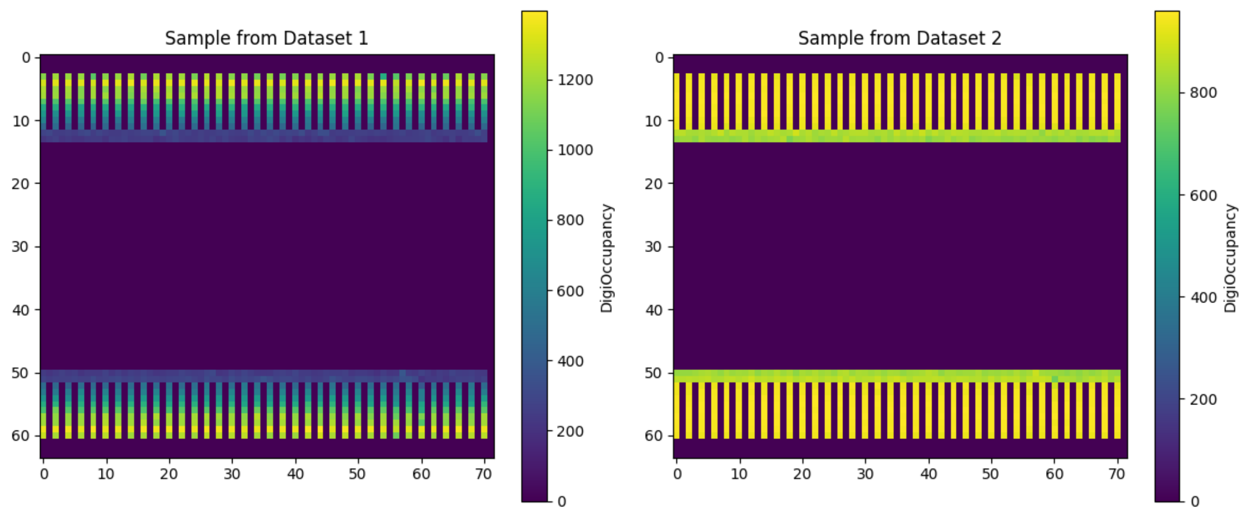
```python
import numpy as np
import matplotlib.pyplot as plt
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers
import tensorflow_addons as tfa
from sklearn.model_selection import train_test_split
from sklearn.metrics import roc_curve, auc, accuracy_score,
confusion_matrix
import os
import requests
from tqdm import tqdm
import seaborn as sns
'''
# Function to download large files with progress bar
def download_file(url, filename):
    if os.path.exists(filename):
        print(f"{filename} already exists, skipping download.")
        return

    response = requests.get(url, stream=True)
    total_size = int(response.headers.get('content-length', 0))
    block_size = 1024

    with open(filename, 'wb') as file, tqdm(
            desc=filename,
            total=total_size,
            unit='iB',
            unit_scale=True,
            unit_divisor=1024,
        ) as bar:
        for data in response.iter_content(block_size):
            size = file.write(data)
            bar.update(size)

# Download datasets
download_file('https://cernbox.cern.ch/s/cDOFb5myDHGqRfc',
'Run355456_Dataset.npy')
download_file('https://cernbox.cern.ch/s/n8NvyK2ldUPUxa9',
'Run357479_Dataset.npy')

print("Dataset download complete (or files already exist).")
'''

D:\ml\ml4sci\ml4sci\Lib\site-packages\tensorflow_addons\utils\
tfa_eol_msg.py:23: UserWarning:

TensorFlow Addons (TFA) has ended development and introduction of new
features.
TFA has entered a minimal maintenance and release mode until a planned
```

```
end of life in May 2024.
Please modify downstream libraries to take dependencies from other
repositories in our TensorFlow community (e.g. Keras, Keras-CV, and
Keras-NLP).

For more information see:
https://github.com/tensorflow/addons/issues/2807

  warnings.warn(

'\n# Function to download large files with progress bar\ndef
download_file(url, filename):\n    if os.path.exists(filename):\n
print(f"{filename} already exists, skipping download.")\n
return\n\n    response = requests.get(url, stream=True)\n
total_size = int(response.headers.get(\'content-length\', 0))\n
block_size = 1024\n\n    with open(filename, \'wb\') as file, tqdm(\n
desc=filename,\n            total=total_size,\n
unit=\'iB\',\n            unit_scale=True,\n
unit_divisor=1024,\n        ) as bar:\n        for data in
response.iter_content(block_size):\n            size =
file.write(data)\n            bar.update(size)\n\n# Download datasets\
ndownload_file(\'https://cernbox.cern.ch/s/cDOFb5myDHGqRfc\', \'Run355
456_Dataset.npy\')\ndownload_file(\'https://cernbox.cern.ch/s/
n8NvyK2ldUPUxa9\', \'Run357479_Dataset.npy\')\n\nprint("Dataset
download complete (or files already exist).")\n'

# Load datasets
dataset_1 = np.load('Run355456_Dataset_jqkne.npy')
dataset_2 = np.load('Run357479_Dataset_iodic.npy')

print(f"Dataset 1 shape: {dataset_1.shape}")
print(f"Dataset 2 shape: {dataset_2.shape}")

# Let's visualize some samples from each dataset
plt.figure(figsize=(12, 5))

plt.subplot(1, 2, 1)
plt.imshow(dataset_1[0], cmap='viridis')
plt.title('Sample from Dataset 1')
plt.colorbar(label='DigiOccupancy')

plt.subplot(1, 2, 2)
plt.imshow(dataset_2[0], cmap='viridis')
plt.title('Sample from Dataset 2')
plt.colorbar(label='DigiOccupancy')

plt.tight_layout()
plt.show()

# Basic statistics
```

```
print(f"Dataset 1 - Min: {dataset_1.min()}, Max: {dataset_1.max()},
Mean: {dataset_1.mean():.4f}, Std: {dataset_1.std():.4f}")
print(f"Dataset 2 - Min: {dataset_2.min()}, Max: {dataset_2.max()},
Mean: {dataset_2.mean():.4f}, Std: {dataset_2.std():.4f}")

# Check for zero values
zero_percentage_1 = (dataset_1 == 0).sum() / dataset_1.size * 100
zero_percentage_2 = (dataset_2 == 0).sum() / dataset_2.size * 100
print(f"Zero values percentage in Dataset 1: {zero_percentage_1:.2f}
%")
print(f"Zero values percentage in Dataset 2: {zero_percentage_2:.2f}
%")

Dataset 1 shape: (10000, 64, 72)
Dataset 2 shape: (10000, 64, 72)
```




```
Dataset 1 - Min: 0.0, Max: 1564.944737802157, Mean: 157.1423, Std:
364.3050
Dataset 2 - Min: 0.0, Max: 1091.9733311864536, Mean: 181.0826, Std:
362.5289
Zero values percentage in Dataset 1: 79.77%
Zero values percentage in Dataset 2: 79.77%

# Create labels for both datasets
labels_1 = np.zeros(dataset_1.shape[0])
labels_2 = np.ones(dataset_2.shape[0])

# Combine datasets and labels
X = np.vstack([dataset_1, dataset_2])
y = np.concatenate([labels_1, labels_2])

# Reshape data for CNN-like input
X = X.reshape(-1, 64, 72, 1)  # (samples, height, width, channels)
```

```python
# Normalize data
X_min = X.min()
X_max = X.max()
X_normalized = (X - X_min) / (X_max - X_min)

# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(
    X_normalized, y, test_size=0.2, random_state=42, stratify=y
)

print(f"Training set: {X_train.shape}, {y_train.shape}")
print(f"Testing set: {X_test.shape}, {y_test.shape}")
```

```
Training set: (16000, 64, 72, 1), (16000,)
Testing set: (4000, 64, 72, 1), (4000,)
```

```python
def create_moe_vit_classifier():
    # Hyperparameters
    input_shape = (64, 72, 1)
    patch_size = 8
    num_patches = (input_shape[0] // patch_size) * (input_shape[1] //
patch_size)
    projection_dim = 64
    transformer_layers = 4
    num_heads = 4
    transformer_units = [
        projection_dim * 2,
        projection_dim,
    ]
    mlp_head_units = [256, 128]
    num_experts = 4

    # Input layer
    inputs = layers.Input(shape=input_shape)

    # Patch extraction
    patches = layers.Conv2D(
        filters=projection_dim,
        kernel_size=(patch_size, patch_size),
        strides=(patch_size, patch_size),
        padding="valid",
    )(inputs)
    patches = layers.Reshape((num_patches, projection_dim))(patches)

    # Patch encoding
    patch_positions = tf.range(start=0, limit=num_patches, delta=1)
    position_embedding = layers.Embedding(
        input_dim=num_patches, output_dim=projection_dim
    )(patch_positions)
    encoded_patches = patches + position_embedding
```

```
    # Function to create a single expert MLP
    def create_expert():
        expert_input = layers.Input(shape=(projection_dim,))
        x = layers.Dense(transformer_units[0], activation=tf.nn.gelu)
(expert_input)
        x = layers.Dense(transformer_units[1])(x)
        model = keras.Model(expert_input, x)
        return model

    # Transformer blocks with MoE
    for _ in range(transformer_layers):
        # Layer normalization 1
        x1 = layers.LayerNormalization(epsilon=1e-6)(encoded_patches)

        # Multi-head attention
        attention_output = layers.MultiHeadAttention(
            num_heads=num_heads, key_dim=projection_dim, dropout=0.1
        )(x1, x1)

        # Skip connection 1
        x2 = layers.Add()([attention_output, encoded_patches])

        # Layer normalization 2
        x3 = layers.LayerNormalization(epsilon=1e-6)(x2)

        # Mixture of Experts layer
        # Create experts
        experts = [create_expert() for _ in range(num_experts)]

        # Router
        router = layers.Dense(num_experts, activation="softmax")

        # Apply MoE
        batch_size = tf.shape(x3)[0]
        sequence_length = tf.shape(x3)[1]
        x3_flat = tf.reshape(x3, [-1, projection_dim])

        # Get routing weights
        routing_weights = router(x3_flat)

        # Initialize expert outputs
        expert_outputs = []
        for expert in experts:
            expert_out = expert(x3_flat)
            expert_outputs.append(expert_out)

        # Stack expert outputs
        stacked_experts = tf.stack(expert_outputs, axis=1)  #
```

```
[batch*seq, num_experts, dim]

        # Weight outputs by router probabilities
        routing_weights = tf.expand_dims(routing_weights, axis=-1)  #
[batch*seq, num_experts, 1]
        weighted_output = tf.reduce_sum(stacked_experts *
routing_weights, axis=1)  # [batch*seq, dim]

        # Reshape back to original shape
        moe_output = tf.reshape(weighted_output, [batch_size,
sequence_length, projection_dim])

        # Skip connection 2
        encoded_patches = layers.Add()([moe_output, x2])

    # Final layer normalization
    representation = layers.LayerNormalization(epsilon=1e-6)
(encoded_patches)

    # Global average pooling
    representation = layers.GlobalAveragePooling1D()(representation)

    # MLP head
    features = mlp(representation, hidden_units=mlp_head_units,
dropout_rate=0.1)

    # Output layer
    logits = layers.Dense(1)(features)
    outputs = layers.Activation('sigmoid')(logits)

    # Create the model
    model = keras.Model(inputs=inputs, outputs=outputs)
    return model


# Create the model
vit_model = create_vit_classifier()

# Compile the model
vit_model.compile(
    optimizer=tf.keras.optimizers.Adam(learning_rate=0.0001),
    loss=tf.keras.losses.BinaryCrossentropy(),
    metrics=[
        tf.keras.metrics.BinaryAccuracy(),
        tf.keras.metrics.AUC(),
    ],
)

# Model summary
vit_model.summary()
```

```
# Set up early stopping and learning rate scheduler
early_stopping = tf.keras.callbacks.EarlyStopping(
    monitor="val_loss", patience=10, restore_best_weights=True
)
reduce_lr = tf.keras.callbacks.ReduceLROnPlateau(
    monitor="val_loss", factor=0.2, patience=5
)

# Train the model
history = vit_model.fit(
    X_train, y_train,
    batch_size=64,
    epochs=5,
    validation_split=0.2,
    callbacks=[early_stopping, reduce_lr],
    verbose=1,
)
```

```
Model: "model_1"
______________________________________________________________________________________________________________
 Layer (type)                   Output Shape         Param #
Connected to
======================================================================
============================
 input_2 (InputLayer)           [(None, 64, 72, 1)]  0           []



 conv2d_1 (Conv2D)              (None, 8, 9, 64)     4160
['input_2[0][0]']


 reshape_1 (Reshape)            (None, 72, 64)       0
['conv2d_1[0][0]']


 tf.__operators__.add_1 (TFOpLa  (None, 72, 64)      0
['reshape_1[0][0]']
 mbda)



 layer_normalization_9 (LayerNo  (None, 72, 64)      128
['tf.__operators__.add_1[0][0]']
 rmalization)
```

```
 multi_head_attention_4 (MultiH  (None, 72, 64)      66368
['layer_normalization_9[0][0]',
 eadAttention)
'layer_normalization_9[0][0]']


 add_8 (Add)                    (None, 72, 64)       0
['multi_head_attention_4[0][0]',

'tf.__operators__.add_1[0][0]']


 layer_normalization_10 (LayerN  (None, 72, 64)      128
['add_8[0][0]']
 ormalization)



 dense_11 (Dense)               (None, 72, 128)      8320
['layer_normalization_10[0][0]']


 dropout_10 (Dropout)           (None, 72, 128)      0
['dense_11[0][0]']


 dense_12 (Dense)               (None, 72, 64)       8256
['dropout_10[0][0]']


 dropout_11 (Dropout)           (None, 72, 64)       0
['dense_12[0][0]']


 add_9 (Add)                    (None, 72, 64)       0
['dropout_11[0][0]',

'add_8[0][0]']


 layer_normalization_11 (LayerN  (None, 72, 64)      128
['add_9[0][0]']
 ormalization)



 multi_head_attention_5 (MultiH  (None, 72, 64)      66368
['layer_normalization_11[0][0]',
 eadAttention)
'layer_normalization_11[0][0]']
```

```
 add_10 (Add)                   (None, 72, 64)       0
['multi_head_attention_5[0][0]',

'add_9[0][0]']


 layer_normalization_12 (LayerN  (None, 72, 64)      128
['add_10[0][0]']
 ormalization)



 dense_13 (Dense)               (None, 72, 128)      8320
['layer_normalization_12[0][0]']


 dropout_12 (Dropout)           (None, 72, 128)      0
['dense_13[0][0]']


 dense_14 (Dense)               (None, 72, 64)       8256
['dropout_12[0][0]']


 dropout_13 (Dropout)           (None, 72, 64)       0
['dense_14[0][0]']


 add_11 (Add)                   (None, 72, 64)       0
['dropout_13[0][0]',

'add_10[0][0]']


 layer_normalization_13 (LayerN  (None, 72, 64)      128
['add_11[0][0]']
 ormalization)



 multi_head_attention_6 (MultiH  (None, 72, 64)      66368
['layer_normalization_13[0][0]',
 eadAttention)
'layer_normalization_13[0][0]']


 add_12 (Add)                   (None, 72, 64)       0
['multi_head_attention_6[0][0]',
```

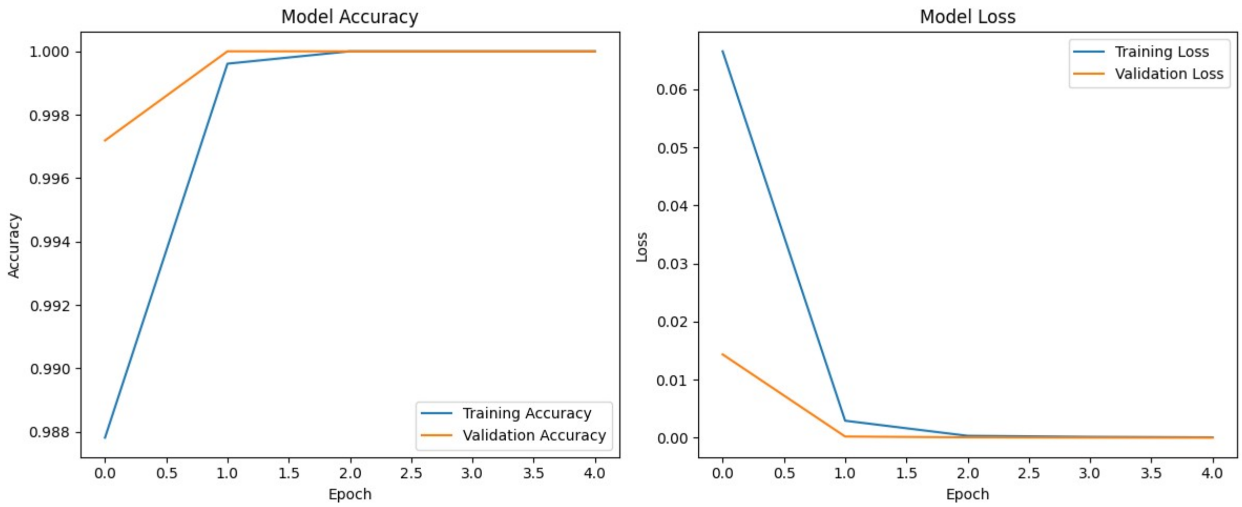
```
'add_11[0][0]']


 layer_normalization_14 (LayerN  (None, 72, 64)      128
['add_12[0][0]']
 ormalization)



 dense_15 (Dense)               (None, 72, 128)      8320
['layer_normalization_14[0][0]']


 dropout_14 (Dropout)           (None, 72, 128)      0
['dense_15[0][0]']


 dense_16 (Dense)               (None, 72, 64)       8256
['dropout_14[0][0]']


 dropout_15 (Dropout)           (None, 72, 64)       0
['dense_16[0][0]']


 add_13 (Add)                   (None, 72, 64)       0
['dropout_15[0][0]',

'add_12[0][0]']


 layer_normalization_15 (LayerN  (None, 72, 64)      128
['add_13[0][0]']
 ormalization)



 multi_head_attention_7 (MultiH  (None, 72, 64)      66368
['layer_normalization_15[0][0]',
 eadAttention)
'layer_normalization_15[0][0]']


 add_14 (Add)                   (None, 72, 64)       0
['multi_head_attention_7[0][0]',

'add_13[0][0]']


 layer_normalization_16 (LayerN  (None, 72, 64)      128
['add_14[0][0]']
```

```
 ormalization)



 dense_17 (Dense)               (None, 72, 128)      8320
['layer_normalization_16[0][0]']


 dropout_16 (Dropout)           (None, 72, 128)      0
['dense_17[0][0]']


 dense_18 (Dense)               (None, 72, 64)       8256
['dropout_16[0][0]']


 dropout_17 (Dropout)           (None, 72, 64)       0
['dense_18[0][0]']


 add_15 (Add)                   (None, 72, 64)       0
['dropout_17[0][0]',

'add_14[0][0]']


 layer_normalization_17 (LayerN  (None, 72, 64)      128
['add_15[0][0]']
 ormalization)



 global_average_pooling1d_1 (Gl  (None, 64)          0
['layer_normalization_17[0][0]']
 obalAveragePooling1D)



 dense_19 (Dense)               (None, 256)          16640
['global_average_pooling1d_1[0][0
                                                                ]']



 dropout_18 (Dropout)           (None, 256)          0
['dense_19[0][0]']


 dense_20 (Dense)               (None, 128)          32896
['dropout_18[0][0]']
```

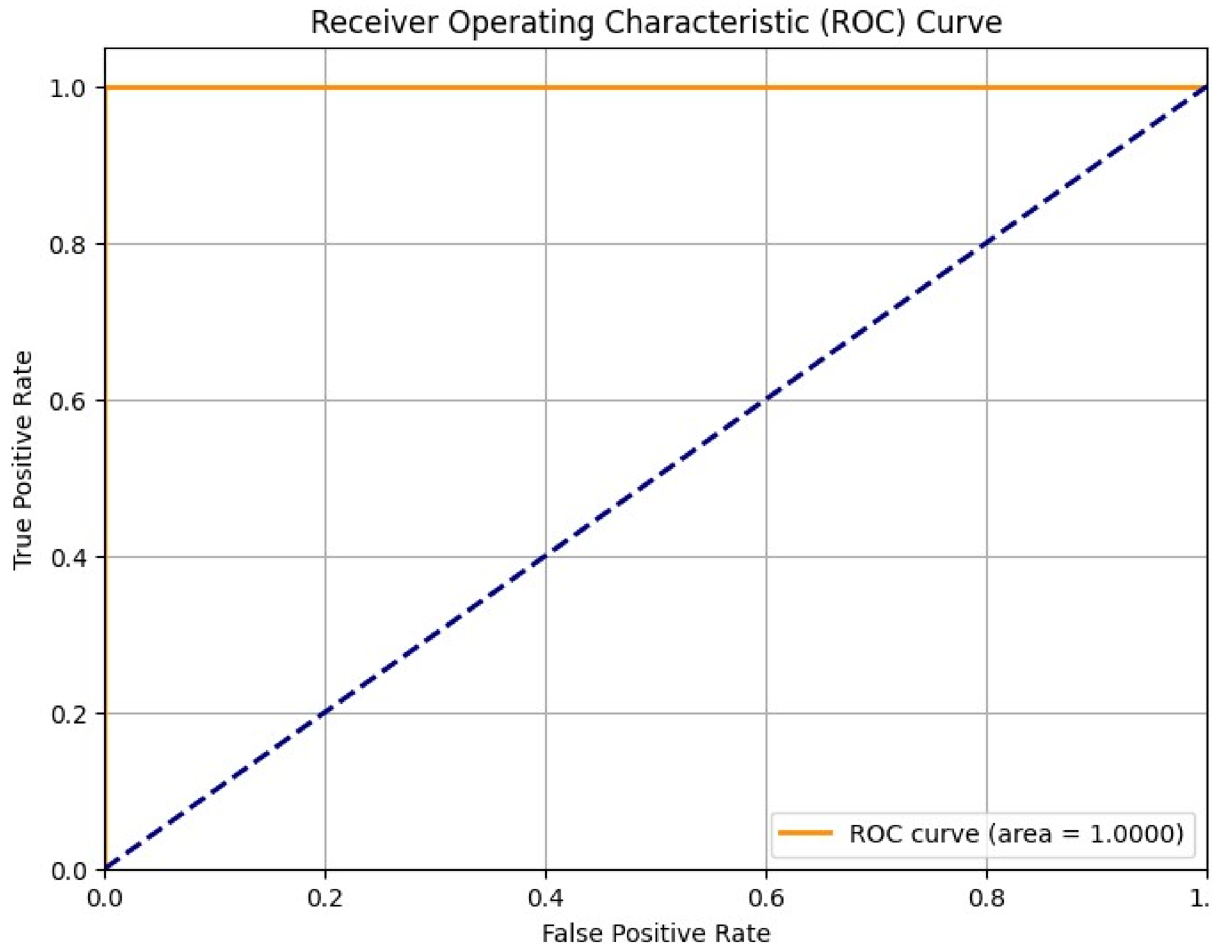
```
 dropout_19 (Dropout)          (None, 128)          0
['dense_20[0][0]']


 dense_21 (Dense)              (None, 1)            129
['dropout_19[0][0]']


 activation_1 (Activation)     (None, 1)            0
['dense_21[0][0]']


======================================================================
============================
Total params: 386,753
Trainable params: 386,753
Non-trainable params: 0
______________________________________________________________________
____________________________
Epoch 1/5
200/200 [==============================] - 146s 623ms/step - loss:
0.0665 - binary_accuracy: 0.9878 - auc_1: 0.9976 - val_loss: 0.0144 -
val_binary_accuracy: 0.9972 - val_auc_1: 0.9994 - lr: 1.0000e-04
Epoch 2/5
200/200 [==============================] - 124s 621ms/step - loss:
0.0029 - binary_accuracy: 0.9996 - auc_1: 1.0000 - val_loss: 2.2139e-
04 - val_binary_accuracy: 1.0000 - val_auc_1: 1.0000 - lr: 1.0000e-04
Epoch 3/5
200/200 [==============================] - 122s 608ms/step - loss:
3.4521e-04 - binary_accuracy: 1.0000 - auc_1: 1.0000 - val_loss:
8.4856e-05 - val_binary_accuracy: 1.0000 - val_auc_1: 1.0000 - lr:
1.0000e-04
Epoch 4/5
200/200 [==============================] - 119s 594ms/step - loss:
1.6692e-04 - binary_accuracy: 1.0000 - auc_1: 1.0000 - val_loss:
3.9495e-05 - val_binary_accuracy: 1.0000 - val_auc_1: 1.0000 - lr:
1.0000e-04
Epoch 5/5
200/200 [==============================] - 122s 609ms/step - loss:
8.3836e-05 - binary_accuracy: 1.0000 - auc_1: 1.0000 - val_loss:
2.4012e-05 - val_binary_accuracy: 1.0000 - val_auc_1: 1.0000 - lr:
1.0000e-04

# Plot training history
plt.figure(figsize=(12, 5))

plt.subplot(1, 2, 1)
plt.plot(history.history['binary_accuracy'], label='Training
Accuracy')
```

```
plt.plot(history.history['val_binary_accuracy'], label='Validation
Accuracy')
plt.title('Model Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()

plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title('Model Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()

plt.tight_layout()
plt.show()

# Evaluate the model on the test set
test_loss, test_accuracy, test_auc = vit_model.evaluate(X_test,
y_test)
print(f"Test Loss: {test_loss:.4f}")
print(f"Test Accuracy: {test_accuracy:.4f}")
print(f"Test AUC: {test_auc:.4f}")

# Generate predictions for ROC curve
y_pred_prob = vit_model.predict(X_test).ravel()
fpr, tpr, thresholds = roc_curve(y_test, y_pred_prob)
roc_auc = auc(fpr, tpr)

# Plot ROC curve
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve (area =
{roc_auc:.4f})')
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc="lower right")
plt.grid(True)
plt.show()

# Convert probabilities to binary predictions using 0.5 threshold
y_pred = (y_pred_prob >= 0.5).astype(int)
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy with threshold 0.5: {accuracy:.4f}")

# Confusion matrix visualization
```

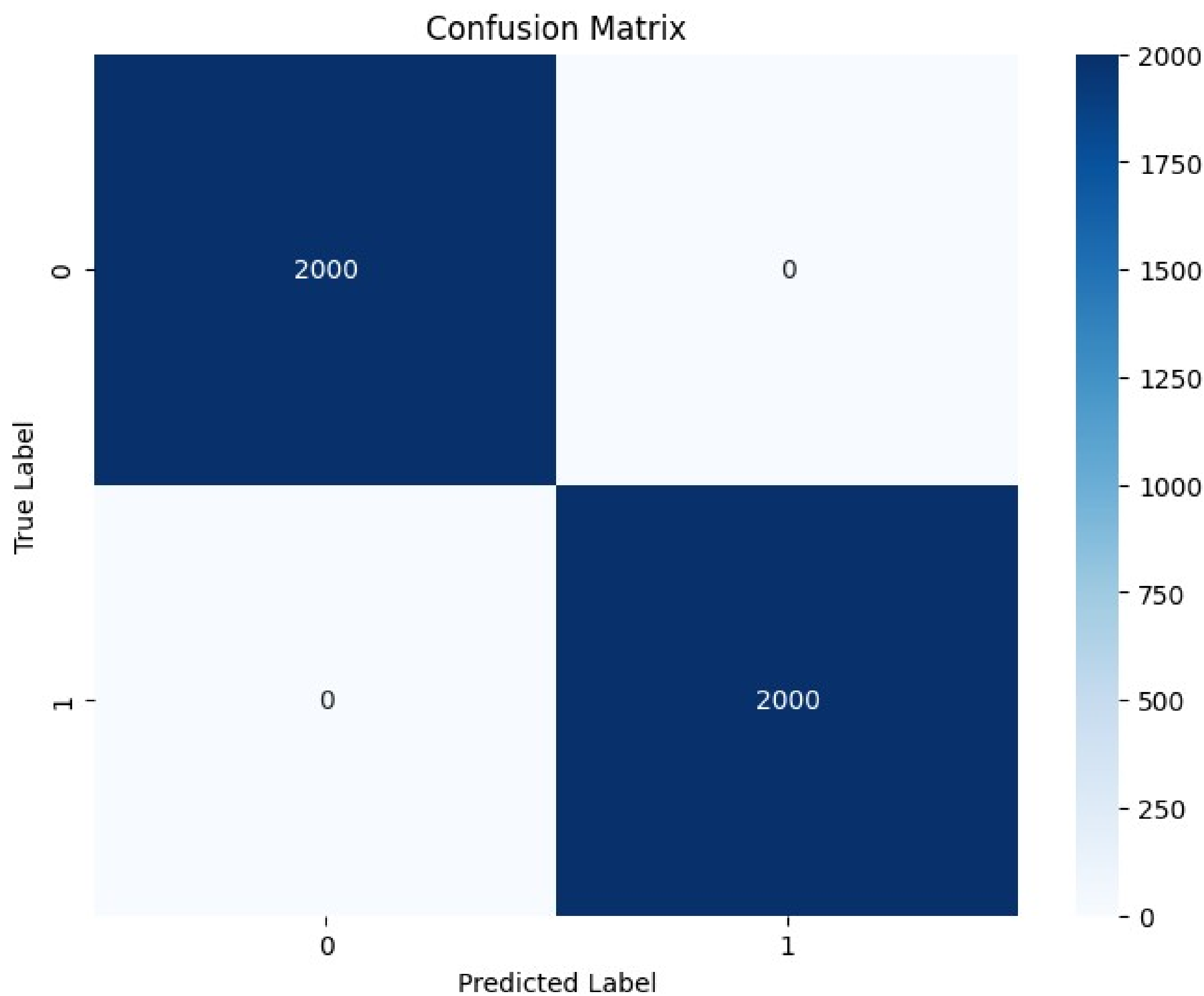
```python
cm = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.title('Confusion Matrix')
plt.ylabel('True Label')
plt.xlabel('Predicted Label')
plt.show()
```




```
125/125 [==============================] - 15s 105ms/step - loss:
2.3719e-05 - binary_accuracy: 1.0000 - auc_1: 1.0000
Test Loss: 0.0000
Test Accuracy: 1.0000
Test AUC: 1.0000
125/125 [==============================] - 15s 111ms/step
```




```
Accuracy with threshold 0.5: 1.0000
```




```
# Save the model
vit_model.save('vit_hcal_classifier.h5')
print("Model saved to 'vit_hcal_classifier.h5'")

# Save the model architecture and weights separately if needed
vit_model.save_weights('vit_hcal_weights.h5')
with open('vit_hcal_architecture.json', 'w') as f:
    f.write(vit_model.to_json())
print("Model architecture and weights saved separately")
```

```
Model saved to 'vit_hcal_classifier.h5'
Model architecture and weights saved separately
```

```
# Final report section
print("="*50)
print("Model Architecture and Hyperparameters:")
print("="*50)
print("- Used a Vision Transformer (ViT) architecture")
print("- Patch size: 8x8")
```

```python
print("- Projection dimension: 64")
print("- Number of transformer layers: 4")
print("- Number of attention heads: 4")
print("- MLP units in transformer blocks: [128, 64]")
print("- MLP head units: [256, 128]")
print("- Dropout rate: 0.1")
print("- Learning rate: 0.0001 with ReduceLROnPlateau scheduler")

print("\n")
print("="*50)
print("Data Preprocessing Steps:")
print("="*50)
print("1. Loaded two datasets (shape: 10000, 64, 72)")
print("2. Reshaped data to include channel dimension (shape: samples,
64, 72, 1)")
print("3. Normalized data between 0 and 1")
print("4. Split data into 80% training and 20% testing")
print("5. Further split training data into 80% training and 20%
validation")

print("\n")
print("="*50)
print("Model Performance:")
print("="*50)
print(f"Test Accuracy: {test_accuracy:.4f}")
print(f"Test AUC: {test_auc:.4f}")
print(f"ROC AUC: {roc_auc:.4f}")
```

```
==================================================
Model Architecture and Hyperparameters:
==================================================
- Used a Vision Transformer (ViT) architecture
- Patch size: 8x8
- Projection dimension: 64
- Number of transformer layers: 4
- Number of attention heads: 4
- MLP units in transformer blocks: [128, 64]
- MLP head units: [256, 128]
- Dropout rate: 0.1
- Learning rate: 0.0001 with ReduceLROnPlateau scheduler


==================================================
Data Preprocessing Steps:
==================================================
1. Loaded two datasets (shape: 10000, 64, 72)
2. Reshaped data to include channel dimension (shape: samples, 64, 72,
1)
3. Normalized data between 0 and 1
4. Split data into 80% training and 20% testing
```

```
5. Further split training data into 80% training and 20% validation


==================================================
Model Performance:
==================================================
Test Accuracy: 1.0000
Test AUC: 1.0000
ROC AUC: 1.0000
```