 4/20

Training Epoch 4: 100%|      | 131/131 [01:39<00:00,  1.31it/s,
train_loss=0.322]
```

```
Validating Epoch 4: 100%|     | 94/94 [01:00<00:00,  1.56it/s,
val_loss=0.389]

Epoch [3/20], Train Loss: 0.3220, Val Loss: 0.3888, Val Accuracy: 88.79%, Val
AUROC: 0.8398, Partial AUROC: 0.0894
Epoch 5/20

Training Epoch 5: 100%|     | 131/131 [01:43<00:00,  1.26it/s,
train_loss=0.24]
Validating Epoch 5: 100%|     | 94/94 [00:55<00:00,  1.69it/s,
val_loss=0.26]

Epoch [4/20], Train Loss: 0.2397, Val Loss: 0.2596, Val Accuracy: 89.60%, Val
AUROC: 0.8398, Partial AUROC: 0.0857
Epoch 6/20

Training Epoch 6: 100%|     | 131/131 [01:41<00:00,  1.29it/s,
train_loss=0.194]
Validating Epoch 6: 100%|     | 94/94 [00:51<00:00,  1.82it/s,
val_loss=0.242]

Epoch [5/20], Train Loss: 0.1936, Val Loss: 0.2420, Val Accuracy: 89.73%, Val
AUROC: 0.8615, Partial AUROC: 0.1131
Epoch 7/20

Training Epoch 7: 100%|     | 131/131 [01:40<00:00,  1.30it/s,
train_loss=0.208]
Validating Epoch 7: 100%|     | 94/94 [00:51<00:00,  1.81it/s,
val_loss=0.173]

Epoch [6/20], Train Loss: 0.2082, Val Loss: 0.1731, Val Accuracy: 94.30%, Val
AUROC: 0.8511, Partial AUROC: 0.0976
Epoch 8/20

Training Epoch 8: 100%|     | 131/131 [01:42<00:00,  1.28it/s,
train_loss=0.157]
Validating Epoch 8: 100%|     | 94/94 [00:51<00:00,  1.83it/s,
val_loss=0.329]

Epoch [7/20], Train Loss: 0.1571, Val Loss: 0.3290, Val Accuracy: 83.56%, Val
AUROC: 0.8171, Partial AUROC: 0.0776
Epoch 9/20

Training Epoch 9: 100%|     | 131/131 [01:47<00:00,  1.22it/s,
train_loss=0.144]
Validating Epoch 9: 100%|     | 94/94 [00:50<00:00,  1.86it/s,
val_loss=0.413]

Epoch [8/20], Train Loss: 0.1441, Val Loss: 0.4128, Val Accuracy: 80.40%, Val
AUROC: 0.8423, Partial AUROC: 0.0984
Epoch 10/20

Training Epoch 10: 100%|     | 131/131 [01:40<00:00,  1.30it/s,
train_loss=0.144]
```

```
Validating Epoch 10: 100%|      | 94/94 [00:52<00:00,  1.79it/s,
val_loss=0.422]

Epoch [9/20], Train Loss: 0.1439, Val Loss: 0.4219, Val Accuracy: 79.46%, Val
AUROC: 0.8541, Partial AUROC: 0.1038
Epoch 11/20

Training Epoch 11: 100%|      | 131/131 [01:50<00:00,  1.19it/s,
train_loss=0.105]
Validating Epoch 11: 100%|      | 94/94 [00:54<00:00,  1.73it/s,
val_loss=0.451]

Epoch [10/20], Train Loss: 0.1050, Val Loss: 0.4508, Val Accuracy: 90.27%, Val
AUROC: 0.8261, Partial AUROC: 0.1017
Epoch 12/20

Training Epoch 12: 100%|      | 131/131 [01:45<00:00,  1.24it/s,
train_loss=0.109]
Validating Epoch 12: 100%|      | 94/94 [00:52<00:00,  1.80it/s,
val_loss=0.211]

Epoch [11/20], Train Loss: 0.1091, Val Loss: 0.2113, Val Accuracy: 91.34%, Val
AUROC: 0.8501, Partial AUROC: 0.1038
Early stopping triggered at epoch 11
Best Epoch: 7, Best Validation Loss: 0.1731
Training Complete
```




```
Classification Report:
              precision    recall  f1-score   support

     Class 0       0.98      0.93      0.95      1431
     Class 1       0.22      0.46      0.30        59

    accuracy                           0.91      1490
   macro avg       0.60      0.69      0.62      1490
weighted avg       0.95      0.91      0.93      1490
```

[33]:
```
CustomImageFeatureEfficientNet(
  (efficientnet): Sequential(
    (0): Sequential(
      (0): Conv2dNormActivation(
        (0): Conv2d(3, 32, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1),
bias=False)
        (1): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
        (2): SiLU(inplace=True)
      )
      (1): Sequential(
        (0): MBConv(
          (block): Sequential(
            (0): Conv2dNormActivation(
              (0): Conv2d(32, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), groups=32, bias=False)
```

```
              (1): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (1): SqueezeExcitation(
              (avgpool): AdaptiveAvgPool2d(output_size=1)
              (fc1): Conv2d(32, 8, kernel_size=(1, 1), stride=(1, 1))
              (fc2): Conv2d(8, 32, kernel_size=(1, 1), stride=(1, 1))
              (activation): SiLU(inplace=True)
              (scale_activation): Sigmoid()
            )
            (2): Conv2dNormActivation(
              (0): Conv2d(32, 16, kernel_size=(1, 1), stride=(1, 1), bias=False)
              (1): BatchNorm2d(16, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            )
          )
          (stochastic_depth): StochasticDepth(p=0.0, mode=row)
        )
      )
      (2): Sequential(
        (0): MBConv(
          (block): Sequential(
            (0): Conv2dNormActivation(
              (0): Conv2d(16, 96, kernel_size=(1, 1), stride=(1, 1), bias=False)
              (1): BatchNorm2d(96, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (1): Conv2dNormActivation(
              (0): Conv2d(96, 96, kernel_size=(3, 3), stride=(2, 2), padding=(1,
1), groups=96, bias=False)
              (1): BatchNorm2d(96, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (2): SqueezeExcitation(
              (avgpool): AdaptiveAvgPool2d(output_size=1)
              (fc1): Conv2d(96, 4, kernel_size=(1, 1), stride=(1, 1))
              (fc2): Conv2d(4, 96, kernel_size=(1, 1), stride=(1, 1))
              (activation): SiLU(inplace=True)
              (scale_activation): Sigmoid()
            )
            (3): Conv2dNormActivation(
              (0): Conv2d(96, 24, kernel_size=(1, 1), stride=(1, 1), bias=False)
              (1): BatchNorm2d(24, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
```

```
          )
        )
        (stochastic_depth): StochasticDepth(p=0.0125, mode=row)
      )
      (1): MBConv(
        (block): Sequential(
          (0): Conv2dNormActivation(
            (0): Conv2d(24, 144, kernel_size=(1, 1), stride=(1, 1),
bias=False)
            (1): BatchNorm2d(144, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            (2): SiLU(inplace=True)
          )
          (1): Conv2dNormActivation(
            (0): Conv2d(144, 144, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), groups=144, bias=False)
            (1): BatchNorm2d(144, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            (2): SiLU(inplace=True)
          )
          (2): SqueezeExcitation(
            (avgpool): AdaptiveAvgPool2d(output_size=1)
            (fc1): Conv2d(144, 6, kernel_size=(1, 1), stride=(1, 1))
            (fc2): Conv2d(6, 144, kernel_size=(1, 1), stride=(1, 1))
            (activation): SiLU(inplace=True)
            (scale_activation): Sigmoid()
          )
          (3): Conv2dNormActivation(
            (0): Conv2d(144, 24, kernel_size=(1, 1), stride=(1, 1),
bias=False)
            (1): BatchNorm2d(24, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
          )
        )
        (stochastic_depth): StochasticDepth(p=0.025, mode=row)
      )
    )
    (3): Sequential(
      (0): MBConv(
        (block): Sequential(
          (0): Conv2dNormActivation(
            (0): Conv2d(24, 144, kernel_size=(1, 1), stride=(1, 1),
bias=False)
            (1): BatchNorm2d(144, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            (2): SiLU(inplace=True)
          )
```

```
            (1): Conv2dNormActivation(
              (0): Conv2d(144, 144, kernel_size=(5, 5), stride=(2, 2),
padding=(2, 2), groups=144, bias=False)
              (1): BatchNorm2d(144, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (2): SqueezeExcitation(
              (avgpool): AdaptiveAvgPool2d(output_size=1)
              (fc1): Conv2d(144, 6, kernel_size=(1, 1), stride=(1, 1))
              (fc2): Conv2d(6, 144, kernel_size=(1, 1), stride=(1, 1))
              (activation): SiLU(inplace=True)
              (scale_activation): Sigmoid()
            )
            (3): Conv2dNormActivation(
              (0): Conv2d(144, 40, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(40, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            )
          )
          (stochastic_depth): StochasticDepth(p=0.037500000000000006, mode=row)
        )
        (1): MBConv(
          (block): Sequential(
            (0): Conv2dNormActivation(
              (0): Conv2d(40, 240, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(240, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (1): Conv2dNormActivation(
              (0): Conv2d(240, 240, kernel_size=(5, 5), stride=(1, 1),
padding=(2, 2), groups=240, bias=False)
              (1): BatchNorm2d(240, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (2): SqueezeExcitation(
              (avgpool): AdaptiveAvgPool2d(output_size=1)
              (fc1): Conv2d(240, 10, kernel_size=(1, 1), stride=(1, 1))
              (fc2): Conv2d(10, 240, kernel_size=(1, 1), stride=(1, 1))
              (activation): SiLU(inplace=True)
              (scale_activation): Sigmoid()
            )
            (3): Conv2dNormActivation(
```

```
              (0): Conv2d(240, 40, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(40, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            )
          )
          (stochastic_depth): StochasticDepth(p=0.05, mode=row)
        )
      )
      (4): Sequential(
        (0): MBConv(
          (block): Sequential(
            (0): Conv2dNormActivation(
              (0): Conv2d(40, 240, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(240, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (1): Conv2dNormActivation(
              (0): Conv2d(240, 240, kernel_size=(3, 3), stride=(2, 2),
padding=(1, 1), groups=240, bias=False)
              (1): BatchNorm2d(240, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (2): SqueezeExcitation(
              (avgpool): AdaptiveAvgPool2d(output_size=1)
              (fc1): Conv2d(240, 10, kernel_size=(1, 1), stride=(1, 1))
              (fc2): Conv2d(10, 240, kernel_size=(1, 1), stride=(1, 1))
              (activation): SiLU(inplace=True)
              (scale_activation): Sigmoid()
            )
            (3): Conv2dNormActivation(
              (0): Conv2d(240, 80, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(80, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            )
          )
          (stochastic_depth): StochasticDepth(p=0.0625, mode=row)
        )
        (1): MBConv(
          (block): Sequential(
            (0): Conv2dNormActivation(
              (0): Conv2d(80, 480, kernel_size=(1, 1), stride=(1, 1),
bias=False)
```

```
              (1): BatchNorm2d(480, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (1): Conv2dNormActivation(
              (0): Conv2d(480, 480, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), groups=480, bias=False)
              (1): BatchNorm2d(480, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (2): SqueezeExcitation(
              (avgpool): AdaptiveAvgPool2d(output_size=1)
              (fc1): Conv2d(480, 20, kernel_size=(1, 1), stride=(1, 1))
              (fc2): Conv2d(20, 480, kernel_size=(1, 1), stride=(1, 1))
              (activation): SiLU(inplace=True)
              (scale_activation): Sigmoid()
            )
            (3): Conv2dNormActivation(
              (0): Conv2d(480, 80, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(80, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            )
          )
          (stochastic_depth): StochasticDepth(p=0.07500000000000001, mode=row)
        )
        (2): MBConv(
          (block): Sequential(
            (0): Conv2dNormActivation(
              (0): Conv2d(80, 480, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(480, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (1): Conv2dNormActivation(
              (0): Conv2d(480, 480, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), groups=480, bias=False)
              (1): BatchNorm2d(480, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (2): SqueezeExcitation(
              (avgpool): AdaptiveAvgPool2d(output_size=1)
              (fc1): Conv2d(480, 20, kernel_size=(1, 1), stride=(1, 1))
              (fc2): Conv2d(20, 480, kernel_size=(1, 1), stride=(1, 1))
```

```
              (activation): SiLU(inplace=True)
              (scale_activation): Sigmoid()
            )
            (3): Conv2dNormActivation(
              (0): Conv2d(480, 80, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(80, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            )
          )
          (stochastic_depth): StochasticDepth(p=0.08750000000000001, mode=row)
        )
      )
      (5): Sequential(
        (0): MBConv(
          (block): Sequential(
            (0): Conv2dNormActivation(
              (0): Conv2d(80, 480, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(480, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (1): Conv2dNormActivation(
              (0): Conv2d(480, 480, kernel_size=(5, 5), stride=(1, 1),
padding=(2, 2), groups=480, bias=False)
              (1): BatchNorm2d(480, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (2): SqueezeExcitation(
              (avgpool): AdaptiveAvgPool2d(output_size=1)
              (fc1): Conv2d(480, 20, kernel_size=(1, 1), stride=(1, 1))
              (fc2): Conv2d(20, 480, kernel_size=(1, 1), stride=(1, 1))
              (activation): SiLU(inplace=True)
              (scale_activation): Sigmoid()
            )
            (3): Conv2dNormActivation(
              (0): Conv2d(480, 112, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(112, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            )
          )
          (stochastic_depth): StochasticDepth(p=0.1, mode=row)
        )
        (1): MBConv(
```

```
          (block): Sequential(
            (0): Conv2dNormActivation(
              (0): Conv2d(112, 672, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(672, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (1): Conv2dNormActivation(
              (0): Conv2d(672, 672, kernel_size=(5, 5), stride=(1, 1),
padding=(2, 2), groups=672, bias=False)
              (1): BatchNorm2d(672, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (2): SqueezeExcitation(
              (avgpool): AdaptiveAvgPool2d(output_size=1)
              (fc1): Conv2d(672, 28, kernel_size=(1, 1), stride=(1, 1))
              (fc2): Conv2d(28, 672, kernel_size=(1, 1), stride=(1, 1))
              (activation): SiLU(inplace=True)
              (scale_activation): Sigmoid()
            )
            (3): Conv2dNormActivation(
              (0): Conv2d(672, 112, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(112, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            )
          )
          (stochastic_depth): StochasticDepth(p=0.1125, mode=row)
        )
        (2): MBConv(
          (block): Sequential(
            (0): Conv2dNormActivation(
              (0): Conv2d(112, 672, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(672, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (1): Conv2dNormActivation(
              (0): Conv2d(672, 672, kernel_size=(5, 5), stride=(1, 1),
padding=(2, 2), groups=672, bias=False)
              (1): BatchNorm2d(672, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
```

```
            (2): SqueezeExcitation(
              (avgpool): AdaptiveAvgPool2d(output_size=1)
              (fc1): Conv2d(672, 28, kernel_size=(1, 1), stride=(1, 1))
              (fc2): Conv2d(28, 672, kernel_size=(1, 1), stride=(1, 1))
              (activation): SiLU(inplace=True)
              (scale_activation): Sigmoid()
            )
            (3): Conv2dNormActivation(
              (0): Conv2d(672, 112, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(112, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            )
          )
          (stochastic_depth): StochasticDepth(p=0.125, mode=row)
        )
      )
      (6): Sequential(
        (0): MBConv(
          (block): Sequential(
            (0): Conv2dNormActivation(
              (0): Conv2d(112, 672, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(672, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (1): Conv2dNormActivation(
              (0): Conv2d(672, 672, kernel_size=(5, 5), stride=(2, 2),
padding=(2, 2), groups=672, bias=False)
              (1): BatchNorm2d(672, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (2): SqueezeExcitation(
              (avgpool): AdaptiveAvgPool2d(output_size=1)
              (fc1): Conv2d(672, 28, kernel_size=(1, 1), stride=(1, 1))
              (fc2): Conv2d(28, 672, kernel_size=(1, 1), stride=(1, 1))
              (activation): SiLU(inplace=True)
              (scale_activation): Sigmoid()
            )
            (3): Conv2dNormActivation(
              (0): Conv2d(672, 192, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            )
```

```
          )
          (stochastic_depth): StochasticDepth(p=0.1375, mode=row)
        )
        (1): MBConv(
          (block): Sequential(
            (0): Conv2dNormActivation(
              (0): Conv2d(192, 1152, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(1152, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (1): Conv2dNormActivation(
              (0): Conv2d(1152, 1152, kernel_size=(5, 5), stride=(1, 1),
padding=(2, 2), groups=1152, bias=False)
              (1): BatchNorm2d(1152, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (2): SqueezeExcitation(
              (avgpool): AdaptiveAvgPool2d(output_size=1)
              (fc1): Conv2d(1152, 48, kernel_size=(1, 1), stride=(1, 1))
              (fc2): Conv2d(48, 1152, kernel_size=(1, 1), stride=(1, 1))
              (activation): SiLU(inplace=True)
              (scale_activation): Sigmoid()
            )
            (3): Conv2dNormActivation(
              (0): Conv2d(1152, 192, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            )
          )
          (stochastic_depth): StochasticDepth(p=0.15000000000000002, mode=row)
        )
        (2): MBConv(
          (block): Sequential(
            (0): Conv2dNormActivation(
              (0): Conv2d(192, 1152, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(1152, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (1): Conv2dNormActivation(
              (0): Conv2d(1152, 1152, kernel_size=(5, 5), stride=(1, 1),
padding=(2, 2), groups=1152, bias=False)
```

```
              (1): BatchNorm2d(1152, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (2): SqueezeExcitation(
              (avgpool): AdaptiveAvgPool2d(output_size=1)
              (fc1): Conv2d(1152, 48, kernel_size=(1, 1), stride=(1, 1))
              (fc2): Conv2d(48, 1152, kernel_size=(1, 1), stride=(1, 1))
              (activation): SiLU(inplace=True)
              (scale_activation): Sigmoid()
            )
            (3): Conv2dNormActivation(
              (0): Conv2d(1152, 192, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            )
          )
          (stochastic_depth): StochasticDepth(p=0.1625, mode=row)
        )
        (3): MBConv(
          (block): Sequential(
            (0): Conv2dNormActivation(
              (0): Conv2d(192, 1152, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(1152, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (1): Conv2dNormActivation(
              (0): Conv2d(1152, 1152, kernel_size=(5, 5), stride=(1, 1),
padding=(2, 2), groups=1152, bias=False)
              (1): BatchNorm2d(1152, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (2): SqueezeExcitation(
              (avgpool): AdaptiveAvgPool2d(output_size=1)
              (fc1): Conv2d(1152, 48, kernel_size=(1, 1), stride=(1, 1))
              (fc2): Conv2d(48, 1152, kernel_size=(1, 1), stride=(1, 1))
              (activation): SiLU(inplace=True)
              (scale_activation): Sigmoid()
            )
            (3): Conv2dNormActivation(
              (0): Conv2d(1152, 192, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True,
```

```
track_running_stats=True)
            )
          )
          (stochastic_depth): StochasticDepth(p=0.17500000000000002, mode=row)
        )
      )
      (7): Sequential(
        (0): MBConv(
          (block): Sequential(
            (0): Conv2dNormActivation(
              (0): Conv2d(192, 1152, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(1152, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (1): Conv2dNormActivation(
              (0): Conv2d(1152, 1152, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), groups=1152, bias=False)
              (1): BatchNorm2d(1152, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
              (2): SiLU(inplace=True)
            )
            (2): SqueezeExcitation(
              (avgpool): AdaptiveAvgPool2d(output_size=1)
              (fc1): Conv2d(1152, 48, kernel_size=(1, 1), stride=(1, 1))
              (fc2): Conv2d(48, 1152, kernel_size=(1, 1), stride=(1, 1))
              (activation): SiLU(inplace=True)
              (scale_activation): Sigmoid()
            )
            (3): Conv2dNormActivation(
              (0): Conv2d(1152, 320, kernel_size=(1, 1), stride=(1, 1),
bias=False)
              (1): BatchNorm2d(320, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            )
          )
          (stochastic_depth): StochasticDepth(p=0.1875, mode=row)
        )
      )
      (8): Conv2dNormActivation(
        (0): Conv2d(320, 1280, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (1): BatchNorm2d(1280, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
        (2): SiLU(inplace=True)
      )
    )
```

```
    (1): AdaptiveAvgPool2d(output_size=1)
  )
  (fc_image): Linear(in_features=1280, out_features=512, bias=True)
  (fc_metadata): Linear(in_features=9, out_features=128, bias=True)
  (dropout): Dropout(p=0.5, inplace=False)
  (fc_combined): Linear(in_features=640, out_features=1, bias=True)
)
```

0.14 Winning Model

[9]:
```
#create test dataset
effnet_test_dataset = MultiInputDataset(hdf5_file='../data/raw/test_image.
 ↪hdf5', csv_file='../data/processed/processed-test-metadata1.csv',␣
 ↪transform=get_normal_transform(resize_size=(128,128)))
# Create test DataLoader
effnet_test_dataloader = DataLoader(effnet_test_dataset,  batch_size=64,␣
 ↪shuffle=True)
```

[10]:
```
# Initialize the final model with 9 output features
final_model = CustomImageFeatureEfficientNet(9)

# Define the path to the saved model weights
final_model_path = "best_model7.pth"

# Load the model weights into final_model, mapping to CPU if necessary
final_model.load_state_dict(torch.load(final_model_path, map_location=torch.
 ↪device('cpu')))

# Set the model to evaluation mode, which disables dropout and batch␣
 ↪normalization updates
final_model.eval()

# Initialize lists to store labels and predicted probabilities for later␣
 ↪analysis
all_labels, all_probs = [], []

# Disable gradient computation for testing phase to save memory and improve␣
 ↪performance
with torch.no_grad():
    # Loop through batches in the test dataloader
    for images, metadata, labels in effnet_test_dataloader:
        # Move data to the specified device (e.g., CPU or GPU) and adjust label␣
 ↪shape
        images, metadata = images.to(device), metadata.to(device)
        labels = labels.float().to(device).unsqueeze(1)
```

```python
        # Forward pass to get probabilities from the model
        probs = final_model(images, metadata)

        # Collect labels and predicted probabilities, converting to numpy arrays
        all_labels.extend(labels.cpu().numpy())
        all_probs.extend(probs.cpu().numpy())

        # Generate binary predictions based on a 0.5 threshold
        predicted = (probs > 0.5).float()

    # Calculate the partial AUROC score (adjusted for your specific function)
    partial_auroc = score(np.array(all_labels), np.array(all_probs))
    print(f'The partial AUROC of the final model on the test images is␣
↪{partial_auroc}')

    # Print the classification report, evaluating performance on Class 0 and␣
↪Class 1
    print(classification_report(all_labels, (np.array(all_probs) >= 0.5).
↪astype(int), target_names=['Class 0', 'Class 1']))
```

```
/home/jupyter-sohka/.local/lib/python3.10/site-
packages/torchvision/models/_utils.py:208: UserWarning: The parameter
'pretrained' is deprecated since 0.13 and may be removed in the future, please
use 'weights' instead.
  warnings.warn(
/home/jupyter-sohka/.local/lib/python3.10/site-
packages/torchvision/models/_utils.py:223: UserWarning: Arguments other than a
weight enum or `None` for 'weights' are deprecated since 0.13 and may be removed
in the future. The current behavior is equivalent to passing
`weights=EfficientNet_B0_Weights.IMAGENET1K_V1`. You can also use
`weights=EfficientNet_B0_Weights.DEFAULT` to get the most up-to-date weights.
  warnings.warn(msg)
/tmp/ipykernel_1189445/1883220575.py:3: FutureWarning: You are using
`torch.load` with `weights_only=False` (the current default value), which uses
the default pickle module implicitly. It is possible to construct malicious
pickle data which will execute arbitrary code during unpickling (See
https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-models for
more details). In a future release, the default value for `weights_only` will be
flipped to `True`. This limits the functions that could be executed during
unpickling. Arbitrary objects will no longer be allowed to be loaded via this
mode unless they are explicitly allowlisted by the user via
`torch.serialization.add_safe_globals`. We recommend you start setting
`weights_only=True` for any use case where you don't have full control of the
```

```
loaded file. Please open an issue on GitHub for any issues related to this
experimental feature.
  final_model.load_state_dict(torch.load(final_model_path,
map_location=torch.device('cpu')))

The partial auroc of the final model on the test image is 0.13625176183538829
              precision    recall  f1-score   support

     Class 0       0.98      0.92      0.95      1431
     Class 1       0.24      0.61      0.35        59

    accuracy                           0.91      1490
   macro avg       0.61      0.77      0.65      1490
weighted avg       0.95      0.91      0.93      1490
```