ANOMALY DETECTION
IN MACHINES

Pandas
python
NumPy
scikit learn
matplotlib

ANOMALY DETECTION IN MACHINES

Anomaly Detection in machines involves identifying patterns that deviate significantly from the normal behavior of the system. This Technique is used to detect faults, unusual behavior in machinery.

WHY IT IS NECESSARY IN REAL WORLD:

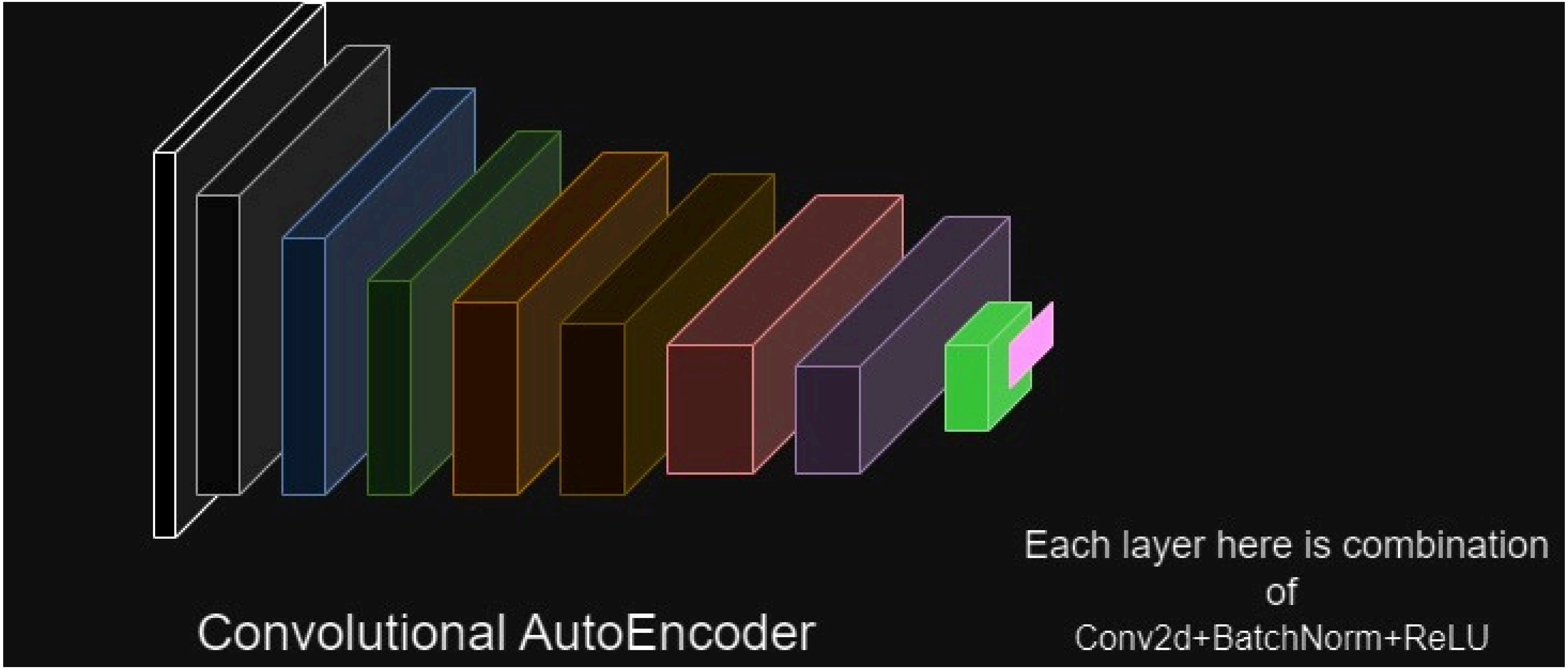
1) EARLY DETECTION OF MALFUNCTIONS
2)FRAUD DETECTION
3)CYBER SECURITY
4)QUALITY CONTROL
5)HEALTH MONITORING
6)IMPROVING PREDICTIVE MAINTENANCE

DATA WORKING AND CREATION

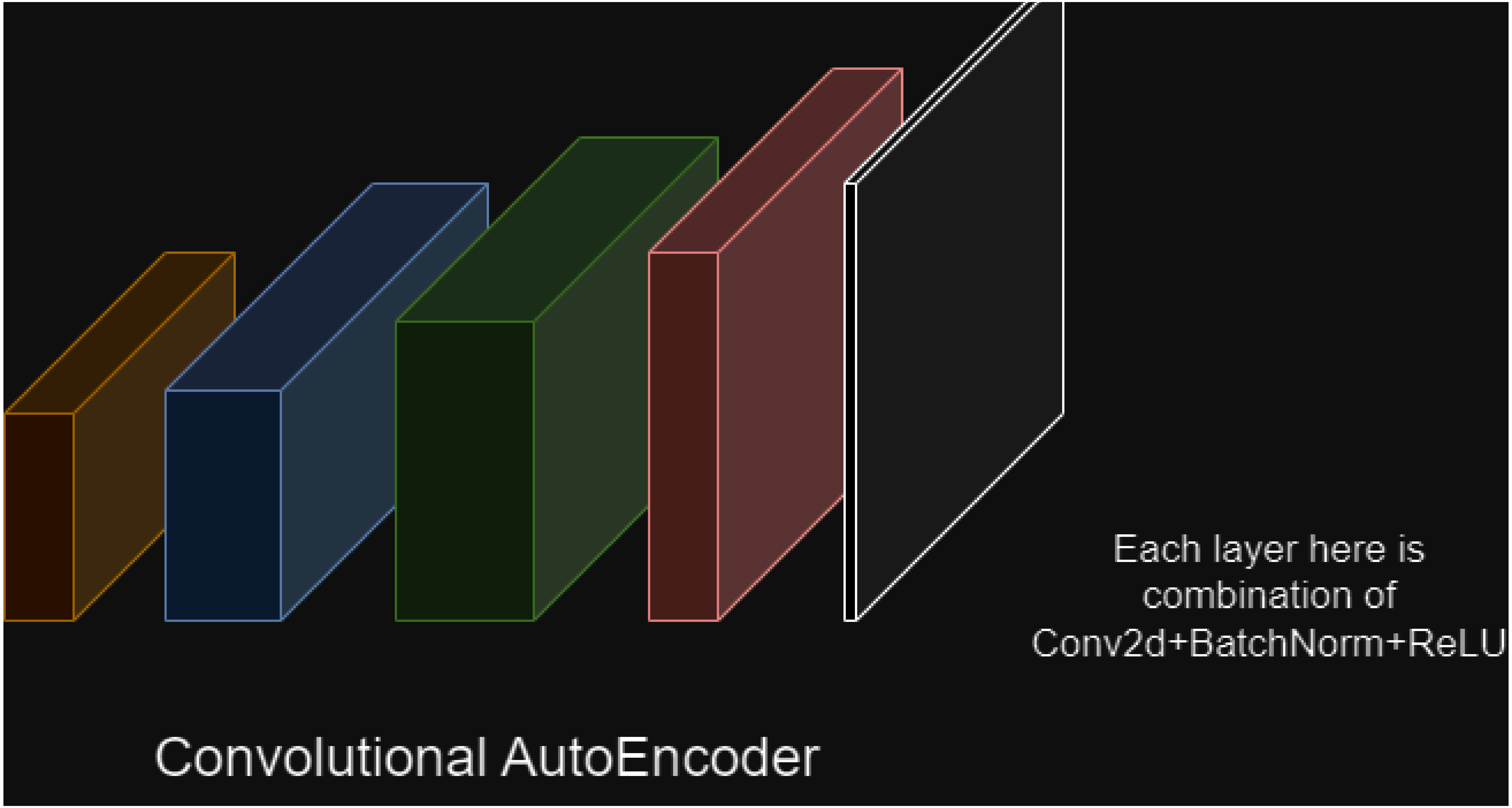
Downloaded the dataset from the MVTechAD

Created the validation data from the given Test data

ENCODER ARCHITECTURE



DECODER ARCHITECTURE



CODE:

```
import os
import torch
import torch.nn as nn
import torch.optim as optim
import torchvision.transforms as transforms
from torchvision.datasets import ImageFolder
from torch.utils.data import DataLoader
from sklearn.metrics import accuracy_score
import numpy as np
import matplotlib.pyplot as plt
from torch.optim.lr_scheduler import StepLR

# Set up device
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')

# Define transformations
transform = transforms.Compose([
    transforms.Resize((64, 64)),
    transforms.ToTensor(),
    transforms.Normalize((0.5,), (0.5,))
])
```

```python
# Load datasets
data_dir = 'data/'
train_dataset = ImageFolder( 'train1', transform=transform)
val_dataset = ImageFolder( 'val', transform=transform)
test_dataset = ImageFolder( 'test', transform=transform)

train_loader = DataLoader(train_dataset, batch_size=1024, shuffle=True)
val_loader = DataLoader(val_dataset, batch_size=1024, shuffle=False)
test_loader = DataLoader(test_dataset, batch_size=1024, shuffle=False)
```

```python
class ConvAutoencoder(nn.Module):
    def __init__(self, color_mode='rgb'):
        super(ConvAutoencoder, self).__init__()
        # Define the number of channels based on the color mode
        channels = 1 if color_mode == 'grayscale' else 3
        # Encoder
        self.encoder = nn.Sequential(
            nn.Conv2d(channels, 32, kernel_size=4, stride=2, padding=1),  # 64x64 -> 32x32
            nn.BatchNorm2d(32),
            #nn.LeakyReLU(0.3, inplace=True),
            nn.ReLU(inplace=True),
            nn.Conv2d(32, 32, kernel_size=4, stride=2, padding=1),        # 32x32 -> 16x16
            nn.BatchNorm2d(32),
            #nn.LeakyReLU(0.3, inplace=True),
            nn.ReLU(inplace=True),
            nn.Conv2d(32, 32, kernel_size=4, stride=2, padding=1),        # 16x16 -> 8x8
            nn.BatchNorm2d(32),
            #nn.LeakyReLU(0.3, inplace=True),
            nn.ReLU(inplace=True),
            nn.Conv2d(32, 32, kernel_size=3, stride=1, padding=1),        # 8x8 -> 8x8
            nn.BatchNorm2d(32),
            #nn.LeakyReLU(0.3, inplace=True),
            nn.ReLU(inplace=True),
            nn.Conv2d(32, 64, kernel_size=4, stride=2, padding=1),        # 8x8 -> 4x4
            nn.BatchNorm2d(64),
            #nn.LeakyReLU(0.3, inplace=True),
            nn.ReLU(inplace=True),
            nn.Conv2d(64, 64, kernel_size=3, stride=1, padding=1),        # 4x4 -> 4x4
            nn.BatchNorm2d(64),
```

```
nn.ReLU(inplace=True),
nn.Conv2d(64, 64, kernel_size=3, stride=1, padding=1),        # 4x4 -> 4x4
nn.BatchNorm2d(64),
#nn.LeakyReLU(0.3, inplace=True),
nn.ReLU(inplace=True),
nn.Conv2d(64, 128, kernel_size=4, stride=2, padding=1),       # 4x4 -> 2x2
nn.BatchNorm2d(128),
#nn.LeakyReLU(0.3, inplace=True),
nn.ReLU(inplace=True),
nn.Conv2d(128, 64, kernel_size=3, stride=1, padding=1),       # 2x2 -> 2x2
nn.BatchNorm2d(64),
#nn.LeakyReLU(0.3, inplace=True),
nn.ReLU(inplace=True),
nn.Conv2d(64, 32, kernel_size=3, stride=1, padding=1),        # 2x2 -> 2x2
nn.BatchNorm2d(32),
#nn.LeakyReLU(0.3, inplace=True),
nn.ReLU(inplace=True),
nn.Conv2d(32, 1, kernel_size=2, stride=1, padding=0)          # 2x2 -> 1x1
```

```python
# Decoder
self.decoder = nn.Sequential(
    nn.ConvTranspose2d(1, 32, kernel_size=4, stride=2, padding=1),    # 1x1 -> 2x2
    nn.BatchNorm2d(32),
    #nn.LeakyReLU(0.3, inplace=True),
    nn.ReLU(inplace=True),
    nn.ConvTranspose2d(32, 64, kernel_size=4, stride=2, padding=1),   # 2x2 -> 4x4
    nn.BatchNorm2d(64),
    #nn.LeakyReLU(0.3, inplace=True),
    nn.ReLU(inplace=True),
    nn.ConvTranspose2d(64, 128, kernel_size=4, stride=2, padding=1),  # 4x4 -> 8x8
    nn.BatchNorm2d(128),
    #nn.LeakyReLU(0.3, inplace=True),
    nn.ReLU(inplace=True),
    nn.ConvTranspose2d(128, 64, kernel_size=4, stride=2, padding=1),  # 8x8 -> 16x16
    nn.BatchNorm2d(64),
    #nn.LeakyReLU(0.3, inplace=True),
    nn.ReLU(inplace=True),
    nn.ConvTranspose2d(64, 32, kernel_size=4, stride=2, padding=1),   # 16x16 -> 32x32
    nn.BatchNorm2d(32),
    #nn.LeakyReLU(0.3, inplace=True),
    nn.ReLU(inplace=True),
    nn.ConvTranspose2d(32, 3, kernel_size=4, stride=2, padding=1),   # 32x32 -> 64x64

    nn.Sigmoid()  # Normalize to [0, 1]
)
```

```python
    def forward(self, x):
        encoded = self.encoder(x)
        decoded = self.decoder(encoded)
        return decoded

# Example of usage
# Create the model
color_mode = 'rgb'  # or 'grayscale'
model = ConvAutoencoder(color_mode).to(device)
# Initialize the CAE2 model
#model = Autoencoder().to(device)
#criterion = nn.MSELoss()
import torch
import torch.nn.functional as F
from pytorch_msssim import ssim, ms_ssim, SSIM, MS_SSIM

# Define a custom loss function combining MSE and SSIM
class CombinedLoss(torch.nn.Module):
    def __init__(self, alpha=0.5):
        super(CombinedLoss, self).__init__()
        self.alpha = alpha  # Weighting factor between MSE and SSIM

    def forward(self, output, target):
        mse_loss = F.mse_loss(output, target)
        ssim_loss = 1 - ssim(output, target, data_range=target.max() - target.min(), size_average=True)
        combined_loss = self.alpha * mse_loss + (1 - self.alpha) * ssim_loss
        return combined_loss
```

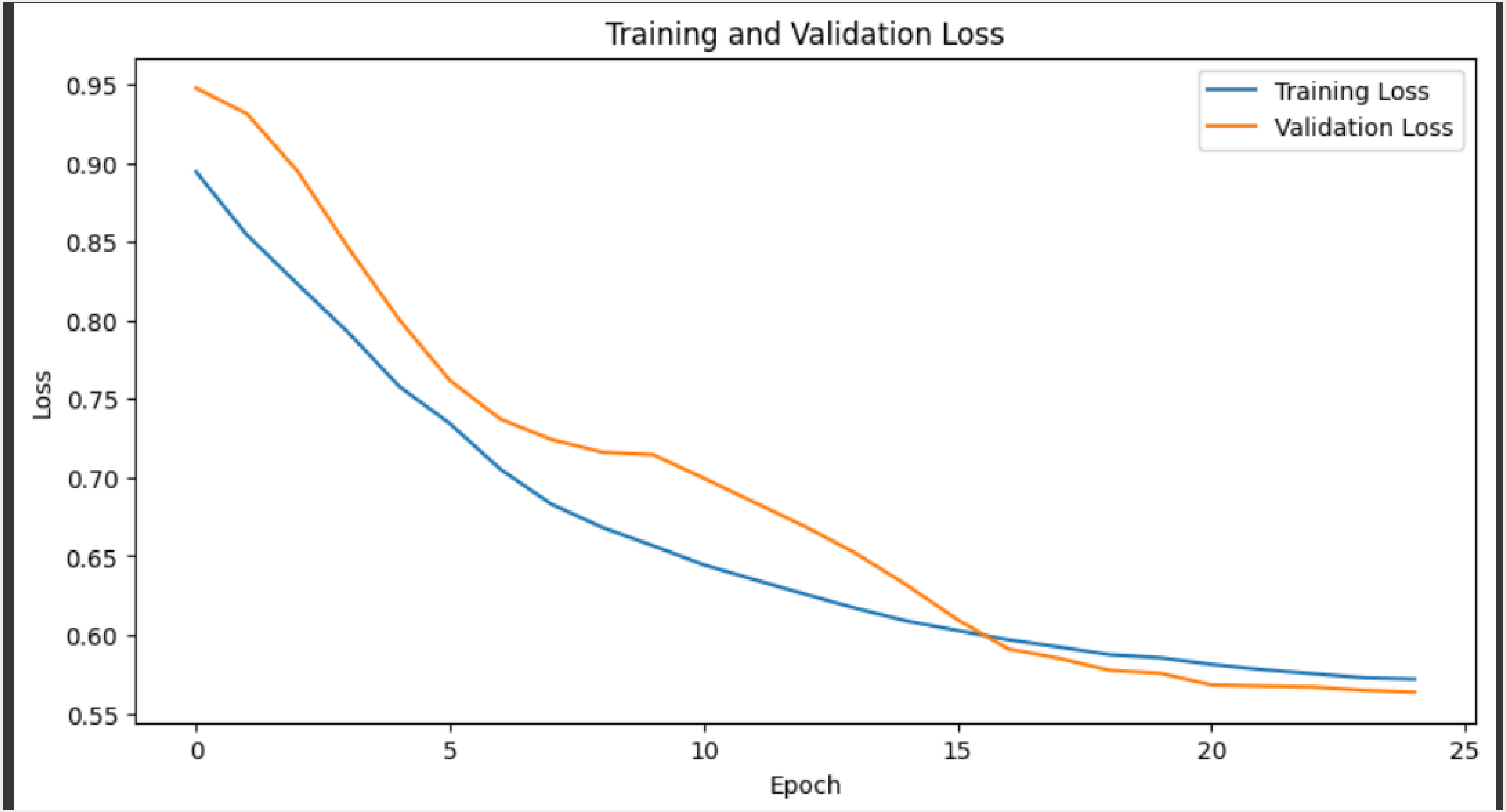
```python
# Usage in your training loop
criterion = CombinedLoss(alpha=0.5)  # You can adjust alpha to balance the losses

optimizer = optim.Adam(model.parameters(), lr=0.001)
#optimizer = optim.SGD(model.parameters(), lr=0.01, momentum=0.9, weight_decay=1e-4)
#scheduler = StepLR(optimizer, step_size=1, gamma=0.1)
# Training the CAE2 model
num_epochs = 25
train_losses = []
val_losses = []

for epoch in range(num_epochs):
    model.train()
    running_train_loss = 0.0
    for images, _ in train_loader:
        images = images.to(device)
        optimizer.zero_grad()
        outputs = model(images)
        loss = criterion(outputs, images)
        loss.backward()
        optimizer.step()
        running_train_loss += loss.item()

    avg_train_loss = running_train_loss / len(train_loader)
    train_losses.append(avg_train_loss)
```

```python
    # Validation Phase
    model.eval()
    running_val_loss = 0.0
    with torch.no_grad():
        for images, _ in val_loader:
            images = images.to(device)
            outputs = model(images)
            loss = criterion(outputs, images)
            running_val_loss += loss.item()

    avg_val_loss = running_val_loss / len(val_loader)
    val_losses.append(avg_val_loss)

    print(f'Epoch [{epoch+1}/{num_epochs}], Train Loss: {avg_train_loss:.4f}, Val Loss: {avg_val_loss:.4f}')

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

```python
# Plot histogram of training reconstruction errors
model.eval()
train_reconstruction_errors = []
with torch.no_grad():
    for images, _ in train_loader:
        images = images.to(device)
        outputs = model(images)
        #mse_loss = nn.functional.mse_loss(outputs, images, reduction='none').mean(dim=[1, 2, 3])
        for i in range(images.size(0)):  # Iterate over each image in the batch
            loss = criterion(outputs[i].unsqueeze(0), images[i].unsqueeze(0))
            train_reconstruction_errors.append(loss.item())
        #train_reconstruction_errors.extend(loss.cpu().numpy())

plt.figure(figsize=(10, 5))
plt.hist(train_reconstruction_errors, bins=50, alpha=0.75, color='green')
plt.xlabel('Reconstruction Error')
plt.ylabel('Frequency')
plt.title('Histogram of Reconstruction Errors on Training Set')
plt.show()
```

```python
# Evaluate the CAE2 model on test set
model.eval()
reconstruction_errors = []
true_labels = []

with torch.no_grad():
    for images, labels in test_loader:
        images = images.to(device)
        outputs = model(images)
        #mse_loss = nn.functional.mse_loss(outputs, images, reduction='none').mean([1, 2, 3])
        # Usage in your training loop
        criterion = CombinedLoss(alpha=0.5)
        for i in range(images.size(0)):  # Iterate over each image in the batch
            loss = criterion(outputs[i].unsqueeze(0), images[i].unsqueeze(0))
            reconstruction_errors.append(loss.item())

        #reconstruction_errors.extend(loss.cpu().numpy())
        true_labels.extend(labels.cpu().numpy())

# Classify test images as good (0) or anomaly (1) based on threshold
predicted_labels = [1 if (0.21<error<0.31) or (0.53<error<0.67) or (0.69<error < 0.76) or (0.78<error<0.81) else 0 for error in reconstruction_errors]

# Calculate accuracy
accuracy = accuracy_score(true_labels, predicted_labels)
print(f'Accuracy: {accuracy:.4f}')
```

```
Accuracy: 0.7710
```


Training and Validation Loss
Training Loss
Validation Loss
Loss
Epoch
0.95
0.90
0.85
0.80
0.75
0.70
0.65
0.60
0.55
0
5
10
15
20
25


Histogram of Reconstruction Errors on Training Set
Frequency
Reconstruction Error
0
50
100
150
200
250
300
350
0.2
0.3
0.4
0.5
0.6
0.7
0.8