```
import pandas as pd
import numpy as np
import os
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from tensorflow.keras.models import Sequential
from tensorflow.keras.utils import to_categorical
from sklearn.metrics import classification_report, confusion_matrix
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.utils import resample
from sklearn.metrics import classification_report, confusion_matrix
import tensorflow as tf
from tensorflow.keras.layers import Conv1D, MaxPool1D, Flatten, Dense, Dropout, BatchNormalization, Input
from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint

import warnings
warnings.filterwarnings('ignore')
```

```
import kagglehub
path = kagglehub.dataset_download('shayanfazeli/heartbeat')

print(path)
```

```
Using Colab cache for faster access to the 'heartbeat' dataset.
/kaggle/input/heartbeat
```

Load Data

```
import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))
```

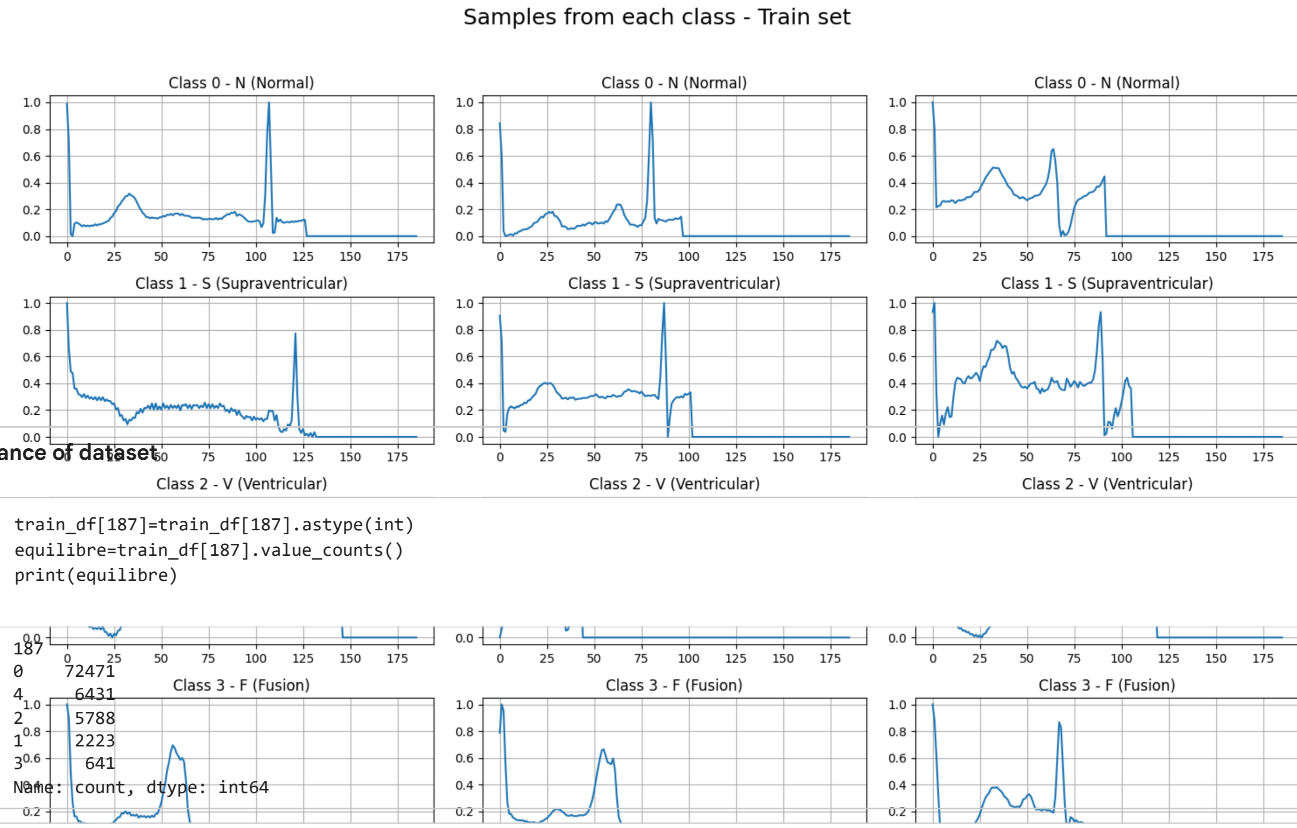
```
/kaggle/input/heartbeat/ptbdb_abnormal.csv
/kaggle/input/heartbeat/ptbdb_normal.csv
/kaggle/input/heartbeat/mitbih_test.csv
/kaggle/input/heartbeat/mitbih_train.csv
```

```
train_df=pd.read_csv('/kaggle/input/heartbeat/mitbih_train.csv',header=None)
test_df=pd.read_csv('/kaggle/input/heartbeat/mitbih_test.csv',header=None)

print(f"Train shape: {train_df.shape}")
print(f"Test shape: {test_df.shape}")
```

```
Train shape: (87554, 188)
Test shape: (21892, 188)
```

```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np



def show_samples_per_class(df, title, samples_per_class=3):
    fig, axes = plt.subplots(5, samples_per_class, figsize=(samples_per_class*5, 12))
    fig.suptitle(title, fontsize=18, y=1.02)

    class_names = ["N (Normal)", "S (Supraventricular)", "V (Ventricular)", "F (Fusion)", "Q (Unknown)"]

    for cls in range(5):
        cls_samples = df[df[187] == cls].sample(n=samples_per_class, random_state=cls)

        for i in range(samples_per_class):
            signal = cls_samples.iloc[i, :186].values
            axes[cls, i].plot(signal)
            axes[cls, i].set_title(f'Class {cls} - {class_names[cls]}')
            axes[cls, i].grid(True)

    plt.tight_layout()
```

```
    plt.show()

show_samples_per_class(train_df, "Samples from each class - Train set", samples_per_class=3)
show_samples_per_class(test_df,  "Samples from each class - Test set",  samples_per_class=3)
```

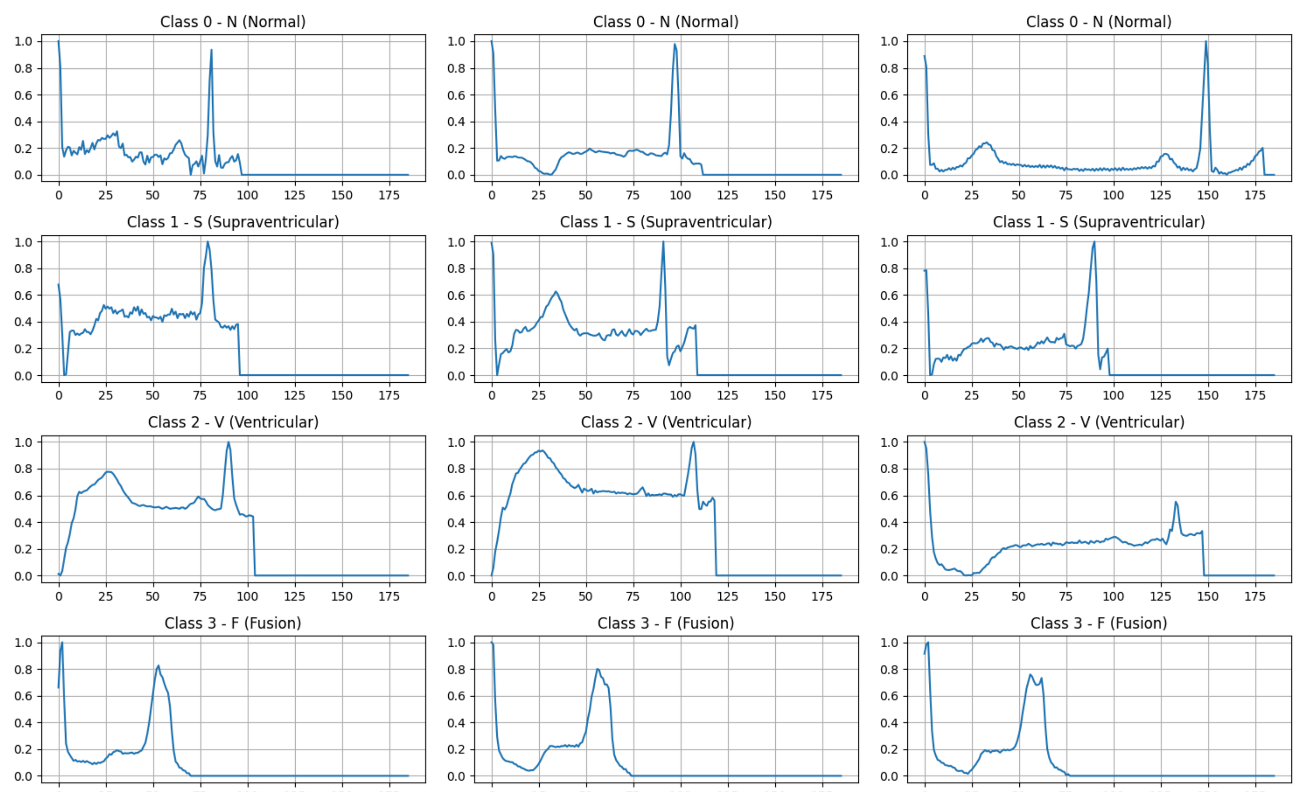


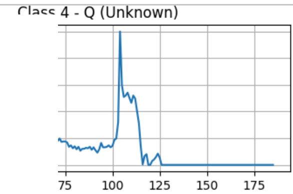
Balance of dataset

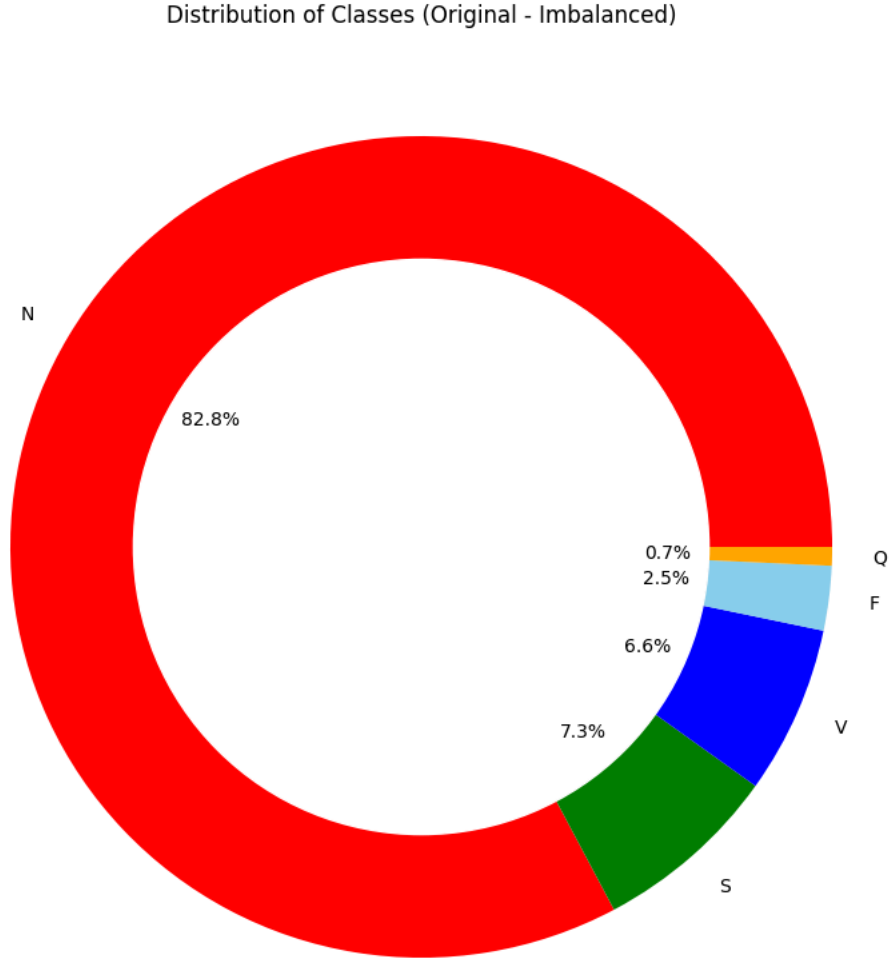
```
train_df[187]=train_df[187].astype(int)
equilibre=train_df[187].value_counts()
print(equilibre)
```

```
187
0    72471
4     6431
2     5788
1     2223
3      641
Name: count, dtype: int64
```

```
equilibre = train_df[187].value_counts()

plt.figure(figsize=(10,10))
my_circle = plt.Circle((0,0), 0.7, color='white')
plt.pie(equilibre, labels=['N','S','V','F','Q'],
        colors=['red','green','blue','skyblue','orange'], autopct='%1.1f%%')
p = plt.gcf()
p.gca().add_artist(my_circle)
plt.title("Distribution of Classes (Original - Imbalanced)")
plt.show()
```








```
train_set, val_set = train_test_split(train_df, test_size=0.2, random_state=42, stratify=train_df[187])

df_0 = train_set[train_set[187] == 0]
df_1 = train_set[train_set[187] == 1]
df_2 = train_set[train_set[187] == 2]
df_3 = train_set[train_set[187] == 3]
df_4 = train_set[train_set[187] == 4]

n_samples = len(df_0)

df_1_upsampled = resample(df_1, replace=True, n_samples=n_samples, random_state=42)
df_2_upsampled = resample(df_2, replace=True, n_samples=n_samples, random_state=42)
df_3_upsampled = resample(df_3, replace=True, n_samples=n_samples, random_state=42)
df_4_upsampled = resample(df_4, replace=True, n_samples=n_samples, random_state=42)

train_balanced = pd.concat([df_0, df_1_upsampled, df_2_upsampled, df_3_upsampled, df_4_upsampled])

print("Data processing complete.")
print(f"Original Train size: {len(train_set)}")
print(f"Balanced Train size: {len(train_balanced)}")
print(f"Validation size (Untouched): {len(val_set)}")
```

```
Data processing complete.
Original Train size: 70043
Balanced Train size: 289885
Validation size (Untouched): 17511
```

```
def preprocess_input(df):
    X = df.iloc[:, :-1].values
    y = df.iloc[:, -1].values

    X = X.reshape(X.shape[0], X.shape[1], 1)
```

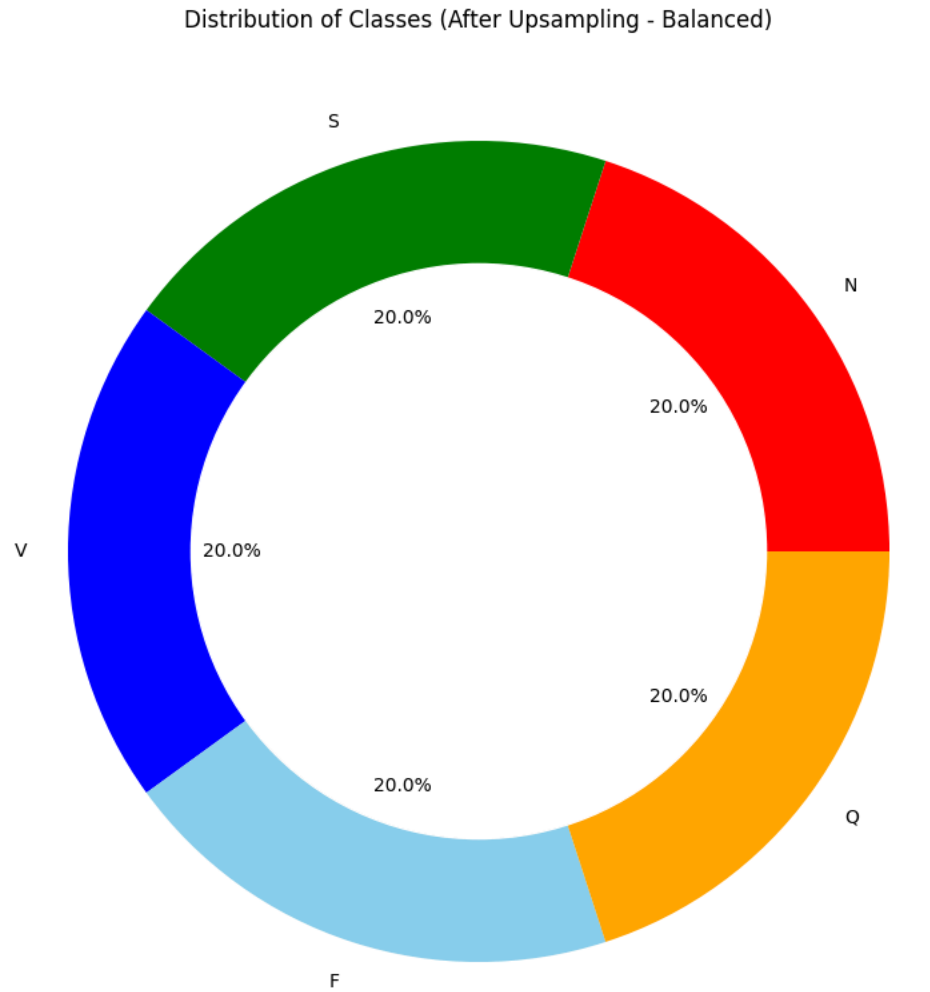
```
    y = to_categorical(y)
    return X, y

X_train, y_train = preprocess_input(train_balanced)
X_val, y_val = preprocess_input(val_set)
X_test, y_test = preprocess_input(test_df)

print(f"X_train shape: {X_train.shape}")
print(f"X_val shape: {X_val.shape}")
print(f"X_test shape: {X_test.shape}")
```

```
X_train shape: (289885, 187, 1)
X_val shape: (17511, 187, 1)
X_test shape: (21892, 187, 1)
```

```
equilibre=train_df[187].value_counts()
print(equilibre)
```

```
187
0    72471
4     6431
2     5788
1     2223
3      641
Name: count, dtype: int64
```

```
equilibre_balanced = train_balanced[187].value_counts()

plt.figure(figsize=(10,10))
my_circle = plt.Circle((0,0), 0.7, color='white')
plt.pie(equilibre_balanced, labels=['N','S','V','F','Q'],
        colors=['red','green','blue','skyblue','orange'], autopct='%1.1f%%')
p = plt.gcf()
p.gca().add_artist(my_circle)
plt.title("Distribution of Classes (After Upsampling - Balanced)")
plt.show()
```




```
def create_model(input_shape):
    model = Sequential([
        Input(shape=input_shape),

        Conv1D(64, 6, activation='relu'),
        BatchNormalization(),
        MaxPool1D(pool_size=3, strides=2, padding="same"),

        Conv1D(64, 3, activation='relu'),
        BatchNormalization(),
        MaxPool1D(pool_size=2, strides=2, padding="same"),

        Conv1D(64, 3, activation='relu'),
        BatchNormalization(),
        MaxPool1D(pool_size=2, strides=2, padding="same"),

        Flatten(),
        Dense(64, activation='relu'),
        Dense(32, activation='relu'),

        Dense(5, activation='softmax')
    ])

    model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
    return model

model = create_model(input_shape=(X_train.shape[1], 1))
model.summary()
```

Model: "sequential_1"

Layer (type)	Output Shape	Param #
conv1d_3 (Conv1D)	(None, 182, 64)	448
batch_normalization_3 (BatchNormalization)	(None, 182, 64)	256
max_pooling1d_3 (MaxPooling1D)	(None, 91, 64)	0
conv1d_4 (Conv1D)	(None, 89, 64)	12,352
batch_normalization_4 (BatchNormalization)	(None, 89, 64)	256
max_pooling1d_4 (MaxPooling1D)	(None, 45, 64)	0
conv1d_5 (Conv1D)	(None, 43, 64)	12,352
batch_normalization_5 (BatchNormalization)	(None, 43, 64)	256
max_pooling1d_5 (MaxPooling1D)	(None, 22, 64)	0
flatten_1 (Flatten)	(None, 1408)	0
dense_3 (Dense)	(None, 64)	90,176
dense_4 (Dense)	(None, 32)	2,080
dense_5 (Dense)	(None, 5)	165

Total params: 118,341 (462.27 KB)

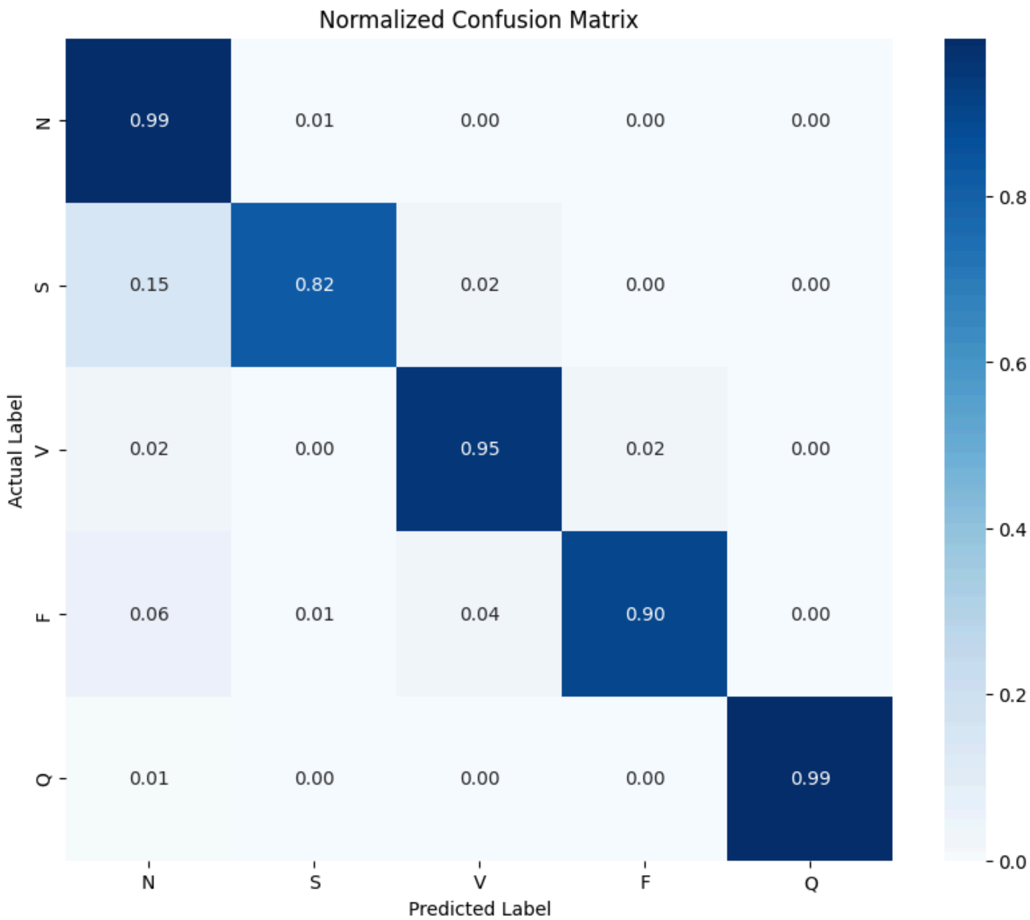
```
callbacks = [
    EarlyStopping(monitor='val_loss', patience=8, verbose=1, restore_best_weights=True),
    ModelCheckpoint('best_model.keras', monitor='val_loss', save_best_only=True, verbose=1)
]

history = model.fit(
    X_train, y_train,
    epochs=50,
    batch_size=32,
    validation_data=(X_val, y_val),
    callbacks=callbacks
)
```

```
Epoch 1/50
9059/9059 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - accuracy: 0.9335 - loss: 0.1880
Epoch 1: val_loss improved from inf to 0.17039, saving model to best_model.keras
9059/9059 ━━━━━━━━━━━━━━━━━━━━ 45s 4ms/step - accuracy: 0.9335 - loss: 0.1880 - val_accuracy: 0.9472 - val_loss: 0.1704
Epoch 2/50
9046/9059 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - accuracy: 0.9884 - loss: 0.0368
Epoch 2: val_loss improved from 0.17039 to 0.09379, saving model to best_model.keras
9059/9059 ━━━━━━━━━━━━━━━━━━━━ 36s 4ms/step - accuracy: 0.9884 - loss: 0.0368 - val_accuracy: 0.9788 - val_loss: 0.0938
Epoch 3/50
9047/9059 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - accuracy: 0.9936 - loss: 0.0211
Epoch 3: val_loss did not improve from 0.09379
9059/9059 ━━━━━━━━━━━━━━━━━━━━ 36s 4ms/step - accuracy: 0.9936 - loss: 0.0211 - val_accuracy: 0.9770 - val_loss: 0.1068
Epoch 4/50
9048/9059 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - accuracy: 0.9956 - loss: 0.0148
Epoch 4: val_loss did not improve from 0.09379
9059/9059 ━━━━━━━━━━━━━━━━━━━━ 36s 4ms/step - accuracy: 0.9956 - loss: 0.0148 - val_accuracy: 0.9778 - val_loss: 0.1279
Epoch 5/50
9058/9059 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - accuracy: 0.9964 - loss: 0.0125
Epoch 5: val_loss did not improve from 0.09379
9059/9059 ━━━━━━━━━━━━━━━━━━━━ 41s 4ms/step - accuracy: 0.9964 - loss: 0.0125 - val_accuracy: 0.9750 - val_loss: 0.1433
Epoch 6/50
9055/9059 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - accuracy: 0.9973 - loss: 0.0094
Epoch 6: val_loss did not improve from 0.09379
9059/9059 ━━━━━━━━━━━━━━━━━━━━ 36s 4ms/step - accuracy: 0.9973 - loss: 0.0094 - val_accuracy: 0.9829 - val_loss: 0.1137
Epoch 7/50
9055/9059 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - accuracy: 0.9978 - loss: 0.0081
Epoch 7: val_loss did not improve from 0.09379
9059/9059 ━━━━━━━━━━━━━━━━━━━━ 36s 4ms/step - accuracy: 0.9978 - loss: 0.0081 - val_accuracy: 0.9796 - val_loss: 0.1227
Epoch 8/50
9054/9059 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - accuracy: 0.9980 - loss: 0.0071
Epoch 8: val_loss did not improve from 0.09379
9059/9059 ━━━━━━━━━━━━━━━━━━━━ 37s 4ms/step - accuracy: 0.9980 - loss: 0.0071 - val_accuracy: 0.9840 - val_loss: 0.1164
Epoch 9/50
9049/9059 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - accuracy: 0.9981 - loss: 0.0063
Epoch 9: val_loss did not improve from 0.09379
```

```
9059/9059 ━━━━━━━━━━━━━━━━━━━━ 36s 4ms/step - accuracy: 0.9981 - loss: 0.0063 - val_accuracy: 0.9823 - val_loss: 0.1412
Epoch 10/50
9055/9059 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - accuracy: 0.9982 - loss: 0.0064
Epoch 10: val_loss did not improve from 0.09379
9059/9059 ━━━━━━━━━━━━━━━━━━━━ 36s 4ms/step - accuracy: 0.9982 - loss: 0.0064 - val_accuracy: 0.9853 - val_loss: 0.1255
Epoch 10: early stopping
Restoring model weights from the end of the best epoch: 2.
```

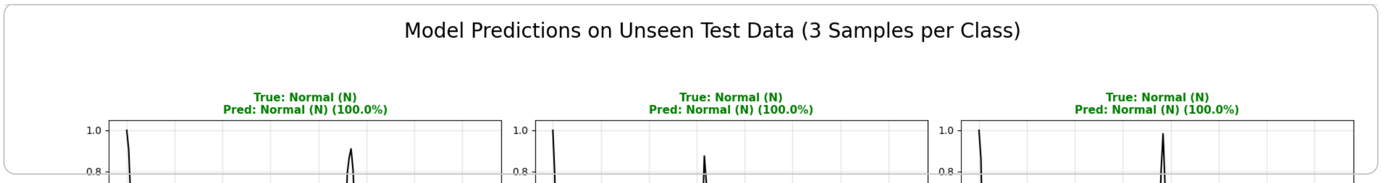
```
loss, accuracy = model.evaluate(X_test, y_test)
print(f"Test Accuracy: {accuracy * 100:.2f}%")

y_pred = model.predict(X_test)
y_pred_classes = np.argmax(y_pred, axis=1)
y_true = np.argmax(y_test, axis=1)

print("\nClassification Report:")
print(classification_report(y_true, y_pred_classes, target_names=['Normal (N)', 'Supraventricular (S)', 'Ventricular (V)', 'Fus

plt.figure(figsize=(10, 8))
cm = confusion_matrix(y_true, y_pred_classes)
cm_normalized = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]

sns.heatmap(cm_normalized, annot=True, fmt='.2f', cmap='Blues',
            xticklabels=['N', 'S', 'V', 'F', 'Q'],
            yticklabels=['N', 'S', 'V', 'F', 'Q'])
plt.title('Normalized Confusion Matrix')
plt.ylabel('Actual Label')
plt.xlabel('Predicted Label')
plt.show()
```

```
685/685 ━━━━━━━━━━━━━━━━━━━━ 2s 3ms/step - accuracy: 0.9847 - loss: 0.0541
Test Accuracy: 97.94%
685/685 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step

Classification Report:
                      precision    recall  f1-score   support

          Normal (N)       0.99      0.99      0.99     18118
Supraventricular (S)       0.83      0.82      0.83       556
     Ventricular (V)       0.94      0.95      0.94      1448
          Fusion (F)       0.59      0.90      0.71       162
         Unknown (Q)       0.99      0.99      0.99      1608

            accuracy                           0.98     21892
           macro avg       0.87      0.93      0.89     21892
        weighted avg       0.98      0.98      0.98     21892
```




```python
import matplotlib.pyplot as plt
import numpy as np

class_map = {0: 'Normal (N)', 1: 'Supraventricular (S)',
             2: 'Ventricular (V)', 3: 'Fusion (F)', 4: 'Unknown (Q)'}

fig, axes = plt.subplots(5, 3, figsize=(18, 20))
fig.suptitle("Model Predictions on Unseen Test Data (3 Samples per Class)", fontsize=20, y=1.02)
plt.subplots_adjust(hspace=0.5)

for class_id in range(5):
    specific_class_data = test_df[test_df[187] == class_id]

    if len(specific_class_data) < 3:
        print(f"Warning: Not enough samples for class {class_id}")
        continue

    random_samples = specific_class_data.sample(3)

    for i in range(3):
        signal = random_samples.iloc[i, :-1].values
        model_input = signal.reshape(1, 187, 1)
```

```
        prediction_prob = model.predict(model_input, verbose=0)
        predicted_class = np.argmax(prediction_prob)
        confidence = np.max(prediction_prob) * 100

        ax = axes[class_id, i]
        ax.plot(signal, color='black' if class_id == predicted_class else 'red')

        title_color = 'green' if class_id == predicted_class else 'red'

        ax.set_title(f"True: {class_map[class_id]}\nPred: {class_map[predicted_class]} ({confidence:.1f}%)",
                     color=title_color, fontsize=11, fontweight='bold')
        ax.grid(True, alpha=0.3)

        if i == 0:
            ax.set_ylabel("Amplitude")

plt.tight_layout()
plt.show()
```




```
df_normal = pd.read_csv(os.path.join(path, 'ptbdb_normal.csv'), header=None)
df_abnormal = pd.read_csv(os.path.join(path, 'ptbdb_abnormal.csv'), header=None)
df_ptb = pd.concat([df_normal, df_abnormal], axis=0)
df_ptb.columns = [f'sample_{i}' for i in range(df_ptb.shape[1]-1)] + ['label']
```

```
def trim_padding(signal):
    signal = np.array(signal)
    last_nonzero = np.max(np.nonzero(signal)) if np.any(signal != 0) else 0
    return signal[:last_nonzero + 1]
```

```
X_ptb = []
y_ptb = df_ptb['label'].values.astype(int)
for i in range(len(df_ptb)):
    signal = df_ptb.iloc[i, :-1].values
    trimmed = trim_padding(signal)
    X_ptb.append(trimmed)

max_len_ptb = max(len(s) for s in X_ptb)
print(f"Maximum signal length: {max_len_ptb}")
```

```
Maximum signal length: 186
```

```
X_ptb_padded = np.array([np.pad(s, (0, max_len_ptb - len(s)), 'constant') for s in X_ptb])
X_ptb_padded = X_ptb_padded[..., np.newaxis]

X_ptb_train, X_ptb_test, y_ptb_train, y_ptb_test = train_test_split(X_ptb_padded, y_ptb, test_size=0.2, random_state=42, strati

num_classes = 2
y_ptb_train_cat = to_categorical(y_ptb_train, num_classes=num_classes)
y_ptb_test_cat = to_categorical(y_ptb_test, num_classes=num_classes)
```

```
from tensorflow.keras.layers import MaxPooling1D
model_ptb = Sequential()
model_ptb.add(Conv1D(filters=32, kernel_size=5, activation='relu', input_shape=(max_len_ptb, 1)))
model_ptb.add(MaxPooling1D(pool_size=2))
model_ptb.add(Conv1D(filters=64, kernel_size=5, activation='relu'))
model_ptb.add(MaxPooling1D(pool_size=2))
model_ptb.add(Flatten())
model_ptb.add(Dense(128, activation='relu'))
model_ptb.add(Dropout(0.5))
model_ptb.add(Dense(num_classes, activation='softmax'))

model_ptb.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

history_ptb = model_ptb.fit(X_ptb_train, y_ptb_train_cat, epochs=20, batch_size=32, validation_split=0.2)
```

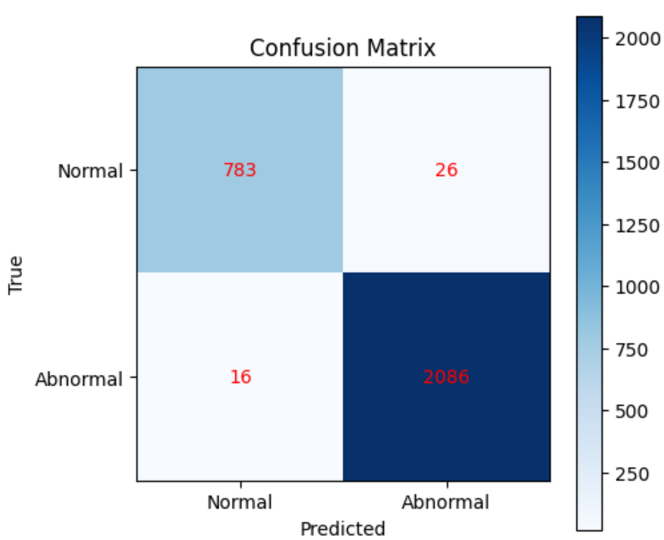
```
Epoch 1/20
291/291 ━━━━━━━━━━━━━━━━━━━━ 7s 7ms/step - accuracy: 0.7677 - loss: 0.4685 - val_accuracy: 0.8557 - val_loss: 0.3248
Epoch 2/20
291/291 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.8476 - loss: 0.3407 - val_accuracy: 0.8695 - val_loss: 0.2886
Epoch 3/20
291/291 ━━━━━━━━━━━━━━━━━━━━ 2s 3ms/step - accuracy: 0.8882 - loss: 0.2675 - val_accuracy: 0.8643 - val_loss: 0.2696
Epoch 4/20
291/291 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.9165 - loss: 0.2082 - val_accuracy: 0.9438 - val_loss: 0.1566
Epoch 5/20
291/291 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.9336 - loss: 0.1781 - val_accuracy: 0.9463 - val_loss: 0.1435
Epoch 6/20
291/291 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.9380 - loss: 0.1591 - val_accuracy: 0.9553 - val_loss: 0.1174
Epoch 7/20
291/291 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.9541 - loss: 0.1367 - val_accuracy: 0.9657 - val_loss: 0.0984
Epoch 8/20
291/291 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.9657 - loss: 0.1057 - val_accuracy: 0.9687 - val_loss: 0.0899
Epoch 9/20
291/291 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.9631 - loss: 0.1015 - val_accuracy: 0.9584 - val_loss: 0.1036
Epoch 10/20
291/291 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.9725 - loss: 0.0810 - val_accuracy: 0.9777 - val_loss: 0.0682
Epoch 11/20
291/291 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.9791 - loss: 0.0615 - val_accuracy: 0.9790 - val_loss: 0.0715
```

```
Epoch 12/20
291/291 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.9758 - loss: 0.0740 - val_accuracy: 0.9837 - val_loss: 0.0494
Epoch 13/20
291/291 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.9836 - loss: 0.0514 - val_accuracy: 0.9824 - val_loss: 0.0519
Epoch 14/20
291/291 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.9837 - loss: 0.0485 - val_accuracy: 0.9845 - val_loss: 0.0473
Epoch 15/20
291/291 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.9854 - loss: 0.0424 - val_accuracy: 0.9712 - val_loss: 0.0852
Epoch 16/20
291/291 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.9839 - loss: 0.0438 - val_accuracy: 0.9850 - val_loss: 0.0537
Epoch 17/20
291/291 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.9881 - loss: 0.0392 - val_accuracy: 0.9858 - val_loss: 0.0511
Epoch 18/20
291/291 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.9871 - loss: 0.0411 - val_accuracy: 0.9858 - val_loss: 0.0463
Epoch 19/20
291/291 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.9876 - loss: 0.0319 - val_accuracy: 0.9871 - val_loss: 0.0409
Epoch 20/20
291/291 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.9916 - loss: 0.0278 - val_accuracy: 0.9897 - val_loss: 0.0338
```

```python
loss, acc = model_ptb.evaluate(X_ptb_test, y_ptb_test_cat)
print(f'PTBDB Test Loss: {loss}')
print(f'PTBDB Test Accuracy: {acc}')

y_pred_ptb = np.argmax(model_ptb.predict(X_ptb_test), axis=1)
print(classification_report(y_ptb_test, y_pred_ptb, target_names=['Normal', 'Abnormal']))
```

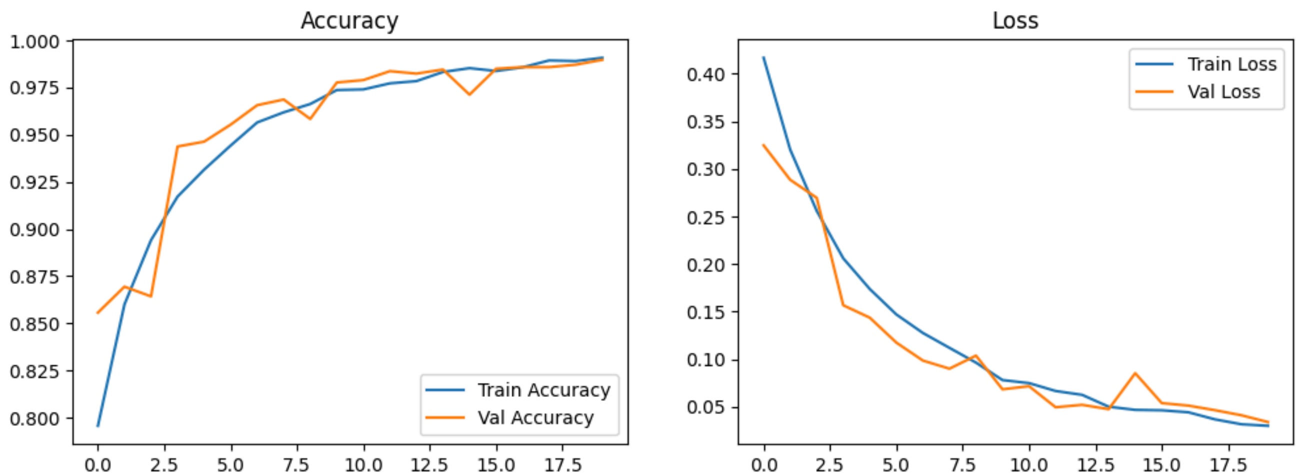
```
91/91 ━━━━━━━━━━━━━━━━━━━━ 1s 12ms/step - accuracy: 0.9874 - loss: 0.0485
PTBDB Test Loss: 0.06826324015855789
PTBDB Test Accuracy: 0.9855719804763794
91/91 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step
              precision    recall  f1-score   support

      Normal       0.98      0.97      0.97       809
    Abnormal       0.99      0.99      0.99      2102

    accuracy                           0.99      2911
   macro avg       0.98      0.98      0.98      2911
weighted avg       0.99      0.99      0.99      2911
```

```python
cm = confusion_matrix(y_ptb_test, y_pred_ptb)
plt.figure(figsize=(5,5))
plt.imshow(cm, cmap='Blues', interpolation='nearest')
plt.title('Confusion Matrix')
plt.colorbar()
plt.xticks([0,1], ['Normal', 'Abnormal'])
plt.yticks([0,1], ['Normal', 'Abnormal'])
plt.xlabel('Predicted')
plt.ylabel('True')
for i in range(2):
    for j in range(2):
        plt.text(j, i, cm[i, j], ha='center', va='center', color='red')
plt.show()
```




```python
plt.figure(figsize=(12,4))
plt.subplot(1,2,1)
```

```
plt.plot(history_ptb.history['accuracy'], label='Train Accuracy')
plt.plot(history_ptb.history['val_accuracy'], label='Val Accuracy')
plt.title('Accuracy')
plt.legend()

plt.subplot(1,2,2)
plt.plot(history_ptb.history['loss'], label='Train Loss')
plt.plot(history_ptb.history['val_loss'], label='Val Loss')
plt.title('Loss')
plt.legend()
plt.show()
```




```
for i in range(3):
    plt.figure(figsize=(12,4))
    plt.plot(X_ptb_padded[i].flatten())
    plt.title(f'Sample {i} - Label: {y_ptb[i]}')
    plt.show()
```