

QNN

May 1, 2025

```
[1]: import pandas as pd
df1=pd.read_csv(r"D:\dataset\new_data.csv")
df1
```

```
[1]:
```

	Destination Port	Flow Duration	Total Length of Fwd Packets	\
0	54865	3	12	
1	55054	109	6	
2	55055	52	6	
3	46236	34	6	
4	54863	3	12	
...	
2520793	53	32215	112	
2520794	53	324	84	
2520795	58030	82	31	
2520796	53	1048635	192	
2520797	53	94939	188	

	Total Length of Bwd Packets	Fwd Packet Length Max	\
0	0	6	
1	6	6	
2	6	6	
3	6	6	
4	0	6	
...	
2520793	152	28	
2520794	362	42	
2520795	6	31	
2520796	256	32	
2520797	226	47	

	Fwd Packet Length Min	Fwd Packet Length Mean	\
0	6	6.0	
1	6	6.0	
2	6	6.0	
3	6	6.0	
4	6	6.0	
...	
2520793	28	28.0	

2520794	42	42.0
2520795	0	15.5
2520796	32	32.0
2520797	47	47.0

	Fwd Packet Length Std	Bwd Packet Length Max \
0	0.00000	0
1	0.00000	6
2	0.00000	6
3	0.00000	6
4	0.00000	0
...
2520793	0.00000	76
2520794	0.00000	181
2520795	21.92031	6
2520796	0.00000	128
2520797	0.00000	113

	Bwd Packet Length Min	...	Active Mean	Active Std	Active Max \
0	0	...	0.0	0.0	0
1	6	...	0.0	0.0	0
2	6	...	0.0	0.0	0
3	6	...	0.0	0.0	0
4	0	...	0.0	0.0	0
...
2520793	76	...	0.0	0.0	0
2520794	181	...	0.0	0.0	0
2520795	6	...	0.0	0.0	0
2520796	128	...	0.0	0.0	0
2520797	113	...	0.0	0.0	0

	Active Min	Idle Mean	Idle Std	Idle Max	Idle Min	Label \
0	0	0.0	0.0	0	0	1
1	0	0.0	0.0	0	0	1
2	0	0.0	0.0	0	0	1
3	0	0.0	0.0	0	0	1
4	0	0.0	0.0	0	0	1
...
2520793	0	0.0	0.0	0	0	1
2520794	0	0.0	0.0	0	0	1
2520795	0	0.0	0.0	0	0	1
2520796	0	0.0	0.0	0	0	1
2520797	0	0.0	0.0	0	0	1

	outlier
0	1
1	1

2	1
3	1
4	1
...	...
2520793	1
2520794	1
2520795	1
2520796	1
2520797	1

[2520798 rows x 62 columns]

```
[4]: #df1=df1.drop(columns=['outlier'])
df1
```

```
[4]:
```

	Destination Port	Flow Duration	Total Length of Fwd Packets	\
0	54865	3	12	
1	55054	109	6	
2	55055	52	6	
3	46236	34	6	
4	54863	3	12	
...	
2520793	53	32215	112	
2520794	53	324	84	
2520795	58030	82	31	
2520796	53	1048635	192	
2520797	53	94939	188	

	Total Length of Bwd Packets	Fwd Packet Length Max	\
0	0	6	
1	6	6	
2	6	6	
3	6	6	
4	0	6	
...	
2520793	152	28	
2520794	362	42	
2520795	6	31	
2520796	256	32	
2520797	226	47	

	Fwd Packet Length Min	Fwd Packet Length Mean	\
0	6	6.0	
1	6	6.0	
2	6	6.0	
3	6	6.0	
4	6	6.0	

...
2520793	28	28.0
2520794	42	42.0
2520795	0	15.5
2520796	32	32.0
2520797	47	47.0

	Fwd Packet Length Std	Bwd Packet Length Max \
0	0.00000	0
1	0.00000	6
2	0.00000	6
3	0.00000	6
4	0.00000	0
...
2520793	0.00000	76
2520794	0.00000	181
2520795	21.92031	6
2520796	0.00000	128
2520797	0.00000	113

	Bwd Packet Length Min	...	min_seg_size_forward	Active Mean \
0	0	...	20	0.0
1	6	...	20	0.0
2	6	...	20	0.0
3	6	...	20	0.0
4	0	...	20	0.0
...
2520793	76	...	20	0.0
2520794	181	...	20	0.0
2520795	6	...	32	0.0
2520796	128	...	20	0.0
2520797	113	...	20	0.0

	Active Std	Active Max	Active Min	Idle Mean	Idle Std \
0	0.0	0	0	0.0	0.0
1	0.0	0	0	0.0	0.0
2	0.0	0	0	0.0	0.0
3	0.0	0	0	0.0	0.0
4	0.0	0	0	0.0	0.0
...
2520793	0.0	0	0	0.0	0.0
2520794	0.0	0	0	0.0	0.0
2520795	0.0	0	0	0.0	0.0
2520796	0.0	0	0	0.0	0.0
2520797	0.0	0	0	0.0	0.0

Idle Max	Idle Min	Label
----------	----------	-------

0	0	0	1
1	0	0	1
2	0	0	1
3	0	0	1
4	0	0	1
...
2520793	0	0	1
2520794	0	0	1
2520795	0	0	1
2520796	0	0	1
2520797	0	0	1

[2520798 rows x 61 columns]

```
[5]: X = df1.drop(columns=['Label'])
y = df1['Label']

# Increase range to ensure at least 5647 samples
X = X.iloc[30900:309300]
y = y.iloc[30900:309300]

print(X.shape[0])

sampled_indices = X.sample(n=300, random_state=42).index
X = X.loc[sampled_indices]
y = y.loc[sampled_indices]
X = df1.drop(columns=['Label'])
y = df1['Label']

X = X.iloc[30900:309300]
y = y.iloc[30900:309300]

print("Initial shape:", X.shape[0])

# Sample 13 points
sampled_indices = X.sample(n=300, random_state=42).index
X = X.loc[sampled_indices]
y = y.loc[sampled_indices]

# Get label distribution
print("Label distribution in sampled data:")
print(y.value_counts())
```

278400

Initial shape: 278400

Label distribution in sampled data:

Label

1	182
---	-----

```
-1    118
Name: count, dtype: int64
```

```
[6]: # Sample 300 points
sampled_indices = X.sample(n=300, random_state=42).index
X = X.loc[sampled_indices]
y= y.loc[sampled_indices]

# Convert -1 to 0 for binary classification
Y= y.replace({-1: 0})

# Check label distribution
print("Label distribution in sampled data:")
print(Y.value_counts())
```

```
Label distribution in sampled data:
Label
1    182
0    118
Name: count, dtype: int64
```

```
[7]: from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
import matplotlib.pyplot as plt
import pandas as pd
import numpy as np
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split
from sklearn.decomposition import PCA
scaler = MinMaxScaler(feature_range=(0, np.pi))
X = scaler.fit_transform(X)
# Standardize the features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
pca = PCA(n_components=0.90)
X_pca = pca.fit_transform(X_scaled)

# Number of components selected
n_components_selected = pca.n_components_
print(f"Number of components to retain 90% variance: {n_components_selected}")

# Now let's plot how much variance each component explains

# If you want to see how each component contributes
pca_full = PCA()
pca_full.fit(X)
explained_variance_ratio = pca_full.explained_variance_ratio_
```

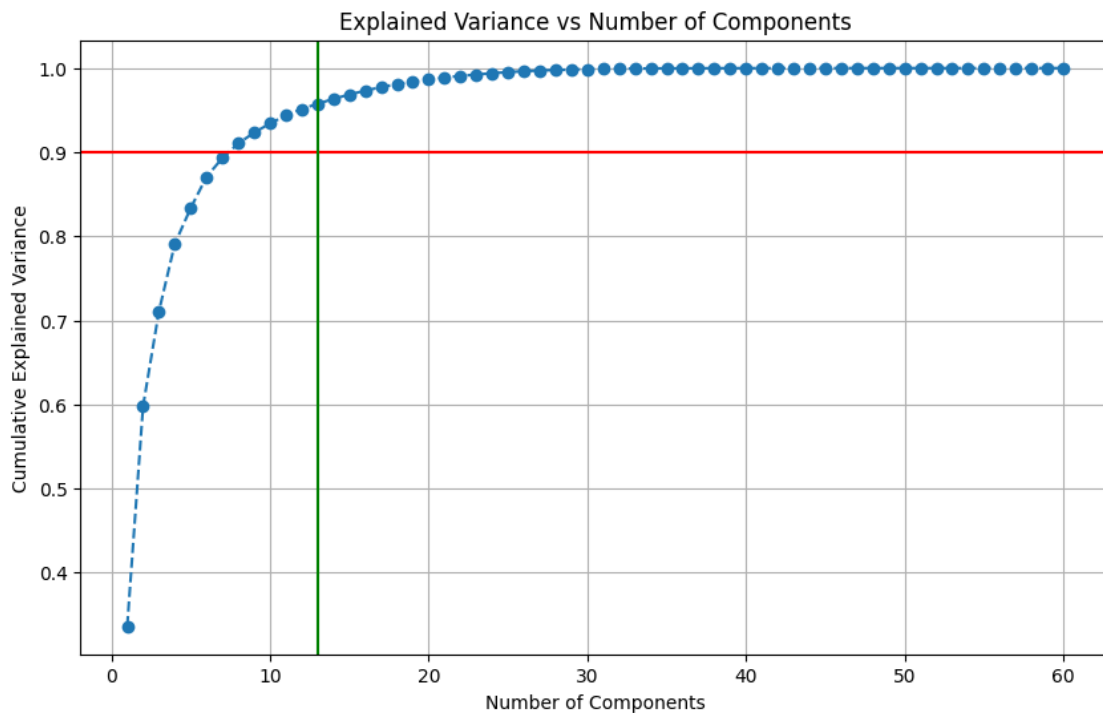
```

# Cumulative variance
cumulative_variance = explained_variance_ratio.cumsum()

# Plot
plt.figure(figsize=(10,6))
plt.plot(range(1, len(cumulative_variance)+1), cumulative_variance, marker='o',
         linestyle='--')
plt.axhline(y=0.90, color='r', linestyle='-')
plt.axvline(x=n_components_selected, color='g', linestyle='-')
plt.title('Explained Variance vs Number of Components')
plt.xlabel('Number of Components')
plt.ylabel('Cumulative Explained Variance')
plt.grid(True)
plt.show()

```

Number of components to retain 90% variance: 13



```

[8]: pca = PCA(n_components=13)
     X_reduced = pca.fit_transform(X_scaled)

```

```

[9]: from qiskit.circuit.library import ZFeatureMap, ZZFeatureMap, PauliFeatureMap

     #from qiskit_algorithms.utils import algorithm_globals
     from qiskit_machine_learning.kernels import FidelityQuantumKernel

```

```

from qiskit_machine_learning.algorithms import PegasosQSVC
from qiskit_machine_learning.algorithms import QSVC
from qiskit.providers import BackendV2 as Backend
from qiskit.transpiler import Target
from qiskit.circuit.library import ZFeatureMap, ZZFeatureMap
# from qiskit_algorithms.utils import algorithm_globals
from qiskit_machine_learning.kernels import FidelityQuantumKernel
from qiskit_machine_learning.algorithms import PegasosQSVC
from qiskit_machine_learning.algorithms import QSVC
from qiskit.primitives import StatevectorSampler, Sampler
from qiskit_machine_learning.state_fidelities import ComputeUncompute
from qiskit_machine_learning.algorithms import QSVC# number of qubits is equal
↳to the number of features
num_qubits = 13
feature_map = ZFeatureMap(feature_dimension=num_qubits, reps=2)
sampler = Sampler()
fidelity = ComputeUncompute(sampler=sampler)
qkernel = FidelityQuantumKernel(fidelity=fidelity, feature_map=feature_map)

```

C:\Users\HP\AppData\Local\Temp\ipykernel_16096\3878349687.py:19:

DeprecationWarning: The class ``qiskit.primitives.sampler.Sampler`` is deprecated as of qiskit 1.2. It will be removed no earlier than 3 months after the release date. All implementations of the `BaseSamplerV1` interface have been deprecated in favor of their V2 counterparts. The V2 alternative for the `Sampler` class is `StatevectorSampler`.

```
sampler = Sampler()
```

C:\Users\HP\AppData\Local\Temp\ipykernel_16096\3878349687.py:20:

DeprecationWarning: V1 Primitives are deprecated as of qiskit-machine-learning 0.8.0 and will be removed no sooner than 4 months after the release date. Use V2 primitives for continued compatibility and support.

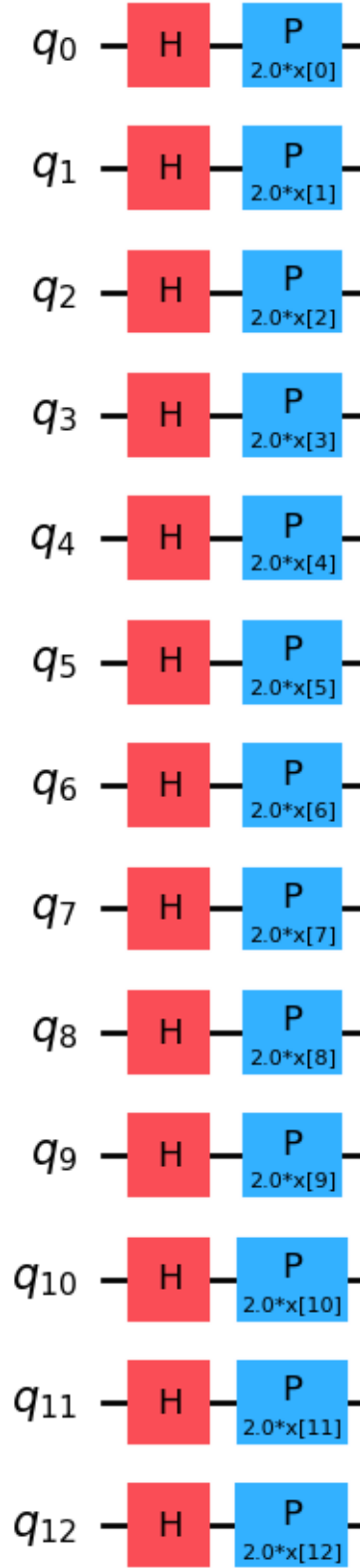
```
fidelity = ComputeUncompute(sampler=sampler)
```

```

[10]: feature_map = ZFeatureMap(feature_dimension=num_qubits, reps=1)
      #Decompose Circuit
      feature_map.decompose().draw('mpl')

```

[10]:



```
[11]: from qiskit_machine_learning.algorithms import QSVC
      from qiskit.providers import BackendV2 as Backend
      from qiskit.transpiler import Target
      from sklearn.model_selection import train_test_split
      from sklearn.metrics import accuracy_score, classification_report
      import pandas as pd
      from qiskit_aer import Aer
      from qiskit.primitives import Sampler

      from qiskit_aer import AerSimulator
      from qiskit_ibm_runtime import QiskitRuntimeService, Sampler, Session
```

```
[13]: backend = AerSimulator()
      # Create sampler with the backend
      from qiskit_ibm_runtime import SamplerV2 as Sampler

      sampler = Sampler(backend)
      # sampler= StatevectorSampler()
```

```
[14]: print("Label counts:", Y.value_counts())
```

```
Label counts: Label
1      182
0      118
Name: count, dtype: int64
```

```
[15]: # Imports (if not done already)
      import torch
      from torch import nn
      from sklearn.model_selection import train_test_split
      from qiskit.circuit.library import ZZFeatureMap, TwoLocal
      from qiskit_machine_learning.neural_networks import EstimatorQNN
      from qiskit_machine_learning.connectors import TorchConnector

      # Assumes: X and y already reduced, scaled, and cleaned
      # Example: X_reduced = PCA(n_components=0.90).fit_transform(StandardScaler().
      ↪ fit_transform(X))

      # Split data
      X_train, X_test, Y_train, Y_test = train_test_split(X_reduced, Y, test_size=0.
      ↪ 2, random_state=42)

      # Convert to PyTorch tensors
      X_train_tensor = torch.tensor(X_train, dtype=torch.float32)
      y_train_tensor = torch.tensor(Y_train.values, dtype=torch.float32)
```

```
[22]: unique_labels, counts = torch.unique(y_train_tensor, return_counts=True)
      for label, count in zip(unique_labels, counts):
          print(f"Label {int(label.item())}: {int(count.item())} samples")
```

Label 0: 95 samples
Label 1: 145 samples

```
[16]: # Define quantum feature map and ansatz
      num_qubits = 13 # e.g., 13 if PCA gives 13 components
      feature_map = ZZFeatureMap(feature_dimension=num_qubits, reps=2)
      ansatz = TwoLocal(num_qubits=num_qubits, rotation_blocks='ry',
          ↪ entanglement_blocks='cz')
```

```
[23]: # Build EstimatorQNN
      from qiskit import QuantumCircuit
      from qiskit.circuit.library import ZZFeatureMap, RealAmplitudes
      from qiskit_machine_learning.circuit.library import QNNCircuit

      from qiskit_machine_learning.neural_networks import EstimatorQNN

      qnn_qc = QNNCircuit(num_qubits)

      qnn = EstimatorQNN(
          circuit=qnn_qc
      )

      qc = QuantumCircuit(num_qubits)
      qc.compose(feature_map, inplace=True)
      qc.compose(ansatz, inplace=True)

      qnn = EstimatorQNN(
          circuit=qc,
          input_params=feature_map.parameters,
          weight_params=ansatz.parameters)
```

C:\Users\HP\AppData\Local\Temp\ipykernel_16096\3226022641.py:10:
DeprecationWarning: V1 Primitives are deprecated as of qiskit-machine-learning 0.8.0 and will be removed no sooner than 4 months after the release date. Use V2 primitives for continued compatibility and support.

```
qnn = EstimatorQNN(
```

C:\Users\HP\AppData\Local\Temp\ipykernel_16096\3226022641.py:18:
DeprecationWarning: V1 Primitives are deprecated as of qiskit-machine-learning 0.8.0 and will be removed no sooner than 4 months after the release date. Use V2 primitives for continued compatibility and support.

```
qnn = EstimatorQNN(
```

```
[24]: # Wrap QNN as PyTorch model
      model = TorchConnector(qnn)
```

```

# Define loss and optimizer
criterion = nn.BCELoss()
optimizer = torch.optim.Adam(model.parameters(), lr=0.01)

# Training loop
epochs = 10
for epoch in range(epochs):
    optimizer.zero_grad()
    output = model(X_train_tensor).squeeze() # ensure shape matches
    loss = criterion(output, y_train_tensor)
    loss.backward()
    optimizer.step()
    print(f"Epoch {epoch+1}/{epochs}, Loss: {loss.item():.4f}")

```

```

-----
RuntimeError                                Traceback (most recent call last)
Cell In[24], line 13
     11 optimizer.zero_grad()
     12 output = model(X_train_tensor).squeeze() # ensure shape matches
--> 13 loss = criterion(output, y_train_tensor)
     14 loss.backward()
     15 optimizer.step()

File c:\Users\HP\.conda\envs\QML\Lib\site-packages\torch\nn\modules\module.py:
  1751, in Module._wrapped_call_impl(self, *args, **kwargs)
    1749     return self._compiled_call_impl(*args, **kwargs) # type: ignore[misc]
    1750 else:
-> 1751     return self._call_impl(*args, **kwargs)

File c:\Users\HP\.conda\envs\QML\Lib\site-packages\torch\nn\modules\module.py:
  1762, in Module._call_impl(self, *args, **kwargs)
    1757 # If we don't have any hooks, we want to skip the rest of the logic in
    1758 # this function, and just call forward.
    1759 if not (self._backward_hooks or self._backward_pre_hooks or self._
  1760         or _global_backward_pre_hooks or _global_backward_hooks
    1761         or _global_forward_hooks or _global_forward_pre_hooks):
-> 1762     return forward_call(*args, **kwargs)
    1764 result = None
    1765 called_always_called_hooks = set()

File c:\Users\HP\.conda\envs\QML\Lib\site-packages\torch\nn\modules\loss.py:699
  698 def forward(self, input: Tensor, target: Tensor) -> Tensor:
--> 699     return F.binary_cross_entropy(

```

```

700         input, target, weight=self.weight, reduction=self.reduction
701     )

```

```

File c:\Users\HP\.conda\envs\QML\Lib\site-packages\torch\nn\functional.py:3569,
in binary_cross_entropy(input, target, weight, size_average, reduce, reduction)
3566     new_size = _infer_size(target.size(), weight.size())
3567     weight = weight.expand(new_size)
-> 3569 return torch._C._nn.binary_cross_entropy(input, target, weight,
reduction_enum)

```

RuntimeError: all elements of input should be between 0 and 1

```

[26]: # Ensure y has only 0s and 1s
Y = y.apply(lambda v: 1 if v == 1 else 0)
Y

```

```

[26]: 205540    1
      217555    1
      243760    1
      117487    0
      287476    1
      ..
      196590    1
      147469    0
      187926    0
      153160    0
      83273     0
      Name: Label, Length: 300, dtype: int64

```

```

[33]: from sklearn.model_selection import train_test_split

X_train, X_test, Y_train, Y_test = train_test_split(X_reduced, Y, test_size=0.2,
random_state=42)

```

```

[38]: import torch

X_train_tensor = torch.tensor(X_train, dtype=torch.float32)
Y_train_tensor = torch.tensor(Y_train.values, dtype=torch.float32)

# If needed, clamp values to [0,1] to eliminate stray floats
Y_train_tensor = torch.clamp(Y_train_tensor, 0.0, 1.0)

# Print unique labels to be sure
print("Unique labels:", torch.unique(Y_train_tensor))

```

Unique labels: tensor([0., 1.])

```
[40]: # Train
```

```
[41]: import torch.nn.functional as F

# Training loop
epochs = 10
for epoch in range(epochs):
    optimizer.zero_grad()

    raw_output = model(X_train_tensor).squeeze()

    # Apply sigmoid to get values in [0, 1]
    output = torch.sigmoid(raw_output)

    # Match target shape
    y_target = Y_train_tensor.view_as(output)

    # Compute loss
    loss = criterion(output, y_target)
    loss.backward()
    optimizer.step()

    print(f"Epoch {epoch+1}/{epochs}, Loss: {loss.item():.4f}")
```

```
Epoch 1/10, Loss: 0.6925
Epoch 2/10, Loss: 0.6924
Epoch 3/10, Loss: 0.6922
Epoch 4/10, Loss: 0.6921
Epoch 5/10, Loss: 0.6919
Epoch 6/10, Loss: 0.6918
Epoch 7/10, Loss: 0.6917
Epoch 8/10, Loss: 0.6915
Epoch 9/10, Loss: 0.6914
Epoch 10/10, Loss: 0.6913
```

```
[42]: # Convert test data to tensors
X_test_tensor = torch.tensor(X_test, dtype=torch.float32)
Y_test_tensor = torch.tensor(Y_test.values, dtype=torch.float32)

# Clamp labels to ensure they are within [0, 1]
Y_test_tensor = torch.clamp(Y_test_tensor, 0.0, 1.0)
```

```
[43]: # Set model to evaluation mode
model.eval()

with torch.no_grad():
    # Forward pass
    raw_preds = model(X_test_tensor).squeeze()
```

```

preds = torch.sigmoid(raw_preds)

# Threshold to get binary predictions
preds_class = (preds >= 0.5).float()

# Match shape with ground truth
y_true = Y_test_tensor.view_as(preds)

```

```

[44]: from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score

accuracy = accuracy_score(y_true, preds_class)
precision = precision_score(y_true, preds_class)
recall = recall_score(y_true, preds_class)
f1 = f1_score(y_true, preds_class)

print(f"Accuracy: {accuracy:.4f}")
print(f"Precision: {precision:.4f}")
print(f"Recall: {recall:.4f}")
print(f"F1-score: {f1:.4f}")

```

```

Accuracy: 0.5167
Precision: 0.6429
Recall: 0.4865
F1-score: 0.5538

```

```

[45]: # Set model to evaluation mode
model.eval()

with torch.no_grad():
    # Training predictions
    raw_train_preds = model(X_train_tensor).squeeze()
    train_preds = torch.sigmoid(raw_train_preds)
    train_preds_class = (train_preds >= 0.5).float()

    y_train_true = Y_train_tensor.view_as(train_preds)

    # Convert to NumPy
    y_train_true_np = y_train_true.numpy()
    train_preds_class_np = train_preds_class.numpy()

    # Compute training accuracy
    from sklearn.metrics import accuracy_score
    train_accuracy = accuracy_score(y_train_true_np, train_preds_class_np)
    print(f"Training Accuracy: {train_accuracy:.4f}")

```

```

Training Accuracy: 0.6458

```

```
[46]: # Test predictions
raw_test_preds = model(X_test_tensor).squeeze()
test_preds = torch.sigmoid(raw_test_preds)
test_preds_class = (test_preds >= 0.5).float()

y_test_true = Y_test_tensor.view_as(test_preds)

# Convert to NumPy
y_test_true_np = y_test_true.numpy()
test_preds_class_np = test_preds_class.numpy()

# Compute test accuracy
test_accuracy = accuracy_score(y_test_true_np, test_preds_class_np)
print(f"Testing Accuracy : {test_accuracy:.4f}")
```

Testing Accuracy : 0.5167

```
[47]: import torch
import torch.nn as nn
import torch.optim as optim
from sklearn.metrics import accuracy_score
import numpy as np

# Define a simplified model with dropout and batch normalization
class Net(nn.Module):
    def __init__(self, input_dim):
        super(Net, self).__init__()
        self.fc1 = nn.Linear(input_dim, 64)
        self.bn1 = nn.BatchNorm1d(64)
        self.dropout1 = nn.Dropout(0.3)
        self.fc2 = nn.Linear(64, 32)
        self.bn2 = nn.BatchNorm1d(32)
        self.dropout2 = nn.Dropout(0.3)
        self.fc3 = nn.Linear(32, 1)

    def forward(self, x):
        x = torch.relu(self.bn1(self.fc1(x)))
        x = self.dropout1(x)
        x = torch.relu(self.bn2(self.fc2(x)))
        x = self.dropout2(x)
        x = self.fc3(x)
        return x

# Tensors from your preprocessed data
X_train_tensor = torch.tensor(X_train, dtype=torch.float32)
Y_train_tensor = torch.tensor(Y_train.values, dtype=torch.float32).view(-1, 1)
X_test_tensor = torch.tensor(X_test, dtype=torch.float32)
Y_test_tensor = torch.tensor(Y_test.values, dtype=torch.float32).view(-1, 1)
```



```

# Initialize model
input_dim = X_train_tensor.shape[1]
model = Net(input_dim)

# Define loss and optimizer (with weight decay for L2 regularization)
criterion = nn.BCEWithLogitsLoss()
optimizer = optim.Adam(model.parameters(), lr=0.001, weight_decay=1e-4) # L2
↳ regularization

# Training loop
epochs = 20
for epoch in range(epochs):
    model.train()
    optimizer.zero_grad()

    output = model(X_train_tensor)
    loss = criterion(output, Y_train_tensor)
    loss.backward()
    optimizer.step()

    print(f"Epoch {epoch+1}/{epochs}, Loss: {loss.item():.4f}")

# Evaluation on training set
model.eval()
with torch.no_grad():
    train_output = torch.sigmoid(model(X_train_tensor)).squeeze()
    train_preds = (train_output >= 0.5).float()
    train_acc = accuracy_score(Y_train_tensor.numpy(), train_preds.numpy())
    print(f"Training Accuracy: {train_acc:.4f}")

# Evaluation on test set
test_output = torch.sigmoid(model(X_test_tensor)).squeeze()
test_preds = (test_output >= 0.5).float()
test_acc = accuracy_score(Y_test_tensor.numpy(), test_preds.numpy())
print(f"Testing Accuracy: {test_acc:.4f}")

```

```

Epoch 1/20, Loss: 0.7985
Epoch 2/20, Loss: 0.7564
Epoch 3/20, Loss: 0.7441
Epoch 4/20, Loss: 0.7032
Epoch 5/20, Loss: 0.6897
Epoch 6/20, Loss: 0.6845
Epoch 7/20, Loss: 0.6519
Epoch 8/20, Loss: 0.6310
Epoch 9/20, Loss: 0.6099
Epoch 10/20, Loss: 0.6118
Epoch 11/20, Loss: 0.5788

```

Epoch 12/20, Loss: 0.5919
 Epoch 13/20, Loss: 0.5679
 Epoch 14/20, Loss: 0.5692
 Epoch 15/20, Loss: 0.5505
 Epoch 16/20, Loss: 0.5260
 Epoch 17/20, Loss: 0.5194
 Epoch 18/20, Loss: 0.5194
 Epoch 19/20, Loss: 0.5040
 Epoch 20/20, Loss: 0.4861
 Training Accuracy: 0.9708
 Testing Accuracy: 0.9333

```
[48]: from sklearn.metrics import classification_report, confusion_matrix

# Ensure model is in evaluation mode
model.eval()

with torch.no_grad():
    # Predictions on test set
    test_output = torch.sigmoid(model(X_test_tensor)).squeeze()
    test_preds = (test_output >= 0.5).float().numpy()
    y_true = Y_test_tensor.numpy()

    # Classification Report
    print("Classification Report:")
    print(classification_report(y_true, test_preds, target_names=["Normal",
↵ "Anomaly"]))

    # Confusion Matrix
    cm = confusion_matrix(y_true, test_preds)
    print("Confusion Matrix:")
    print(cm)
```

Classification Report:

	precision	recall	f1-score	support
Normal	0.85	1.00	0.92	23
Anomaly	1.00	0.89	0.94	37
accuracy			0.93	60
macro avg	0.93	0.95	0.93	60
weighted avg	0.94	0.93	0.93	60

Confusion Matrix:

```
[[23  0]
 [ 4 33]]
```